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THE EVOLUTION OF FIRMS AND INDUSTRIES

International Perspectives

SEPPO LAAKSONEN (ED.)

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PREFACE:
Promising New Research on Comparative Analysis of Enterprise Data

Traditional economic research on businesses has been based on aggregated data such as industries, if empirical data have been utilised at all. Fortunately advanced economists have not been satisfied to such a situation and have begun to require micro data for use. At the same time, more sophisticated econometric theory and softwares have been developed, so that today researchers in many countries are able to use longitudinal micro data, originally derived from censuses, registers and surveys. The future of researchers in enterprise-based micro data is not automatically rosy, since this kind of research is more demanding for reasons such as:

1 It is a newer field, and thus favouring this type of research may be a drawback for traditional research. This being the case, opposing reactions from traditional researchers arise and hinder the development of newer ideas.

2 It is more complicated theoretically, methodologically and practically, since it calls for the competence of economic theory, econometric and statistical methods, data environment as well as computer/software techniques. These factors usually lead the use of research teams, not of individuals.

3 The requirements placed on comparisons are of even greater importance than in traditional research. Comparisons between regions, between industries, and between and within firms are interesting, but comparisons between countries and cultures are still more interesting and motivated.

4 It is fairly easy to convince end-users of the usefulness of this research since it is very close to the real life of enterprises and other business units, but it is not easy to satisfy their needs, as these should be met immediately, and not after a number of years, which is often the time that needed because of many problems faced by beginners.

The motivation of most readers of this volume to use micro data of firms is maybe not difficult, since I assume that the readers have already either worked in the field, or are planning to start work in this field. I want, however, to quote some authorities to strengthen the readers belief to this research:

"The data – collected at an expense of tens of millions of dollars – lie unanalyzed in Census Bureau files. Though less apt to draw headlines than Congressional junkets and the overpayment of welfare recipients, this state of affairs is equally wasteful," wrote F. M. Scherer in 1980, based on a paper of R.H. McGuckin (1995) who at that time was the director of the CES (Center of Economic Studies) of the Bureau of U.S. Census. The CES has been a pioneer in utilising micro data of firms.

"Statistics involves analysing population characteristics in terms of probability distribution. In this sense, aggregated data are of very little use for statistical analysis. There is the need to deal with individual figures in order to analyse conditional distributions, correlations and all kinds of micro-phenomena. -- To better understand the economy, it is necessary to understand the contributions being made to it not only by the sectors, but also, by the individual enterprises." The writer here is P. Nanopoulos (1995), director of Eurostat. It is worth observing that essentially he is a policy maker of the European Commission, and in this capacity got the Eurostat project of enterprise panels started in the early 1990s.

The Eurostat Panels Project, which I was managing at that time, organised the first International Eurostat Workshop on *Techniques of Enterprise Panels* in Luxembourg, February 1994. This meeting had an audience of about one hundredth economists, statisticians and policy makers from all the world. Later, in 1995, the proceedings of the 35 papers was published. Many participants of the Luxembourg workshop met again in Washington, May 1995, at the Conference on *The Effects of Technology and Innovation on Firm Performance and Employment* arranged by the U.S. Academy of Sciences. The papers, some of which being preliminary, were distributed to all participants, but not published. The role of policy makers, both from governmental and private institutes, was considerable in Washington, their purpose being to find from the newest research auxiliary information for decision making. The third example of the meetings with parallel targets is the one held in Paris, November 1994, and organised by the OECD. This meeting was initiated by the 1994 G-7 Jobs Summit in Detroit where ministers requested that the OECD push forward its *work on the dynamics of job creation and job loss, focusing both on improving data comparability and deepening our analytical understanding of this process.* A special publication from 1996 is also available, see the reference list.

The above mentioned examples unavoidably lead to the conclusion that there was and will be the need for further meetings. Although only few participants from Finland attended in the said meetings, it was seen that we have good potential for research in this field, due to our rich data base. However this potential has not been used sufficiently. In order to push forward Finnish research and activate new researchers in this area, and of course in order to continue the traditions of the meetings in Luxembourg, Paris and Washington, the *Statistical Methods and Research Branch* of Statistics Finland together with two Finnish scientific associations (the Finnish Statistical Society and The Finnish Society for Economic Research), one university (Department of Statistics at the Swedish School of Economics and Business Administration) and one private research institute (The Research Institute of the Finnish Economy), decided to arrange a summer conference on the theme *Comparative Analysis of Enterprise Data, held on* 17–19 June 1996 in Helsinki. It was termed the *Caed'96 Conference,* as the attached logo also illustrates.

Our targets for the conference were:

A forum for economists, econometricians, statisticians, methodologists and policy makers who are interested in

- creating micro data on enterprises and other businesses, and in
- better utilizing them in economic and statistical research, and further in
- improving international and regional comparability of business data.

While a number of finalized and preliminary papers will be presented, the conference aims at giving the motivation for future research on methods and applications of international comparisons. It is the place where those who have similar interests will meet.

These targets were fairly well met, thanks to more than 40 paper contributors, about 60 other participants, 12 members of the scientific advisory committee[1], and local organisers[2]. We were happy in finding some financial sponsors[3] for the conference, too. *I wish to thank warmly all of you.*

Editing of the Proceedings

Any paper presented at a conference is of a great value, but if it is also revised and published, its value is even greater and more permanent, as well as easier to evaluate, and criticise too. We wanted to offer the opportunity for the contributors of the Caed'96 conference to publish an improved version of their papers in the Research Reports Series of Statistics Finland. This opportunity was utilised very well, and thus we have included 30 papers in this volume, which have been developed and often shortened since the 1996 June version. Some papers that are not published here, have been submitted to a journal or to other forums (see e.g. Baldwin 1996, Netherlands Official Statistics 11, 1996). The rest of the papers were not ready for publishing yet. The proceedings cover several countries, a number of fields from various international aspects. The overall representativeness is not complete, except maybe for Finland, since the eight Finnish papers included give a very good overview of the current Finnish activities in micro-based enterprise research.

The proceedings are divided into the six parts. Part A aims at giving motivation to the micro analysis of firms and international comparisons. There are very useful proposals from J. Wagner for further international cooperation, a fine summary by B. Jensen and R. McGuckin on recent results in this area, and some authentic comparison results across three countries and

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1 Gerhard Arminger, University of Wuppertal (Germany), Lutz Bellman, Employment Research Institute, Nuremberg (Germany), Silvia Biffignandi, University of Bergamo (Italy), Pierre Blanchard, University of Paris XII (France), Daniel Defays, Eurostat (Luxembourg), Tor Eriksson, University of Aarhus (Denmark), Tim Jones, Office for National Statistics (ONS) of the UK, Robert H. McGuckin, Center for Economic Studies, later The Conference Board (USA), Photis Nanopoulos, Eurostat (Luxembourg), Haim Regev, Central Bureau of Statistics (Israel), Bill Pattinson, Australian Bureau of Statistics, Kees Zeelenberg, Statistics Netherlands.

2 Seppo Laaksonen, Statistics Finland and the Finnish Statistical Society, Mika Maliranta, Statistics Finland, Markus Jäntti, The Finnish Society for Economic Research, Gunnar Rosenqvist, The Swedish School of Economics and Business Administration, Reija Lilja, The Research Institute of the Finnish Economy, and The Secretariat consisting of Minna Hänninen, Tuula Jonasson, Marjo Koponen, Milla Laaksonen, Erika Ristiluoma and Mette Sundqvist.

3 Statistics Finland, The Swedish School of Economics, Research Institute for the Finnish Economy, SITRA, Foundation for Economic Education, The Jahnsson Foundation, Eurostat, Nokia.

continents, written by K. Motohashi. The authors of Parts B and C give some starting points for tools, methods and other techniques for collecting and handling enterprise data. It is useful to understand that completed statistical data files require much work and harmonisation with classifications and indexations, as well as attempts to construct better and better sampling frames and to design samples in a co-ordinated and optimal manner. The paper by G. Arminger demonstrates well that statistical methodology may look very difficult, but can be fairly easily computable thanks to new softwares.

The last three parts concentrate on concrete exercises on micro data analyses that are longitudinal in most cases. Part D first starts with enterprise demography, a new interesting research area, which should be taken into account in other dynamic analyses, such as the ones presented in Parts E and F. We see clearly that recent research has focused much on the effects of research and development (R&D) expenditure, technology and innovations on the performance and productivity of firms. The papers in Part E give interesting new findings on these questions. However, we know that much more research has been done and much more is under consideration. The topic in Part F is narrower in scope than that in Part E, focusing on the econometric applications in wages using enterprise and establishment data. Although the last paper in this book does not cover wages formation widely, it is by no means the least interesting one. Instead it sums up the basic themes of the conference very well, by comparing exporting firms between the U.S. and Germany.

We received the papers in slightly different formats, but we have tried to do our best in harmonising these styles. This was not an easy task, and I hope that no serious mistakes occurred. My excellent partner in this work has been *Minna Hänninen*, who did a good job in carrying out responsible tasks in the conference organisation too. I thus particularly wish to thank her for her productivity and innovativity. Last but not least, I wish to recognise the superb editorial work provided by *Hilkka Lehikoinen*.

Helsinki, March 1997

Seppo Laaksonen
Editor

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Part C: Frames and Sampling

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Part E: R&D, Performance and Productivity

Part F: Wages, Technology, Exports

Part A

Need for Comparative Micro Analysis of Enterprises

Wagner

What is to be done to facilitate international comparisons using enterprise data?

- To deal with the problem of incomparability, any effort should be made to reach a high degree of *ex-post comparability* by 'harmonising' existing data sets across countries. Therefore, one should at least try to avoid the problem of incomparability by implementing *ex-ante comparability.*
- To tackle the problem of lack of knowledge of country-specific institutional details, the formation of international networks of researchers interested in specific questions is an obvious strategy. Here a congress like this one comes in, and thanks to Internet & Co. the transaction costs related to international co-operation are diminishing rapidly.

Jensen and McGuckin

Competition must be understood as a process in which some firms choose correctly and grow while other firms choose poorly and die; the growth of the successful firms at the expense of less successful rivals drives economic growth.

The relationship of a plant's age to performance is similar to the effect of a plant's size on performance. This is not unexpected because both variables are intimately related to the competitive process. The more a firm grows (the bigger it is) the more likely it is to survive another period (the older it is). But, while size and age are correlated, age has an independent effect on performance.

... unobserved business unit characteristics like management practices, production process, and so forth, play a large role in performance differences. In turn, the important determinants of plant performance are now beginning to be studied by economists. Many of these, for example, differences in plant technologies (process and products) and managerial skills and practices, have been the provence of the case study or business school approach.

How stable are intraindustry distributions of plant characteristics over time? The evidence on persistence is relatively new, but a picture of how the distribution of plants evolves over time is beginning to emerge.

Motohashi

... by addressing issues of international studies of microdata sets. Two issues are raised; one is differences in data and the other is differences in nation's economy itself. As for the first one, one should be careful for the data unit as well as definitions of variables. As for the second one, in an interpretation of comparative quantitative results, one should take into account various kinds of factors coming from different economic situations.

Although the data similarity of Japan and the U.S. implies that the Japanese economy is less dynamic as compared to the U.S., its comparison to France is difficult due to the data unit differences.

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THE USE OF ENTERPRISE PANEL DATA FOR INTERNATIONAL COMPARISONS: Payoffs, Problems, and Proposals

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This paper discusses payoffs from using longitudinal micro data at the firm level collected in several countries, points to problems that hinder international comparative research based on such data, and makes proposals for promoting their future use.

Key words: Panel Data, International Comparisons, Institutions, Stylized Facts, Comparability.

1. Introduction

Over the past decade, firm level panel data became available to researchers inside and outside the statistical offices in more and more countries, and these newly available data sets lead to a number of important insights, demonstrating that both *micro* data and *longitudinal* data are needed to investigate many important topics in industrial economics, labour economics, etc. (cf. the papers in European Commission 1995). The bulk of this research has a focus on a single country, although often the topics dealt with are investigated in other countries with similar data sets, too. Obviously, therefore, *the use of enterprise panel data for international comparisons* is a topic on the agenda of panelists, and in this lecture I will outline what in my view are the potential *payoffs* we can expect from adding *space* as another dimension to our data sets, where the most important *problems* in this kind of business are to be found, and which *proposals* should be discussed as the next steps in this emerging field.

2. Payoffs

Let me start by considering the question *What can we learn from international comparisons using enterprise data?* In my view, there are three related payoffs from this approach:

1 International comparisons can help us to find out where we have to search for an answer to an economic puzzle, or for a solution for an economic problem under investigation – shall we look at country specific factors like institutions in industrial relations, or shall we focus on the way modern industrial societies are organised in general?

To illustrate, let me consider an example: In the late 1980s a number of papers were published presenting evidence for the existence of substantial rents accruing to labour in different industries. These non-competitive wage differentials which are observed after controlling for individual characteristics (e.g., human capital) and characteristics of the work place (e.g., firm size) qualify as an 'anomaly' (Thaler 1989), and efforts to unravel the mystery of these industry wage patterns are going on. As Krueger and Summers (1987, p. 24f.) pointed out, results from international comparisons on inter-industry wage patterns can have an influence on the direction of this research: *"If the wage differentials ... are due to the particular institutions of the US economy we would not expect to find a similar pattern of wage differences in other countries. On the other hand, if diverse countries have similar wage structures we have evidence that a common thread across all countries, such as technology, is responsible for these wage differences."* (In parentheses I note that I followed this advice in Wagner (1990a), using comparable micro data from five countries, but could not present clear-cut results based thereon because the data sets were both too small and the information in it was too limited in a number of ways.)

Therefore, if you find an empirical result based on one data set from one country that is *puzzling* (e.g., that contradicts sound theoretical priors), replicate your study with other data sets from the same country to see whether the puzzling result is due to data idiosyncrasies, or errors. If the puzzle remains after replication, look at data sets from other countries: If the puzzling result is country specific, look at country specific institutions that can explain it (e.g., legal entry barries in a market, or rules that govern the labour market); if the puzzling result is found in data from other countries, too, start thinking again about your theoretical priors.

2 International comparative research can help to establish 'stylized facts' – or to cast doubts on the general validity of what some people believe to be 'empirical laws'. To quote at some length from a recently published book by Blanchflower and Oswald (1994, 240f.):

"It has been traditional in empirical economic research for investigators to concentrate in depth upon a single country. Although such an approach has advantages – for example, it may make it easier for the economist to be knowledgeable about the institutional background to a problem – its weaknesses are apparent. Patterns found in one nation may be special to that setting. Estimated coefficients may not be deep ones about economic structures, as an analyst would be prone to hope. They may instead reflect mundane problems in measurement that are in turn the product of some peculiarity of data collection, or of data definition, or of national idiosyncrasy. ... Despite tradition, the ability to establish an empirical finding across many nations has intuitive and scientific appeal. The commonsense checks that it offers are obvious."

To give an example, consider the book by Blachflower and Oswald (1994) we just quoted from: The authors used micro data sets for individuals and firms from many countries to investigate the relationship between wages and unemployment, and they found what they termed the wage curve – a downward-sloping convex ceteris paribus relationship between the wage level and the regional rate of unemployment. In their preferred standard specification that has the regional rate of unemployment included in logs the estimated regression coefficient shows that the average unemployment elasticity of pay is approximately –0.1 for the countries under investigation. These findings are considered by Blanchflower and Oswald to establish an empirical law of economics, and given that it is based on data sets from several countries with different institutional settings etc. their plea for a general validity of the wage curve surely is more convincing than it would have been the case when the econometric results were based on US data alone – however, given my own results using a large establishment level data set reported in Wagner (1996) I doubt that there is a wage curve in Germany.

Let me add some remarks on my own experience in a similar field, again related to labour economics and the use of micro data from several countries: In 1988 Wilhelm Lorenz and I published a small paper in which we used several large sets of German data to demonstrate that some important statistical assumptions made when estimating earnings functions of the popular Mincer type – models explaining the wage of an individual by regressing it on the years of schooling and experience of the person – by OLS are not justified (Wagner and Lorenz 1988). Some people argued that these results might be caused by peculiarities of either the German labour market, or the German data sets, or both – an international comparative study that used data from five countries (Wagner 1990b) showed that this was not the case.

Therefore, similarly to the advice given at the end of point (1) above, if you find an empirical result based on one data set from one country that you believe is *valid, and important* to understand an economic issue, replicate your study with other data sets from the same country to make sure that the result is not due to data idiosyncrasies, or errors. If the result still holds after replication, look at results using data sets from other countries: We can speak of generally valid empirical laws only if results hold for all countries and all data sets investigated, or if we have sound explanations why some countries or some data are exceptions.

3 International comparative research is a way to investigate the role of institutions that do not change over time: As pointed out by Mark Doms et al. (1995), identifying the effects of a country's specific institutions (e.g., antitrust policies, or the system of industrial relations) on, for example, productivity growth is not possible by looking at data from this country alone when these institutions do not vary significantly over the time period considered, and this is often the case. However, a comparison across countries (e.g., looking at different institutions, but the same industry) can assist in identifying the effects of various institutions on economic growth.

To give an example of the way cross-country comparisons can help to understand the role of country specific institutions, consider the relationship between unions and investment in research and development (R&D) (Addison and Wagner 1994a): One important empirical regularity in analysis of the effect of U.S. unionism on economic performance is the negative association between union membership / contract coverage density and investment in intangible capital. As in all studies of union impact on economic performance, however, the interpretation of this evidence is controversial – does lower R&D in more highly unionised firms reflect reduced incentives for such investments due to union capture of quasi-rents, or does it instead indicate that unions are concentrated in older plants and mature industries? Given the problems related to measuring the maturity of technology and to the endogeneity of unionism, this issue can not be settled with data from the U.S. alone. Richard Freeman (1991, 160) suggested an indirect and subsidiary test procedure, namely *"to correlate U.S. union density by industry with*

R&D investment by industry in a country whose firms could not possibly be influenced by U.S. unionism (say, Germany or Sweden)." The idea is quite simple: if union density in U.S. industries and R&D investment in the same German industries are significantly negatively correlated, this supports the hypothesis of a mature industry or structural interpretation of the U.S. findings – if the correlation is negligible, the hypothesis of a direct causal influence of U.S. unionism is supported. Using R&D data for German industries and union density data for U.S. industries, Addison and Wagner (1994a) implemented this suggestion by Freeman, and we found results that tentatively support the hypothesis that U.S. unionism reduces R&D actively rather than being associated with industry-specific factors that independently produce lower investments in intangible capital in precisely those sectors where unions are concentrated. The same procedure was used in another paper to investigate this issue for the UK, again using German industry data on R&D as a benchmark (see Addison and Wagner 1994b).

Let me state this third point a little bit more technically: when we have firm panel data, we can control for unobserved heterogeneity of firms by eliminating effects that are specific to a unit of observation but invariant over time, and we can control for effects that are the same for all firms in a certain period but that vary over time. However, we can *not* control for effects that neither vary across firms nor over time – *institutions.* We need one more dimension in our data sets to make this possible – *space,* i.e. comparable data from other countries with different institutions.

3. Problems

Given these payoffs, an obvious question that comes in mind is *Why are there so few international comparisons using establishment data?* In my view there are three main problems:

1 *Restricted availability of data:* Given the strong data protection laws in many countries (e.g., Germany), micro data, and especially firm data from official statistics, are often available to people only who are working in – or in very close co-operation with – the Statistical Office preparing these data (see Wagner 1995 for a description of such a joint project). Similar restrictions regarding the dissemination of enterprise data also often apply to data sets collected in surveys by research teams, because most of the time the promise to keep the data confidential is a prerequisite for a successful survey. Therefore, it is difficult, if not impossible, to get hold of firm level data from various countries.

2 *Incomparability of data across countries:* Everybody who ever tried to do the same empirical investigation using firm data from more than one country knows that this is often a very tricky business. Consider the way the *unit of observation* is defined (Is it the establishment in the sense of a local production unit? Is it a legal unit – enterprise – that may or may not consist of several establishments? Is it something different defined for a certain administrative procedure?), the *population* covered (Are units below a certain threshold of, say, x employees excluded? Is this critical size identical across the countries considered?), the *regions* (Is it possible to compare, say, a *county* in the US with a *Kreis* in Germany? Do the regions used in the data from various countries all come close to labour market regions in an economic sense to the same degree?), and the *variables* to be included (e.g., financial variables that mean different things in different countries because the accounting procedures that form their basis are different) – all these ingredients of the empirical model to be estimated can and often do differ across space. Given these incompatibilities, one can often not state with certainty whether a different outcome of a regression equation is due to institutional differences between countries, or due to measurement error in the sense that X2 in the UK regression is different from X2 in the regression for France (or, contrarily, that the same vector of ß's for Germany and Finland indicates that institutional differences do not matter at all).

3 *Lack of knowledge of country specific institutional details:* This problem is obvious; it is to a large extent due to the fact that the rules of the game in modern industrial societies tend to be rather complex, and that often a sound description is not available in a language that is accessible to a researcher who plans to do an international comparison.

4. Proposals

Given on the one hand the large payoffs mentioned, and the problems identified above on the other hand, the remaining question is *What is to be done to facilitate international comparisons using enterprise data*? Here I want to make three proposals:

1 To deal with the problem of incomparability, any effort should be made to reach a high degree of *ex-post comparability* by 'harmonising' existing data sets across countries. As can be seen from the productivity project by

Doms et al. (1995) this often is a tedious task, and it is not valued by the profession as high as it should be. Moreover, we often end up with only a few variables when we search for the 'smallest common denominator' of data sets from various countries, being forced to drop a lot of information that is not available in comparable form, and this problem tends to become more severe with every country added to the investigation. Therefore, one should at least try to avoid the problem of incomparability by implementing *ex-ante comparability.* By this I mean that, ideally, the survey the data are collected in should be harmonised internationally in any respect from the beginning. Obviously, this is easily said, but extremely difficult to do. But we do have examples for this approach – consider the Community Innovation Survey (European Commission 1994), and the firm panels in Luxembourg, Lorraine, and Wallonia (cf. Tibesar 1995).

2 To tackle the problem of lack of knowledge of country-specific institutional details, the formation of international networks of researchers interested in specific questions is an obvious strategy. Here a congress like this one comes in, and thanks to Internet & Co. the transaction costs related to international co-operation are diminishing rapidly.

3 Formation of international networks may help to solve the problem of limited availability of firm data, too. Furthermore, we should go on dreaming of a data base with firm panel data for many countries located on a server somewhere, and easily accessible in the WWW. There is at least one role model for this using household data – the Luxembourg Income Study (LIS), information on which is available at *http://gerosun.syr.edu.* Surely, given the confidentiality rules these versions of the data have to be anonymized, and might not contain all the information available in the original data sets. However, they can serve as a starting point for international comparison projects.

To conclude, let me quote from Richard Freeman's (1989, p. 209) "Labour Markets in Action":

"The parochialism of concentrating on the experience of only one country is remarkable in a science that purports to rest on a general theory of markets. It limits our progress in understanding how economies function in three ways: first by discarding potential tests of theories (sorely needed in the absence of laboratory experiments); second by ignoring natural experiments in

other countries (sorely needed in the absence of laboratory experiments), and third by making economic institutions peripheral rather than major topics of concern."

I fully subscribe to this position. Furthermore, I believe that in a time when the objects of our research (firms) are more and more linked internationally, we, our research, and the data we use should become linked across space, too.

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FIRM PERFORMANCE AND EVOLUTION: Empirical Regularities in the U.S. Microdata

J. Bradford Jensen,
Center for Economic Studies,
and
Robert H. McGuckin,
The Conference Board,
U.S.A.

This paper presents a view of firm performance, industry evolution, and economic growth that contrasts with the traditional representative firm model. The paper reviews recent empirical work, primarily studies using the Longitudinal Research Database (LRD), that explicitly focuses on individual business units. The major empirical regularity in the studies is that heterogeneity is pervasive – it is found across and within all sectors and across all plant characteristics. Further, firms are not only different in the cross-section. They enter at different times, make different choices, and react differently to economic shocks. Thus, to understand economic performance and competition, one must move beyond representative firm models. Competition must be understood as a process in which some firms choose correctly and grow while other firms choose poorly and die; the growth of the successful firms at the expense of less successful rivals drives economic growth.

Key words: Competition, Economic Growth, Longitudinal Panel Data.

1. Introduction

The main purpose of this paper is to explore what we know and how we think about firm performance, firm and industry evolution, and economic growth. To this end, we report empirical findings from a new literature that explicitly focuses on individual business units. This literature has been spurred by recent theoretical developments and, perhaps more importantly, the development of longitudinal microdata that track individual plants over time. In contrast to traditional empirical studies of competition and economic growth that examine aggregate economic variables such as industry or regional productivity, this new work concentrates on differences in the behaviour of firms and their business units. The results emerging from these analyses confirm the importance of microeconomic approaches to economic research and place the firm at the center of economic growth.

The idea that differences in firms are important to understanding economic growth and the performance of capitalist economies is not new to economists. Schumpeter (1942) describes the process by which competition produces economic growth and improvements in living standards as one of "creative destruction." Firms constantly search for new products and new ways of doing things to try to gain competitive advantage.

"The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportation, the new markets, the new forms of industrial organisation that capitalist enterprise creates" (page 83).

Viewed from this perspective, firms are, to put it colloquially, where the action is. Economic growth is not evenly spread across firms. Some firms make correct choices. These firms prosper and grow. Other firms make mistakes. These firms contract and die. Economic growth is the outcome of successful firms replacing less successful firms. It is the growth of successful firms, and the decline of less successful firms, that raises overall productivity.

While Schumpeter's view of the competitive process is compelling, it has not been the primary foundation for empirical research in economics. Academic research has been structured around the "representative firm" model. In this model, firms in the same industry use the same production processes, produce identical products, and face identical costs. Thus, all firms react similarly to shocks and the "industry" becomes the effective unit of analysis. Using this model has meant that research in industrial organisation and economic growth, both theoretical and empirical, has usually focused on explaining differences in "industry" performance, not the determinants of "firm" performance and success.[1]

Two related impediments account for the paucity of micro approaches to the study of competition and economic growth. First, the lack of statistics at the business unit or plant level has made research in the area difficult. Most

1 This is in sharp contrast to the business literature that focuses on case studies of particular business units and the operation of firms.

governmental statistics are provided at aggregate levels broader than firms or plants.[1] Government data are disseminated in aggregative formats to protect the confidentiality of the data. New programs for data access that provide researchers the means to analyse the microdata and protect respondent confidentiality have been important to the development of the new empirical literature (See McGuckin 1992, 1995; McGuckin and Reznek 1993, 1996).

Second, it is only recently that computer resources have been capable of handling the extensive data and mathematical calculations required for more microeconomic approaches. Both of these previous limitations influenced the direction of economic research toward the representative firm model.[2]

With new empirical research possibilities, the past 15–20 years have seen a number of new models in the economic literature describing firm behaviour and the associated industry dynamics. A common feature of these models is that uncertainty and limited information cause firms to take different approaches to common problems, thereby generating heterogeneity among firms, even within the same industry or product grouping. These theoretical developments, coupled with new databases and powerful computers, have led to a flood of empirical studies of firm behaviour and performance. Generally speaking, the empirical relationships confirm the relevance of the new theoretical approaches. The real world appears much closer to that described by Schumpeter than to the one that exists in most economic models; the behaviour of firms within industries differs dramatically.

Heterogeneity in the distribution of business units is pervasive along a wide variety of dimensions. Even within the same geographic areas and the same four-digit industries and fivedigit product classes, as defined by the Standard Industrial Classification (SIC), firms differ dramatically. Heterogeneity is observed across time as well as in the cross-section (Davis, Haltiwanger, and Schuh 1996). Not only does the growth process differ across firms, it is characterised by large, discrete movements rather than smooth or continuous changes even for those firms in continuous operation (Doms and Dunne 1994; Power 1995). During any time interval, observed changes are

1 Even when microdata on firms is publicly available, it usually is for large, multi-unit firms operating in many industries. Use of firm-level data under these circumstances leads to serious aggregation biases in the study of business behaviour. See McGuckin and Nguyen (1995).

2 A related factor is that most economists simply did not think that the biases inherent in misspecified industry- and economy-wide models were very large. Of course, in the absence of access to the microdata, there was simply no other alternative than to use the aggregative data.

"lumpy" and uneven, some business units open and some grow, while others shrink and die.

Taken together, this evidence rejects representative firm models and empirical analyses based on industry-level observations. Economic performance and competition cannot be understood in terms of differences in the behaviour of an "average" firm in an industrylevel analysis.[1] In fact, most of the observed variation in the data is *within* industries.[2] Moreover, the vast majority of this variation is *not* associated with traditional observables such as location, industry, size, age, or capital. Rather, this variation is associated with unobserved firm- or business unit-specific factors, many of which appear to be longlived attributes of the business unit.

We begin the paper with a brief discussion of the new modelling approaches used to explore firm performance and associated industry dynamics. This section is brief, introduced simply to provide context for the main body of the paper. The primary focus of the paper is to describe empirical regularities emerging from the new research with microdata.

We review the empirical literature and describe the emerging empirical regularities that inform our understanding of firm performance and evolution. We make no attempt to be comprehensive in the studies we cover. References are primarily to studies using the Longitudinal Research Database (LRD), an extensive database of longitudinal plant-level data covering the inputs and outputs of virtually every manufacturing plant in the U.S. since 1963.[3] This database has supported a large volume and wide range of policy and academic research over the last seven or eight years.[4] The discussion of empirical regularities is organised in terms of a simple empirical model that categorises the factors that determine a plant's behaviour into those 1) specific to the plant, 2) associated with the firm that owns or manages it, and 3) related to the industry or products that comprise its output.

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1 For the representative firm model to fail, the functions that aggregate individual firm responses into aggregate variables need to be non-linear. As indicated, this condition is satisfied both in the cross-section and over time.

2 Davis, Haltiwanger, and Schuh (1996) is the most comprehensive source in terms of the number of factors examined. Extensive heterogeneity is not restricted to the U.S. (In addition to the above cited book see Baldwin, Dunne, and Haltiwanger 1994, which compares job flows in the U.S. and Canada).

3 The LRD is housed at CES, an economic research unit of the U.S. Census Bureau.

4 See McGuckin and Pascoe (1988) for a description of the LRD. Research with the LRD is described in McGuckin (1995), McGuckin and Reznek (1993), and the annual reports of the CES.

After describing the empirical regularities in the cross-section, we move to a more dynamic picture of firm performance,[1] reviewing the literature on how firm characteristics change over time and providing some new evidence on how persistent firm performance is across time.

We then describe how understanding the underlying firm-level dynamics is critical to understanding industry performance and structure. Firm dynamics, the growth of successful firms and the demise of unsuccessful firms, determine observable industry characteristics. Further, the underlying heterogeneity of firms affects how the aggregate economy responds to exogenous shocks. While a clearer picture of firm performance and evolution and how these affect aggregate performance is emerging, more work is needed. We suggest areas for future research in our conclusion.

2. Beyond the Representative Firm, Theoretical Background

Competition is a dynamic process involving many dimensions. Modelling it in ways that allow individual firms to differ is necessarily abstract and complex. The criticism of the representative firm approach has a long history. Nelson and Winter (1982) succinctly stated the case for developing explicit models of firm behaviour:

"... it [is] inevitable that models built according to the orthodox blueprints miss completely or deal awkwardly with these [a large degree of uncertainty and limited information available to firms trying to decide what is their best strategy] features of economic change" (page 400).

Firms operating in an uncertain world with limited information choose to produce different products and employ different production methods. In turn, these different choices generate heterogeneity among firms, even among firms classified within the same industry. Firms are different – they enter at different times, have different investment patterns, possess different information, use different production technologies, pay different wages, and so on – and this causes them to react differently to changes in their environment. Thus firms adjust to economic shocks differently, implying that change is idiosyncratic or firmspecific.

Nelson and Winter were not alone in their attempt to develop new approaches to modelling firm behaviour. Jovanovic (1982) and Pakes and Eric-

1 While there have been some panel studies, most of the work to data has been cross-sectional, with the longitudinal data primarily used to construct specific measures of change at the plant level.

son (1989) also developed models of firm performance and behaviour that captured the uncertainty and limited information that characterises firm decision making. In contrast to Nelson and Winter, these authors did not abandon the use of models with long-run equilibrium properties. The equilibrium models feature firms that learn (either actively or passively) about their relative efficiency, their product quality, and/or the profitability of their research and development (R&D) as part of ongoing operations, usually within a specific industry.[1] As the firms learn about themselves, they make decisions about whether to continue in operation or to close. The models predict systematic differences in firm growth, generate testable predictions about the distribution of size, age, and growth rates of firms *within* particular industries. The steady state distribution of firms is characterised by heterogeneous firms (firms with different sizes and ages) in which change has a large idiosyncratic (firm-specific) component. Thus, the models provide a framework for structuring empirical analysis of firm and market behaviour that allows for 1) intra-industry heterogeneity and 2) idiosyncratic (firm-specific) sources of change.

A key issue that the new models highlight is that with heterogeneous firms and idiosyncratic sources of growth, selection mechanisms are very important. That is, the factors that determine which firms survive and grow and which fail and die are important to both firm competition and growth and industry evolution. Firms that are relatively productive will choose to continue in the industry and will grow. Firms that are less productive will lose market share and eventually go out of business. For an excellent example of empirical work using this modelling approach, see Olley and Pakes (1996). As we discuss in more detail below, just what factors determine firm success and failure remains an important open question.

3. Empirical Regularities

Our stated goal is to review what we know and how we think about firm performance and evolution. Recent theoretical developments suggest that given the degree of uncertainty in the environment and the lack of information about the "right" way to do something, there is likely to be considerable firm-level heterogeneity. This heterogeneity is the result of experimentation by different firms. Further, the theoretical literature posits that this heterogeneity will affect

1 In the models, the firm's initial position is based on a random draw from a distribution of efficiencies.

firm-level dynamics and, ultimately, industry and aggregate performance. What does the empirical literature have to say about this view of the world?

The empirical literature has seen extensions that parallel those in theoretical literature. While this research area is still fairly young, a number of empirical regularities have emerged. Of particular interest, the new empirical work confirms the importance of the theoretical approaches outlined above. For example, the most compelling empirical regularity confronting researchers is the tremendous amount of diversity in firm and plant characteristics and behaviour. Even within industries, firms have very different attributes along many observable dimensions such as size, age, wages, productivity, job creation and destruction, investment patterns, and productivity growth. In fact, within-industry differences among firms along practically every dimension show greater variability than the variability of the average of the same variable between industries (Davis, Haltiwanger and Schuh 1996).[1]

While there is tremendous heterogeneity in plant characteristics and plant performance, researchers are identifying relationships between theses characteristics and performance. It is useful to think of this variation in plant performance as attributable to four sources: 1) plantspecific factors, 2) characteristics associated with the firm that owns the plant, 3) factors associated with the industry in which the plant produces, and 4) a stochastic error component.[2] This framework provides a convenient way to categorise the empirical evidence, most of which relies on the plant as the unit of analysis.[3] While the allocation of variables to a particular category is difficult and sometimes arbitrary, from the broad perspective adopted here, such concerns can probably be ignored.

It is also useful to distinguish between observable and unobservable variables within each source. Typical variables in the observable category for plant-specific factors include age, size, and location, all variables that have

1 While some of the heterogeneity within industries may result from poorly defined SICs, this source of error is unlikely to eliminate the heterogeneity since it is observed in virtually all industries and even in product class groupings.

2 We ignore interaction effects for the purposes of this discussion, but they might be significant in the data.

3 McGuckin (1992) argues that the plant is the preferred unit of analysis in most applications. McGuckin and Nguyen (1995) show that for analysis of ownership change, the use of the firm as the unit of analysis leads to aggregation biases that are not present when the plant is the unit of analysis.

been extensively studied.[1] Unobservable variables include many things that are important determinants of behaviour and are now beginning to be studied by economists. Prime examples are employment practices, managerial skills, and business unit organisation and knowledge.[2] These factors have been the subject of both case studies and special surveys. What is new is that with the advent of broadbased, longitudinal data they are now becoming a subject for more generalised economic research. The new longitudinal microdata have begun to allow researchers to control for previously omitted unobservable characteristics.

Plant Effects

We begin our discussion of plant effects by focusing on size and age.[3] We have chosen to treat size and age separately from other observable plant characteristics because they are by far the most studied. In many respects, these characteristics also offer the most severe problems of interpretation.

A. Size and Age

As business unit and firm microdata have become available, studies of the relationships between firm (and plant) growth, survival, and mortality and their differences by size and age have been a main focus of empirical efforts. Most of the early work with the microdata focused on policy issues, using sophisticated econometric techniques to sort out the influences of various sources of measurement error (transitory stochastic influences reflected in base year observations, regression to the mean problems, and arbitrary size classifications). Evans (1987a, 1987b), Hall (1987), and Dunne, Roberts, and Samuelson (1989) are important examples of this work in the industrial organisation tradition, while Brown and Medoff (1990), and Davis, Haltiwanger, and Schuh (1996) provide insights on size-growth relationships from the labour perspective. There is also substantial work from other countries, (e.g., Canada, France, Holland, Australia, and Germany) on the relationship of size and job creation and destruction. While

1 In principle, we also could include "industry" in the list of observable plant characteristics. However, it is useful to distinguish this variable separately since industry has, until recently, been the main unit of observation in empirical work.

2 These idiosyncratic or unobservable factors generally include human and organisational capital. See Gort, Grawbowski, and McGuckin (1985) for a discussion of the differences between the two types of capital.

3 Unless explicitly noted, the results described throughout this section are independent of the particular business unit behaviour or performance measure used as the dependent or the "to be explained" variable.

the precise relationships differ among countries, this literature has made great strides in showing the potential pitfalls in drawing conclusions based on faulty statistical designs.

The focus on age and size distributions can be attributable in part to the relative availability of measures identifying the size and age of a business unit and firm. But the focus on these variables also reflects the importance of the size distribution in industrial organisation analyses, particularly in the antitrust and oligopoly areas and the popularity of industrial policy focused on "small" business. Much of the work reflects attempts to identify the role of small business in job creation and economic growth and has been driven by policy concerns. This is a major reason for the focus on statistical issues in the literature.

The relationship of a plant's age to performance is similar to the effect of a plant's size on performance. This is not unexpected because both variables are intimately related to the competitive process. The more a firm grows (the bigger it is) the more likely it is to survive another period (the older it is). But, while size and age are correlated, age has an independent effect on performance. For example, Bates and Nucci (1990) find that the probability of firm failure is inversely related with age, even after controlling for the size of the business.

This is not the place to undertake a detailed discussion of size and age. Numerous empirical studies suggest that plants of different sizes have significantly different characteristics and performance. Bigger plants tend to be more capital intensive, more productive, more likely to adopt technological innovations, more likely to export, and pay higher wages. Because size is correlated with all of these other characteristics, it is important to control for size in studies examining plant performance. While it is clear that size and age are important observables that need to be controlled for in empirical models of business behaviour, in many respects they raise serious difficulties for empirical researchers. Size and age are outcomes of the competitive process, and to include them in estimating equations designed to explain firm performance begs the question of what factors determine whether firms succeed or fail. Moreover, when the empirical focus is on size and age, the workings of the firm tend to be obscured and the firm is treated as a "black box."

B. Standard Control Variables

Aside from age and size there are a wide range of observable factors that are regularly introduced as explanatory variables in regressions using plant performance as the dependent variable. Virtually every study with the LRD includes regional dummy variables as controls and they are generally significant.

Ownership status is another important variable utilised in empirical studies of plant performance. In empirical studies, plants are often divided into two classes, single-unit and multi-unit plants, for estimating purposes. Single-unit plants belong to firms that have no other operations distinct from the single plant. Multi-unit plants, in contrast, are plants that are owned by firms with other establishments. Typically, multi-unit plants pay higher wages than single-unit plants. Further, multiunit plants tend to be bigger, more productive (McGuckin, Streitwieser, and Doms 1996), and more likely to export (Bernard and Jensen 1995). While virtually every study of plant performance controls for this aspect of the structure of the firm, it is difficult to determine the exact source of the positive relationship found. A positive relationship is likely associated with a positive firm effect – large successful firms are most likely to be multi-unit. It is also the result of measurement error in the plant's performance measure because inputs supplied by the firm are included in the single unit's costs, but not in the multi-unit's.

Capital intensity – assets per employee – is another plant characteristic that is positively associated with plant performance. Capital intensity is also associated with plant size. Bigger plants are more capital intensive. But, researchers find that capital intensity is positively associated with plant survival and wages even after controlling for other observable plant characteristics such as size (see, for example, Dunne and Roberts 1990).

C. Other Variables

Researchers have been able to merge data from other sources (for example, Special Census Bureau Surveys) to the basic LRD data to create new datasets with additional variables. Such datasets have been invaluable in extending the list of factors that have been empirically linked to business unit performance. Importantly, they tend to bring the detail of the case study approach to the more general setting of the typical economic study. They accomplish this by developing econometric experimental models that exploit general databases with probabilistic designs, like the LRD, to control for selection and other biases inherent in studies relying on particular cases or limited survey information. See Jarmin (1995) for a more complete description of this approach in the context of evaluating a particular government program.

One survey that has been particularly fruitful in this regard is the Survey of Manufacturing Technology (SMT). The SMT is a plant-level survey covering four two-digit manufacturing industries (SICs 34–38). It develops information on the use of 17 relatively recent advanced computer-based technologies. Examples of such technology include robotics and Computer-Added Design (CAD). Dunne (1991) and Dunne and Schmitz (1992) explore the relationship between plant characteristics, wages, and technology adoption using a 1988 version of the survey. In addition, McGuckin, Streitwieser, and Doms (1996), Doms, Dunne, and Troske (1996), and Dunne and Troske (1996), use the 1988 SMT, in conjunction with a newer version of it conducted in 1993, to examine the effects of technology adoption on business unit performance.

These studies suggest that larger plants, multi-unit plants, plants engaged in defense-related production, and plants owned by firms with high R&D to sales ratios are more likely to adopt advanced technologies. More technology-intensive plants pay higher wages, are more productive, and are more likely to survive than non-adopters.

R&D is also important to plant and firm performance. Lichtenberg and Siegel (1989) find that there is a positive association between firm R&D expenditures and plant total factor productivity.

Bernard and Jensen (1995) find that plants that manufacture for export tend to be larger, more productive, more capital intensive, and pay more than plants that do not export. Further, Bernard and Jensen (1996a) find that because these plants are more non-production worker intensive than other non-exporters and have grown as a share of total manufacturing employment, these plants have contributed significantly to the increase in the wage gap between production and non-production workers.

Another in this general line of studies is based on a new database linking workers to the plants that employ them. The database, termed the Worker-Employee Characteristics Database (WECD), contains detailed information on various personal characteristics of the worker, (e.g., age, sex, education, etc.). The use of this information has substantially improved the explained variation in a number of studies of business unit performance. See Troske (1995).

D. A Note on Evidence From an Earlier Period

Most of the work cited so far is based on data from the 1963–1993 period. But some historical work with recently uncovered economic census data provides a similar picture of business success to that found in the LRD. Bresnahan and Raff (1991) observe substantial differences in productivity among automotive plants during the 1930s, a time when mass production technology was replacing craft production. The heterogeneity they find is strongly associated with the technology in use at the plant, with plants using mass production techniques showing significantly higher productivity. Today, the "Toyota system" -craft or custom production through management practices emphasising flexibility in produced products – appears to represent a return to the pre-depression era of made-to-order vehicles, but is now supported by new computer-based technologies that allow for efficient adoption of human and organisation methods unavailable in the earlier period.[1]

Firm Effects

Several studies point to the importance of firm effects in explaining business unit behaviour. For example, Baily, Hulten, and Campbell (1992) find that plants' productivity has an associated "firm" effect. As another example, Streitwieser, (1991) finds that plants classified in the same industry, on the basis of their primary product, differ substantially in their mix of secondary products. Exploiting the fact that many of the plants in the sample are part of multi-unit firms, she finds evidence that these differences in the secondary products produced by manufacturing plants are explained by a plant's ownership structure.[2] Another aspect of ownership status is whether a plant is owned by a multinational firm. Doms and Jensen (1995) find that plants owned by foreign firms and plants owned by U.S. firms with foreign assets are bigger, more productive, and pay higher wages. In terms of explained variance, however, these studies and others introducing a firm fixe-deffect into a cross-section performance regression, find that "firm" effects are small relative to plant-specific factors.

Unfortunately, it is impossible to sort out the precise role of firm and plant-specific effects on plant behaviour without much more sophisticated empirical designs than those available at this time. One problem in studying firm effects is that they are only separately identified in a cross-section analysis for firms composed of multiple plants. This limits sample sizes in many instances. However, it is possible to get some idea about their relative importance by comparing plant performance before and after a firm-level

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1 Bresnahan and Raff (1991) find that differences in pricecost margins between business units were not tied to the type of technology used. They appeared more closely aligned with localised competition in product space. In today's world, global competition probably leaves little room for localised rents.

2 The product structures of plants change, often dramatically, over time. See McGuckin and Peck (1992).

change. One of the most important such changes is an ownership change.[1] There is solid evidence that ownership change is associated with significant improvements in business unit performance. Mergers, divestitures, leveraged buyouts, etc. generate changes in the composition of the firm that affect behaviour. For example, a series of studies have consistently identified ownership change as an event that increases business unit productivity (see, for examples, Lichtenberg and Siegel 1992, Long and Ravenscraft 1993a, and McGuckin and Nguyen 1995).

Studies of job change and investment at the level of the business unit are also consistent with significant firm effects. Both job changes (Davis, Haltiwanger, and Schuh 1996) and investment (Doms and Dunne 1994) are characterised by large lumpy changes. For example, most jobs are created at plants that scale back dramatically. Job change is concentrated in plants increasing or decreasing their workforces by 25 percent or more. A very similar picture emerges for capital – adjustments of over 37 percent in one year and more than 50 percent over two years. Thus, jobs typically are gained or lost and new capital acquisition are concentrated in particular plants. The data show that these large changes are not systematic across plants, even those classified in the same industry.[2] Since dramatic changes in operations such as these are often concentrated in times when ownership is changing, this evidence is consistent with significant firm effects. While this evidence is indirect, McGuckin, Nguyen, and Reznek (1995) provide direct evidence that ownership change is related to employment growth.

Industry Effects

Until recently, much of the empirical literature attempted to explain differences in industry-level variables where industry is defined in terms of the SIC system usually at the three- or four-digit level of detail. This literature is reviewed very well by Schmalensee in the *Handbook of Industrial Organisation (1989).* While

1 Many earlier studies suggest that mergers have neutral or negative effects on acquiring firm's performance. These studies, for the most part, use data from samples composed of large multi-unit firms. Recent work by McGuckin and Nguyen (1996) indicates that such studies are subject to significant aggregation bias that tends to obscure the positive impacts of merger.

2 Most of the job changes described are persistent. On average, 71 percent of all the jobs created last at least one year. 56 percent last for 2 years. Job destructions are even more persistent – 82 percent are not regained in one year, and 74 percent are still lost 2 years later. This suggests that growth or decline in plants is permanent. So these effects involve real restructuring and change – not transitory movements.

the economic meaning of industry-level cross-section regression studies of performance measures (such as profitability and price-cost margins) is murky, such studies do suggest that factors that vary across industries are significant in business performance. For example, Dunne and Roberts (1991) conclude a recent study of exit and entry with three observations:

1 Entry and exit rates vary by industry, both in gross and net terms.

2 These rates are stable across time for individual industries and an industry's relative position in the distribution of entry and exit rates is persistent over time.

3 Consistent with the first two points, positive correlations between industry entry and exit rates are observed at each point in time.

These findings suggest that industry classification is a meaningful concept in the sense that it explains firm behaviour.

This conclusion is supported by various studies incorporating industry effects into empirical models of firm behaviour. Industry is important in explaining differences in firm behaviour in every recent study using the LRD (see, for examples, Bernard and Jensen 1995, Doms and Jensen 1995, McGuckin, Streitwieser, and Doms 1996, Davis, Haltiwanger, and Schuh 1996, and Doms, Dunne, and Troske 1996). Moreover, this is not a recent finding or one limited to the LRD database. Gort, Arora, and McGuckin (1972) find significant industry effects in a fixed effects specification for firm diversification levels measured using Dun and Bradstreet data from the 1960s. Similarly, Cohen and Levin (1989) summarise numerous studies and conclude that "industry" effects explain a significant portion of firm R&D. Schmalensee (1985) in an influential contribution found that industry effects were more important than business unit and firm effects in explaining profitability using Federal Trade Commission line of business data. Later studies by Kessides (1987) and, in a broader treatment of the issue, Rumelt (1991) show that while industry effects are significant in explaining profitability, the importance of the industry effect is dramatically reduced from that suggested in Schmalensee's work.

Recent studies with the LRD, such as those cited above, while not directly replicating the earlier studies, find that industry is a significant source of "explained" variation, but overall it explains very little of the observed variation in plant performance measures along a variety of dimensions. This is consistent with the Rumelt (1991) study that found that plant-specific factors are the more significant determinants of profitability. This means that the source of most of the observed variance in plant behaviour is plant or firm-specific effects.

Other Factors Determining Success

The empirical work discussed above identifies a wide range of characteristics associated with successful performance. Moreover, the results are generally both economically and statistically significant. However, while the relationships are significant, the unexplained residuals associated with them are large (i.e., the explanatory power of the empirical models is strikingly low). The percentage of explained variance tends to be on the order of between 10 percent and 30 percent. Similar levels of explained variation are found for regressions that use change measures – job creation, productivity growth, investment, for examples – as the performance variable. Thus, most of the variance in the data is unexplained and, therefore, idiosyncratic to the business unit.

This suggests that unobserved business unit characteristics like management practices, production process, and so forth, play a large role in performance differences. In turn, the important determinants of plant performance are now beginning to be studied by economists. Many of these, for example, differences in plant technologies (process and products) and managerial skills and practices, have been the provence of the case study or business school approach. However, with the new longitudinal databases covering large sectors of the economy (e.g., manufacturing) it is possible to study within plant factors systematically. In attempts to explain more of the variation in performance, researchers have moved to supplement data in the LRD with other ancillary, special surveys. As illustrated by the research with the SMT, described above, this is where much of the current research activity with the LRD is concentrated.

Persistence

We observe considerable variation in business units in the cross-section. We also observe entry, exit, plants growing, and plants shrinking over time. This leads to the question: How stable are intra-industry distributions of plant characteristics over time? The evidence on persistence is relatively new, but a picture of how the distribution of plants evolves over time is beginning to emerge.

For example, while there is strong evidence that reallocations of resources from low to high productivity plants are the most important factor in the growth of productivity in the economy, there also appears to be substantial persistence in plant productivities (see Baily, Hulten, and Campbell 1992, Bartelsman and Dhrymes 1992, and Dwyer 1995a). The finding of significant persistence in plant productivity performance across time suggests that permanent characteristics of the business unit account for its superior performance. Recent work by Dwyer (1995b) offers strong support for the existence of such permanent characteristics. He estimates that the persistent effects have a half-life of 10–20 years in the textile industry and explain nearly one-half the observed variation in productivity.

Other work also suggests that longlived characteristics are important determinants of performance. In a very comprehensive study of 13 homogeneous products, Roberts and Supina (1994) find "clear patterns of price dispersion among producers with the amount of dispersion varying substantially across products but relatively little over time for a given product." Moreover, they find substantial persistence in the pricing of individual plants compared to what one would expect from random movements. Thus, they conclude that plants have stable permanent differences in costs that are reflected in their product prices, even within narrowly defined product groupings.

The work cited so far on persistence in the productivity distribution – the most general measure of plant efficiency – is usually based on specific industries and time periods. Therefore, it made sense to derive some simple descriptive statistics on persistence across the entire manufacturing sector. For this purpose, we selected from the LRD all plants producing in 1992 (over 350,000) and from this group of plants we identified all those that were operating in 1987. This gave us a sample that included all plants operating in 1992 that were five or more years old. We then classified each of these plants according to its primary four-digit Standard Industrial Classification (SIC) code. There were 458 four-digit industries in manufacturing in 1992.

For each industry, we regressed the plant's relative labour productivity (total shipments/total employment for the plant divided by the average labour productivity for the four-digit industry in which the plant was classified) in 1992 on the similar value for 1987.[1] This yielded 458 regression coefficients,

1 We also carried out the exercise for plants producing in 1982 and 1987, as well as in 1992. This allowed us to use the average labour productivity in 1982 and 1987 as the base year value. By doing this, we are able to, partially at least, control for transitory factors that would be average out due to regression to the mean. The results are broadly consistent with those reported here.

each showing the average relationship between productivity in 1992 and productivity five years earlier for a four-digit industry.

The results of these calculations are displayed in Table 1 and are grouped by the 20 two-digit manufacturing sectors. Plants in industries with a higher coefficient show greater persistence in the sense that their position in the productivity distribution in 1992 is positively correlated with that in 1987. Table 1 shows that the average (unweighted) industry had a regression coefficient of .54 with a variance of .08. But the range was quite wide – from about .75 for food and tobacco to less than .40 for transportation, furniture, and miscellaneous manufacturing.

Since this work is preliminary, we don't want to dwell on it except to note that in all industries, the estimated coefficients are consistent with substantial persistence in the productivity distribution over the fiveyear interval.

But, the regressions also suggest that transitory factors are important. A plant's productivity in 1992 is positively related to its productivity five years

Table 1. **The relationsip between plant productivity 1987 and 1992**

SIC	Number of Four-Digit Industries	Mean Slope	Mean Slope Variance
All Industries	**458**	**0.55**	**0.08177**
20 Food	48	0.61	0.05927
21 Tobacco	4	0.75	.015413
22 Textiles	23	0.54	0.12979
23 Apparel	31	0.57	0.17257
24 Lumber & Wood	17	0.61	0.03069
25 Furniture	13	0.34	0.03788
26 Paper	17	0.66	0.06059
27 Print.& Publ.	14	0.50	0.04253
28 Chemicals	29	0.74	0.08271
29 Petroleum	5	0.68	0.02594
30 Rubber	15	0.51	0.03139
31 Leather	11	0.65	0.15078
32 Stone & Clay	26	0.44	0.04737
33 Primary Metal	26	0.56	0.09480
34 Fab. Metal	38	0.49	0.03913
35 Machinery	51	0.57	0.10563
36 Electronics	37	0.56	0.14573
37 Transportation	18	0.37	0.20866
38 Instruments	17	0.48	0.03910
39 Miscellaneous	18	0.36	0.02993

* The mean slope in the 2-digit industry is obtained by regressing $ln\ P_{92} = a + b\ (ln\ P_{87})$ for each 4-digit manufacturing industry. P = relative productivity.

earlier, but the correlation is far from perfect. Thus, in addition to persistence, there appears to be a good deal of regression to the mean in the data. Because of this, some form of a random shock/measurement error model of productivity dynamics is also working. Dwyer (1995b) offers some support for this view.

Taken together, the evidence suggests that a model combining persistence with random shocks, both common and idiosyncratic, is likely to be necessary if we are to explain productivity dynamics. Such dynamic structural models need to be developed and estimated. Analyses examining the relationships of multiple dimensions of performance are a natural extension of the new empirical literature.

4. Industry Dynamics

While models and empirical work combining the elements of firm-level heterogeneity, firm-level persistence, and firm, sectoral, and aggregate random shocks are relatively new, evidence is emerging suggesting that this is a fruitful way to think about firm and industry evolution. Researchers are beginning to uncover empirical evidence of the aggregate effect of plant- and firm-level changes.

As noted above, Davis, Haltiwanger, and Schuh (1996) find the magnitudes of gross employment changes – both job creations and job destructions – are substantial. On average, 1 in 10 manufacturing jobs are lost in an average year, and 1 in 9 are gained. This means that 19 percent – almost 20 percent of all jobs in manufacturing – are reallocated among plants each year.[1] Clearly, these figures suggest that change – growth and decline – is a dominant characteristic of the economy.

Davis, Haltiwanger, and Schuh also find large gross changes in employment at individual plants in every manufacturing industry during the 1972–1988 period they studied. Regardless of whether an industry showed increase, decrease, or no change in its net employment, the authors observe some plants increasing, some plants decreasing, and some plants not changing their employment. And a similar pattern of large, idiosyncratic changes is observed for capital (see Doms and Dunne 1994 and Power 1995).

How does the heterogeneity among plants, observed for both levels and changes, affect competition and economic growth? If we observe an industry at two points in time we can categorise the firms into three categories,

1 Net changes in jobs – about 1 percent per year – are small relative to gross.

stayers – those operating at both the beginning and the end of the period -entrants, and exits. Davis, Haltiwanger, and Schuh (1996) find that a considerable portion of this reallocation of employment involves plants that operate continuously; annually, only 15 percent of job creation and 22 percent of job destruction are associated with entry and exit, respectively. Even over five-year intervals, entry and exit are not the prime vehicles for expansion and contraction of jobs or output.

The story for productivity is similar. In an important empirical study, Baily, Hulten, and Campbell (1992) investigate the role of plant-level productivity in industry productivity dynamics. Somewhat surprisingly, in light of the large turnover of plants through entry and exit in most industries,[1] the Baily, Hulten, and Campbell study finds that entry and exit are relatively unimportant in aggregate productivity growth, even over the full 15-year period they study. Roughly two-thirds of the aggregate productivity growth is attributable to gains in market shares by the most efficient producers and declines in market share by the least efficient.[2] This basic finding – that the most productive business units grow faster and are less likely to exit – has been confirmed by a host of studies with the LRD (see Dhrymes 1989, Bartelsman and Dhrymes 1992, Olley and Pakes 1996, Dwyer 1995 (a and b), and Roberts and Supina 1994). In turn, there is convincing support for the proposition that economic growth is achieved via a competitive selection process in which the most efficient firms survive.

Caballero, Engel, and Haltiwanger (1995) suggest that understanding the distribution of plant attributes is important to understanding how an industry or sector will respond to a random shock. They examine the response of plant-level investment to changes in tax policy. They find that aggregate investment behaviour depends on plant-level adjustments to capital. This, in turn, depends on the distribution of plant characteristics and past plant decisions. This research begins to integrate aspects of plant heterogeneity, per-

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1 Entry and exit are relatively larger in terms of number of business units – 35 to 40 percent over the typical 5-year period.

2 There are reasons to believe that the entry/exit effects are minimised in their empirical decomposition and that some of the plant-specific growth reflects growth by entrants subsequent to their entry. The problem is that low productivity firms exit and the entrants that replace them also typically exhibit below average productivity at the time of entry. But surviving entrants grow very quickly and improve productivity, reaching average levels in 5 to 10 years. Thus, a good deal of the "plant" growth effect observed by the authors – about one-third of aggregate productivity growth – may be associated with subsequent growth by entrants. Alexander (1994) makes this point on page 8.

sistence, and random shocks into a model of how plants and industries evolve.

As another example, consider the problem of evaluating product choice and energy usage decisions in reaction to a change in energy prices. This kind of problem arises in assessments of economic or environmental policies such as the imposition of an energy tax. In the absence of a model and data at the plant level, an analysis completely describing the effects of the policy change is not possible. In this application, the responses of small, high-millage cars makers and low-mileage care producers will differ. Also, poor people who cannot afford to shift to new, high-mileage cars will bear a significant burden of the tax. They will continue to use their high-mileage cars longer than high-income drivers (income effect). Aside from equity issues, this will affect the dynamic adjustments and delay increases in the miles per gallon of the average car on the road. Pakes (1990) explicitly models the role of plant and firm differences in his analysis of the effect on the auto industry of changes in energy costs.

5. Concluding Observations

Heterogeneity is a fact of life among firms and their business units. It is the most pervasive attribute of the data and is found across all sectors no matter how the sector is defined – by industry, region, size, etc. Once you group business units on one variable, they vary on virtually all others. For example, the various studies find significant differences in the product structure, productivity, productivity growth rates, investment, export activity, merger, organisation, technology, age, mark-up differences, R&D, ability to assimilate new technologies, rate of learning by doing, job creation, job destruction, environmental emissions, capital intensity, etc. among business units classified in the same industry.

Firms are not only different in the cross-section. They enter at different times and make different choices about the products they produce and the technologies they use. In turn, their different circumstances mean that they react differently, even to common external shocks. Heterogeneity is observed across time as well as in the cross-section. During any time interval, observed changes among firms in the same industry are uneven and idiosyncratic as some open and some grow, while others shrink and die.

Thus, to understand economic performance and competition, one must move beyond representative firm models. Since most of the observed variation in the data is *within* industries, economic change cannot be understood in terms of the behaviour of an "average" firm in an industry-level analysis.

The empirical evidence supports the view that some firms will succeed (that is, survive and grow) and some firms will fail (lose market share and go out of business). Thus, competition can be characterised as a process in which successful firms grow and lead industry growth at the expense of less efficient rivals.

But what factors distinguish successful firms from unsuccessful ones? While the empirical evidence has identified a wide variety of factors associated with successful firms, the evidence is not clear on what lies behind the observed relationships. For example, the evidence that adoption of advanced technology is positively related to performance is overwhelming. But does this positive association reflect the impact of the technology on the efficiency (competitiveness) of the adopting firm, or is it primarily a manifestation of well-managed efficient firms being more likely to adopt advanced technologies?

The problem is that much of the research discussed above has used models that explore pairwise correlations among variables. While establishing correlation is an important first step, the results should not be interpreted as causal relationships between business unit characteristics. The observed correlations can reflect a positive relationship between performance and technology adoption because both of these variables are positively correlated with a third, unobserved factor.

This is a real possibility. The vast majority of variation in firm performance is not associated with traditional observables such as location, industry, size, age, or capital. Rather, this variation is associated with unobserved factors specific to the firm or business unit, many of which appear to be permanent attributes of the business unit. One such attribute is the managerial capital of the firm, another is the skills of its workforce.

The most important area for research is the development and estimation of models that disentangle the causes and effects of firm growth.[1] A logical next step in this line of research is to flesh out a more complete picture of the relationships between plant characteristics and plant performance. Causal models would allow us to move beyond more simple correlations to answer such specific questions as: Do plants that have higher wages grow? Or is it that successful plants grow, and then later pay higher wages? What is the relationship of exporting and success? Do exporters become successful firms

1 Bernard and Jensen (1996b,c) begin to disentangle the relationship between plant characteristics, performance, and exporting in a dynamic model. They find that better plants do become exporters and there is some evidence of gains from exporting – thus underlining the need for more sophisticated modelling approaches.

or do successful firms become exporters? How long does it take before strong productivity growth yields improved business outcomes, and what is the strength of that relationship? Answers to these and similar questions can, in turn, help identify firms that show particular potential for success.

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JAPANESE EXPERIENCE OF LONGITUDINAL DATASET ANALYSIS AND INTERNATIONAL PERSPECTIVES

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This paper presents an overview of Japanese case of longitudinal dataset compilation and analysis, based on MITI's Manufacturing Census and Basic Survey of Business Structure and Activities. Author has compiled two kinds of panel data, manufacturing census panel at the establishment and R&D panel at the firm level, by linking micro-data of MITI's census surveys. The first part of this paper is for description of Japanese longitudinal datasets based on existing microdata. Furthermore, the second part of this paper outlines an preliminary result of an international comparable research projects of France, Japan and US on job turnover and size distribution of labour productivity, as well as raising and discussing issues of international study of microdata sets.

Key words: Longitudinal Dataset, International Comparison, Manufacturing Productivity.

1. Introduction

The development and use of longitudinal data sets by the Japanese government is at a very early stage, and only a few pilot studies has been done in the co-ordination with academia or private research institutes. Most of the efforts of statistical agencies have been devoted to collecting accurate data and publishing well-defined aggregate data, but not so much in constructing micro data sets for

1 Views expressed in this paper are those of author's, and not of his organization's.

government use to address policy relevant issues. For researchers outside statistical agencies, it is possible to access the micro data of census surveys, if the purpose of data use is approved by the government; however, this approval is only for specific research topics and for a limited period, and researchers cannot compile longitudinal datasets for general use.

Nevertheless, none can deny the importance of microdata for policy analysis. In any kind of aggregation, there is an aggregation bias due to the heterogeneity of establishments or firms, and aggregated data cannot answer policy relevant questions such as how regulation changes the pattern of entry and exit of firms, a very important question for the Japanese government who is putting significant weight on policy for supporting the start-up of innovative firms. In the line of shaping up competitiveness policy of Japanese industry, MITI has just started to recognise the importance of longitudinal datasets, and some preliminary projects have been initiated.

In this paper, I will introduce a pilot study of longitudinal dataset analysis based on existing two kinds of census survey conducted by MITI, the Census of Manufacturing and Basic Survey of Business Structure and Activity. One of concrete policy needs for longitudinal dataset analysis came from OECD's activity of 'Technology, Productivity and Job Creation', which is a follow-up of G7 Detroit Conference on Employment in 1994. The main focus of this activity is to evaluate technology impacts on productivity and employment, and firm or plant level heterogeneity is important in this area. As a Japanese contribution, MITI decided to conduct research project based on their microdata.

The structure of this paper is as follows. Section 2 describes two main data source of Japanese longitudinal datasets, and is followed by Section 3 for data compilation of two kinds of datasets, one at the establishment level and the other at the firm level. In Section 4, some empirical analysis based on these datasets with raising issues for international comparative works is provided, and Section 5 concludes.

2. MITI's Census Survey of Establishments and Firms

First, it is better to present a big picture of MITI's census surveys whose data are used for compilation of longitudinal datasets at the establishment level and at the firm level. Basically, two kinds of census data are used, Manufacturing Census and Basic Survey of Business Structure and Activity.

a) Survey at the establishment level

Longitudinal dataset at the establishment level is based on Manufacturing Census of Japan, which is done annually for establishments of manufacturing firms. It used to be an annual complete enumeration up to 1980, but since 1981 a survey for all establishments has been done in a calendar year ending in 0, 3, 5 or 8. In the other years, only establishments with more than 3 employees are surveyed. According to the 1993 survey, the latest available one, the number of establishments with more than 3 employees is about 60% of the total (696,090), that of all establishments; however, in terms of shipments, they cover 99% of the total.[1]

Each year, there are two types of surveys, Survey A for establishments with no less than 30 employees and Survey B for others. Basic production activity variables, such as the number employed, labour compensation and capital stock, material inputs and outputs, are collected in both surveys, but Survey A covers items in more detail especially for input variables. For example, the capital stock is disaggregated into buildings, machinery and transporting equipment in Survey A, while only the gross capital stock is collected by Survey B.

The amount and quantity of shipments from establishments is reported by commodity, based on 6-digit commodity code for this survey, and the industry rating of each establishment is done of the 4-digit level. That is, even though an establishment ships two or more kinds of commodities of the 4-digit level, all shipments are counted as the industry which has the largest share. As a result, as well as industry aggregation data, MITI also publishes commodity aggregation data by 6-digit code.

b) Survey at the firm level

There also used to be Survey C of Manufacturing Census, which is a firm level survey, in contrast to the establishment level of Survey A and B. Survey C collected firm activities such as R&D, advertising and international transactions, as well as production activities covered by establishment level surveys. But, Survey C was conducted only in 1987 and 1989 for firms with no less than 50 employees and ¥10 million in capital.

This firm level survey was replaced by the Basic Survey of Business Structure and Activities (BSBSA) in 1991. BSBSA covers most of survey items of Survey C, however it is difficult to compare aggregated data of these surveys due to the differences in the employment and capital cut-off

1 This figure comes from MITI (1995). Aggregated data of manufacturing census survey as well as survey methodology is published as an annual report.

points which is no less than 50 employees and Y 30 million in capital. In this sense, firm level link of these two kinds of survey is essential to look into dynamics of technology and performance. 1994 survey results of BSBSA will be published shortly, and after 1994, annual survey is planned. Since BSBSA covers broad area of survey items, including details in technology activities (not only R&D expenditure, but also patent counts and technology licensing statistics), use of information networks and business activities of foreign affiliates[1], longitudinal analysis on various aspects of firm's business activities is expected in future.

3. Compiling Longitudinal Datasets

Data unit is an important factor for longitudinal data analysis, and appropriate data unit depends on research applications. For an analysis on industrial activities such as R&D, productivity and employment, the question is whether longitudinal dataset is at the establishment level or at the firm level. For analysis on productivity and employment dynamics, establishment level data is preferred, since it represents production unit and it has less problem associated with product mix of large firms.[2] On the other hand, technological impacts on performance can be evaluated more effectively by firm level data, since technological activity such as R&D investment is one of important business strategies of overall firm.

From the viewpoint of data availability in Japan, establishment level census survey has been conducted for a long time, and a history of firm level survey is new, as is mentioned above. However, two types of longitudinal datasets (establishment level and firm level) has been compiled so that they can address overall issues on 'Technology, Productivity and Job Creation'. Compilation of these two kinds of datasets is described as follows.

a) Establishment level datasets

As for the compilation of establishment level datasets, major efforts are spent on dataset linkages of different years. The establishment identification system of Survey A and B of Manufacturing Census is based on a 10 digits code, which is made from a 2-digit prefecture code, a 3-digit city code and a 5-digit estab-

1 Details of surveys items in BSBSA can be found in MITI (1994).

2 OECD (1995) mentioned the other factors for establishment data, such as (1) establishment is the smallest level of aggregation, and (2) scale economy is more associated with establishment.

lishment code. The problem of data linkage is that a 5-digit establishment code, managed by each prefecture of Japan, changes every 5 years. Furthermore, conversion tables of the establishment code, except the most recent one, do not exist in either the central or local governments. Therefore, it is necessary to connect data in the years of ID code changes in other ways.

During the time scope of data 1970 to 1993, changes in the ID code occurred in 1975, 80, 86 and 91. However, only the 1990–91 establishment ID conversion table is available, and in other years, it is necessary to create ID conversion tables, based on various surveyed variables of each establishment. For the actual compilation procedure, it was decided to use only Survey A, for no less than 30 employees establishments, because this detail survey provides more clues for data linkage than Survey B, and it is practical to keep the number of establishment small for pilot study.[1]

Among variables surveyed in Survey A, the following variables were used as keys to matching establishments.

- Location codes (prefecture code, city code and regional code)
- The value amount of inventories
- The value amount of land

As for the first key, there are three locations codes, 2-digit prefecture code, 3-digit city code and 5-digit regional code inside a city. These codes are managed by the central government, and do not change much. Therefore, it is possible to modify them by hand when changes of these code occurred between years to be matched. As for the second key, we can assume that the amount of inventories at the end of this year is equal to that at the beginning of next year. In addition, Survey A breaks total amount of inventory into three parts, products, products work-in-process and raw materials, and each of them can be used as a key. As for the last one, the amount of land at the beginning of this year + net change of land value of this year is assumed the same as that at the beginning of next year. The same assumption must work for other capital amounts such as machinery and buildings. But, since matching performance was found to get worse by adding these variable, they were not used. Based on these keys, data matching was done, and the results are shown in Table 1.

1 The number of establishments with no less than 30 employment in 1993 is about 60,000, and it is still large. But, it is much easier than handling data of all establishments, about 700,000.

Table 1. **Matching performance of Manufacturing Census Survey A.**

# of establishments (year)	# of establishments (year)	# of establishments matched	# of establishments deleted*
57,455 (1974)	56,358 (1975)	31,068	1,499
54,203 (1979)	53,868 (1980)	35,982	1,692
57,626 (1985)	58,349 (1986)	41,586	505

* *note:*
If two or more establishments have identical keys in one of the years compared, these were deleted from this data.

One of problems associated with this methodology arises from only data from Survey A. As is shown in Table 1, the number of unmatched establishments is significant[1], and many of the mismatches occur because there are a significant number of establishments whose employment changes around 30. For example, an establishment, which changed their employment from 29 in 1974 to 30 in 1975, will not be matched, even though it existed through the years. Due to the skewness of the size distribution of establishments, the number of such establishments could be quite large. Another problem is associated with the way of identification of the same establishment, based on its location. Another way of identification is by its owner, and it might be argued that an establishment with new owner has to be treated as a different one due to the change of management.

b) Firm level datasets

As for the firm level datasets of 1987 and 89 from Manufacturing Census Survey C and 1991 from BSBSA, a firm level linkage have been done in the same way as establishment level datasets, since there is no matching table between 1987 and 89.[2] This linkage is more difficult than that of establishment level data, since matching keys of inventory and capital amount cannot be used in data in every two year. Concretely, the following keys are used.

1 For example, in the matching of 1974 and 75, more than 16,387 (57,455 – 31,068) of establishments in 1974 are unmatched.

2 Matching table of Manufacturing Census Survey C in 1989 and BSBSA in 1991 does exist.

- Location codes (prefecture code, city code and regional code)
- 3-digit Industry code

The first one is the same as one used for the establishment data. Conceptually, this key is not appropriate, since firm identification must be made on its legal status, instead of its location. For example, a firm with owner changes has to be treated as a different firm, even though its physical structure is same[1]. In addition, the second key does not allow changes in a firm's main business. However, the probability of above events is supposed to be low in two years. In addition, to avoid miss-matched firm and to omit firms with major restructuring which is likely to happen in owner changes, firms with employment changes with less than 50% and more than 200% are deleted. Starting from more than 10,000 manufacturing firms of each year[2], about balanced panel data of about 3,500 firm has been compiled.

4. Empirical Analysis and Issues for International Comparison

Some policy analysis based on these datasets have been concurrently done with data compilation, since building a bridge between academic oriented longitudinal data analysis and on-going policy needs is the most important task. As is mentioned, one of policy needs for analytical works was cast from the Detroit Summit on Job Creation in March 1994 and OECD's follow-up works on 'Technology, Productivity and Job Creation'. As overall economic growth of OECD countries slows down, how technology affects productivity and employment is becoming a very important policy issue. As a first step of grappling with this topic, the establishment level datasets are used for a comparative study of job turnover and productivity growth for the manufacturing sectors in France, Japan and U.S. (Doms et al. (1995)), and cross sectional data of BSBSA is used for 2 studies of technology and productivity investigation (Motohashi (1995) and Motohashi (1996)). In this paper, I will focus on discussing issues of

1 In cases of the U.S. (Lichtenberg and Siegel (1987)) and Canada (Baldwin (1995)), owner changes of plant by M&A shows beneficially impacts on its productivity.

2 The number of firms for each year is 19,702 in 87, 21,271 in 89 and 13,688 in 91. For Manufacturing Census Survey C, R&D expenditure is surveyed for only firm with no less than 100 employees, and only firms with R&D variables are included in the longitudinal dataset.

longitudinal dataset analysis, especially from the international comparative viewpoints, based on Doms et al. (1995).

The first issue of international comparison is the difference of data, such as data unit and definitions of variables. Unless one controls this issue, it is impossible to say whether international differences come from real effects or data effects. Table 1 gives comparison of longitudinal datasets in three countries. One of major difference of French data from those of Japan or U.S. is that data unit is firm, instead of establishment. The difference of data unit has a significant impacts on gross job turnover measurements is found in one graph of Doms et al. (1995), which provides the distribution of establishment/firm based on the rate of changes in employment. To compare with both France (firm level) and Japan (establishment level), two kinds of U.S. data are provided, and difference in two US data is as large as inter-country difference.

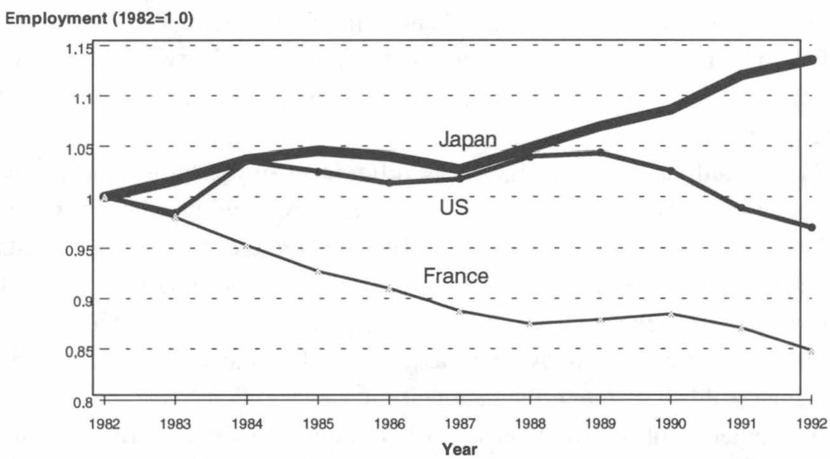
In this study, there seem significant differences of job turnover patterns in these countries. For example, even though the gross job increases were more in Japan than in the other two from 1987 to 92, the percentage of establishments with more than 50% increase of job is less in Japan than in the other two. Although the data similarity of Japan and the U.S. implies that the Japanese economy is less dynamic as compared to the U.S., its comparison to France is difficult due to the data unit differences.

The other result of Doms et al. (1995) shows the size distribution of labour productivity in three countries. In this exercise, bias associated with data unit difference is not so serious, since firms with multiple establishments are only very large ones, which is supposed to be shown up only in the right end of the graph. However, differences in definitions of variables, that of value added in this case, do matter. Value added is basically gross output – material inputs, but due to the difference of survey units, establishment data in the U.S. and Japan does not take into account indirect cost incurred in auxiliary units, while French data does. In addition, there is a significant difference in the treatment of service inputs, such as computer software. Japanese survey does not cover service inputs as a material inputs, while French data can cover that since it can grasp overall firm's activities. Again, Japanese data show more skewness in size distribution of labour productivity as compared to other two countries, but France-US comparison is difficult.

The second issue to be considered in international comparative works comes from differences in nation's economy itself. For example, job creation and destruction shows asymmetric pattern depending on business cycle

(Davis, Haltiwanger and Schuh 1996), and as is shown in Figure 1 (aggregated manufacturing employment changes of three countries), from 1987 to 1992, Japanese economy is in its upturn, while US economy in its downturn. Although the same pattern of less flexible labour market in Japan is confirmed by an analysis from 1982 to 1987 in Doms et al., careful examination is still needed to come up with meaningful conclusions.

Figure 1. **Relative manufacturing employment between 1982 and 1992.**



As for the relationship between technological impacts on productivity and employment, firm level datasets are planned to be used as an international comparative work. In this case again, it is necessary to consider issues raised above. Particularly, R&D expenditure, which are commonly used variables as a proxy of technological attainment of firm, is a difficult variable to achieve international comparability[1]. For example, R&D expenditure consists of various kinds of expenses, such as wages of R&D employees, materials used and capital expenditure, and the coverage of these items may be different among countries. In addition, Manufacturing Census Survey C gives only total R&D expenditure expensed by a firm, which includes outsourced R&D, and it cannot be compared directly to those data from other country's performer based survey data.

1 OECD's Frascati Manual (OECD (1994)) provides detail description of R&D, such as definition of R&D, measures of R&D input and R&D classification, to achieve international comparable R&D data.

Microdata has often been used for analysis on R&D and productivity, since aggregation bias of R&D variables is assumed to be large due to the heterogeneity of technological activities. However, many studies are based on publicly available data such as ones in firm's financial report, which is often under reported in case of Japan. For example, according to the NIKKEI Needs Database, one of the annual report databases in Japan, major automobile companies like Toyota and Honda report no R&D expense, since R&D variables are assumed to be strategically important, and they are unwilling to disclose such data (Griliches and Mairesse (1990)). In this sense, firm level longitudinal datasets based on the government surveys is supposed to provide more accurate evaluation of R&D and productivity relationship, but again, careful examination of data comparability is needed for international studies.

5. Concluding Comments

The above discussion outlined the research project of longitudinal dataset both at the establishment level and at the firm level in Japan, with raising issues for international comparative works. This research project is undertaken for the specific purpose, i.e., micro-data analysis of 'Technology, Productivity and Job Creation', the OECD's G7 follow-up project. As mentioned before, use of micro-data from government surveys in Japan is regulated by the Law of Statistics, and one can use them only when the specific purpose is approved by the government. In addition, this approval is made only for a limited period, and one has to discard all the data after they use them. In this sense, use of micro-data of census survey is very restrictive in Japan. Changing a legislative system toward more open one like the U.S. system[1] will be a well-deserved challenge for enhancing longitudinal dataset analysis in Japan.

For less developed countries on micro-data use, Japanese experience will be a good example with the least cost, since it is based on the existing data as well as linking data by a micro-computer. There are various other kinds of approach to create more accurate datasets, and it is necessary to do careful cost benefit analysis, by thinking what can be done and what cannot by longitudinal datasets. In this sense, to list up policy relevant questions that can be grappled with micro-data sets is useful. For example, starting from general question like how technology changes economic performance, espe-

1 The process of changing US system is documented in McGuckin (1994), and it would be a good guideline for less developed countries on micro-data use including Japan.

cially productivity and employment, one can ask more specific questions like whether there are significant technology spillovers among firms. To address this question, industry aggregated data cannot say much, because inter-firm spillover within same industry is assumed to be larger than inter-industry spillovers.

As for the Japanese datasets at the establishment level, one of the needs is to expand datasets to include smaller establishments. As mentioned above, current datasets, based on only Survey A, have a serious problem with establishments with around 30 employees, and one can only use balanced panel data of matched establishments. Therefore, some interesting topics of industrial dynamics such as entry and exit of establishments are out of the scope of this dataset. However, there are practical problems associated with expansion of datasets; Survey B, the less detail one for less than 30 employment, does not provide enough matching keys for many more of establishments to be matched. And, in this case, time consuming manual work such as matching by name or address will be needed.

Moreover, linking establishment level datasets to firm level datasets has to be investigated in the long term. Firm identifiers are available only for establishments with no less than 20 employees, and this could be linked with firm level datasets based on Survey C and BSBSA. However, just one time firm identifiers cannot take into account a history of establishments such as ownership change, and one cannot ignore the bias associated with differences of cut off points in enumeration among these surveys. To grapple with this problem, it is necessary to co-ordinate with other governmental agencies in charge of other firm level census. In this sense, the Management and Co-ordination Agency plans complete census of establishments and firms in 1996, and it is expected for this survey to be done periodically thereafter.

Finally, I would close this paper by addressing issues of international studies of microdata sets. Two issues are raised; one is differences in data and the other is differences in nation's economy itself. As for the first one, one should be careful for the data unit as well as definitions of variables. As for the second one, in an interpretation of comparative quantitative results, one should take into account various kinds of factors coming from different economic situations. These issues as well as data confidentiality may explain why international works on microdata are very few, but it should be stimulated as a background evidence of international policy co-ordination.

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Appendices

Table 1. **Comparison of Longitudinal, Manufacturing, Micro Datasets in France, Japan and the US**

	US Longitudinal Research Database (LRD)	**Manufacturing Census Panel of Japan**	**Echantillon d'entreprises (Subset of the BIC)**	**SUSE - systeme unifie de statistiques d'entreprises (combination of DGI and EAE)**
Sectors	Manufacturing	Manufacturing	All private sector.	All private and public firms.
Unit of Analysis	Establishment, with firm identifier in every year.	Establishment. Firm identifier available since 1991.	Firm (SIRENE)	Firm (SIRENE)
Years of Coverage	1963, 1967, 1972–1992.	A panel of establishments now exists for 1981–1992. Earlier data may be available.	1978–1992	1984–1992
Sample Charac-teristics	Census every 5 years (approx. 350,000 estabs.), probability sample in the intervening years (approx. 55,000 estabs.)	All establishments with 4 or more employees are surveyed every year (approximately 400,000 establish-ments), and in census years, all establishments are surveyed (approximately 700,00 establish-ments). Micro data is available for establishments with more than 29 employees is not available.	~12,000 observations per year. Accurate probability sample. Easily linked to other datasets.	Complete every year. Small firms, under 20 employees may be under represented (small firms participating in the Forfait or BNC tax systems are not included)
Birth and Death Criteria	Establishments are based on a physical location concept. There-fore, a death is an establishment that closes.	Same as US	Since these data are more of a line of business concept, births and deaths can occur for reasons other than opening new establishments and closing of establishments.	same as BIC
Industry Classifica-tion	4 digit ISIC revision 2	4 digit ISIC revision. 2	4 digit, no ISIC link yet	4 digit , no ISIC link yet

Table 1 (continued)

Employment Data

Level of Employ-ment	March 12th employment	December 31st employment	annual mean number of employees	same as BIC
Salaries	Total annual salaries. Also, supplemental labour costs.	Total annual salaries (including bonuses and other benefits, such as housing allowances.)	Total annual salaries, and total labour costs by skill level- see below	same as BIC
	US Longitudinal Research Database (LRD)	Manufacturing Census Panel of Japan	Echantillon d'entrrprises (Subset of the BIC)	SUSE - systeme unifie de statistiques d'entreprises (combination of DGI and EAE)

Employment Data

Types of Workers	Production workers and non production workers for establishments in the Annual Survey of Manufacturers.	Production and nonproduction worker information available for establishments with at least 30 employees in 1981,84, 87, and 90.	INSEE has linked a sample of workers to the firms where they are employed. This sample contains approximately 4% of all workers. The skill structure of firms can be broken into up to 20 groups.	same as BIC

Production Data

Sales	Yes. Shipments as measured by freight on board prices	Yes, same as US	Yes	same as BIC

Table 1 (continued)

Value Added	Yes. Defintion of value added = sales – change in inventories – cost of purchased materials – cost of energy – cost of contract work + value of receipts of contract work performed.	Same as US with adjustment made for taxes.	Same as US , but differences in cost of purchased materials, due to the difference in survey unit.	same as BIC
Capital	Book value of machinery, equipment, and buildings. 1972-1985, ASM establishments only. 1987 and 1992 for all non-administrative records.	Book value of machinery, equipment.	Book value, as well as estimated one by perpetual inventory method	same as BIC
Materials	Materials and energy separated	same as US	same as US	same as BIC

Note:
Adapted from Doms et. al. (1995) with a little adjustment

Part B

Techniques for Comparisons

Puglisi

The objective of the integrated nomenclature is that of keeping a watch on all the related product classifications of the European Union, making sure that the different product classifications are consistent, can be linked to CPA and are accurately worded in all languages. The objective is that of providing an useful tool to statisticians and nomenclaturists and not that of having a very detailed product classification that will work for all purposes. Everybody will continue to use each product classification separately.

Feldmann

Statistics are only valid if they allow comparisons, for example comparing prices, wage levels, productivity, investment behaviour, expenses for R&D and many more. Different kinds of comparisons are possible and common practice. Rarely are users aware of the possible, but unfortunately sometimes very real, deficiencies of such comparisons.

Comparisons between industrial activities or between sectors of the economy are already misleading if different concepts are inherent in the statistics used. Comparisons between different points in time, for example the present compared with the situation ten years ago are also very common. This may be problematic: if the underlying nomenclature has changed, or the collection method of the data was altered, or different observation units are used, conclusions of the comparisons may be distorted or even misleading.

Even more problematic may be comparisons between different countries, although this is nowadays common practice and there is certainly a growing necessity for this in a single European market with a forthcoming single currency.

Santini

In order to arrive at a complete evaluation of enterprise performance, which is indispensable for effective and appropriate company management planning, it is of fundamental importance to conduct a critical examination of balance-sheet items and the calculation of relevant ratios, accompanied by their careful, critical evaluation, supported by statistical techniques.

Arminger

Comparison of regions, countries and cultures can be a useful method to gain insight into societal structures and processes. Typically, such comparisons have been based on aggregate data. Through the collection of multiregional and multicultural data sets on the individual level it is now possible to gain deeper insight by analysing whether complex multivariate associations that are found in one region or culture also hold for other regions and cultures, or in what ways these associations differ across regions and cultures.

The Evolution of Firms and Industries
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Statistics Finland

AN INTEGRATED CLASSIFICATION OF PRODUCTS ACCORDING TO ECONOMIC ACTIVITIES TO IMPROVE INTERNATIONAL COMPARABILITY OF BUSINESS DATA

Giuseppe Puglisi,
National Statistical Institute of Italy

The activities and products classifications: Nace Rev.1, CPA 96, Prodcom 96, CN 96, have been developed within a harmonised European framework defined by Council Regulations, in order to make information clearer for operators in the Single European Market.

This European classifications system aims to be an integrated system. It means that CPA includes HS/CN references, Prodcom is considered a list of products without CPA headings, that concerns some areas of CPA, but with a greater detail with respect to CPA and, generally, with less detail with respect to CN. The first four digits of CPA, generally, but not always, coincide with Nace Rev.1 codes.

Nevertheless, despite important improvements, the way that nomenclatures could be considered to incorporate each other, may be considered only partially satisfactory from a substantial point of view.

In order to help users of economic nomenclatures to navigate through the new European classifications, some useful nomenclature servers and data bases have been created. In order to have a complementary and useful tool, I proposed to Eurostat in the Nace meeting on September 1995 and to ONU in the Geneva Seminar on 19-20 October 1995, that an expanded eight/ten-digit CPA be set up grouping together the CPA, Prodcom, CN, CPV headings as well as the list of agricultural products contained in CRONOS.

In Italy I prepared a new version of integrated products classification: CPATECO 1996 where the CN 96, Prodcom 96 and the list of CPV Services are incorporated in CPA. The CPATECO 96 is structured as a hierarchical file containing about 18000 items. CPA 96, Prodcom 96, CN 96, CPV headings, distinguished by special symbols close to the description, are integrated in a ' mega-structure.' The objective of the integrated nomenclature is that of keeping a watch on all the related product classifications of the European Union, making sure that the different product classifications are consistent, can be linked to CPA and are accurately worded in all languages. The objective is that of providing an useful tool to statisticians and nomenclaturists and not that of having a very detailed product classification that will work for all purposes. Everybody will continue to use each product classification separately.

Prodcom and HS/NC have a particular function in the measurement of markets and trade performance which is different from the needs of the public procurement field, where particular products are of interest in very fine detail and others much less so. The CPA is the common structure which brings all these things together, necessary for general international statistics. I hope I helped users of nomenclature to navigate from the macro-structure towards the micro-structure of the whole set of goods and services.

Key words: Activities Classification, Combined Nomenclature, Consistent and Harmonised System, Integrated Classification, Merging Procedure, Products Classification.

1. Introduction

This paper gives an overview of the development of activity and product classifications within a harmonised European framework defined by EU Council Regulations in order to clarify the statistical information available to operators in the Single European Market. The document also explains the theoretical approach that I propose to use in order to create from this harmonised European classification system, that aims to be an integrated system, an integrated classification of Products by Economic Activities.

2. Activity and Product Classifications

Two groups of statistical reporting systems can be distinguished within industrial statistics:

The first group allows the observation of the statistical units involved in the production process and measures their *inputs* (capital and labour), turnovers, revenues, etc. These statistical units and the related statistical data are classified according to an economic activity classification, e.g. Nace Rev.1 of the European Union Statistical Office (Eurostat), or ISIC Rev.3 of the United Nations Statistical Office (UNSO).

The second group of industrial statistics describes the *output* of the industry in terms of goods and services produced (i.e. products). These products are classified according to a more or less detailed classification. These classifications can follow different criteria. Production-oriented product classifications are based on the principle of industrial origin, i.e. they combine in one classification group goods and services that are normally produced in only one industry as defined in Nace Rev.1 or ISIC Rev.3. This principle of industrial origin is used to elaborate the Classification of Products by Activity (CPA) and the Prodcom list of Eurostat. Consequently, each product is classified uniquely according to the activity, defined by one class of Nace Rev.1, that characteristically produces this product. Therefore, the structural order of the CPA, and of the Prodcom list, is the same as the order of Nace Rev.1 and the codes of these classifications are similar.

The Harmonised System/Combined Nomenclature (HS/CN) follow criteria that are quite different from industrial origin because they basically take into account the distinctions a custom officer has to make, on the basis of assessing the physical attributes of the goods against the relevant customs declarations. However, sometimes the production method or field of use is distinguished within the classification.

The Central Products Classification (CPC) and the transportable goods classification for International Trade Statistics (SITC) of UNSO both use the headings and subheadings of HS as building blocks for their categories, although they regroup HS categories in a different way.

3. Harmonisation of the European Classification System

At the most detailed level, the first four digits of each sub-category of the CPA (6-digit level) generally, with a few exceptions, coincide with Nace Rev.1 codes. Each sub-category of the CPA concerning transportable goods is generally defined by one or more sub-categorise (6-digit level) of HS and sometimes of CN (8-digit level), but the structural order and the codes of the CPA are totally different from those of the HS/CN.

The CPA contains 2303 sub-categorise (1533 goods, 100 construction works, 670 services) and is considered to be a framework Product Classification. In places, it is much too aggregated to be used in statistical surveys. All the other product classifications used by Member States for special survey purposes have to be related to CPA in strictly defined ways.

This is, for example, already the case for the items of the industrial products list of the European Community (Prodcom) used for production statistics, which are linked to CPA extending the CPA code from 6 to 8 digits. Each position of the Prodcom list (8-digit level) is generally defined by one or more positions (8-digit level) of the Combined Nomenclature (CN), but the structural order and the codes are totally different from those of CN.

The Prodcom list contains about 5700 items. It does not incorporate the CPA headings and does not have a hierarchical structure, except as implicit in its coding. The items of Prodcom do not cover all areas of CPA. In fact, Prodcom does not cover products of agriculture, forestry, live animals and animal products, fish and other fishing products, coal and lignite, peat, crude petroleum, natural gas, uranium and thorium, coke, refined petroleum products and nuclear fuel, some food products, some goods whose end use is for civil aircrafts, electricity, gas and water supply, construction works, trade services and other services. Moreover, Prodcom does not cover second hand goods and recovered secondary raw materials covered by HS/CN.

Generally, we can say that Prodcom has greater detail than the CPA (about double) and less detail than the CN (about one half) which contains over 10000 headings. The Prodcom list should cover the activities listed in the sections C (mining and quarrying), D (manufacturing) and E (electricity, gas and water supply) of Nace Rev.1. The present Prodcom does not however, cover subsections CA: mining and quarrying of energy producing materials, nor does it cover section E, as these fields are already covered by a separate set of Community statistics.

The observation fields covered by CPA, Prodcom, CN are shown in the following table:

Goods and services	**Field identified in**		
	CPA	**Prodcom**	**CN**
Products of agriculture, forestry, fishing	yes	no	yes
Services incidental to agriculture, forestry	yes	no	no
Energy producing materials (mining)	yes	no	yes
Services incidental to oil and gas extraction	yes	no	no
Other mining and quarrying materials	yes	yes	yes
Services incidental to mining and quarrying	yes	no	no
Refined petroleum products, nuclear fuel	yes	no	yes
Services incidental to fuel	yes	no	no
Other products of manufacturing	yes	(yes)	yes
of which: for aircrafts	yes	no	yes
of which: second hand goods and secondary raw materials	yes	no	yes
Services incidental to manufacturing	yes	yes	no
Electricity, gas and water supply	yes	no	(yes)
Constructions	yes	no	no
Trade services, business activity services and other services	yes	no	no

There are well over 4000 headings in the Prodcom list that are in a straightforward way related to the CN. Examples of such headings, together with their HS/CN references, are:

Prodcom	HS/CN *reference*	notes
18.24.42.70	6505	Aggregation of CN
20.30.12.50	4418.50	Aggregation of CN, coincidence with HS
25.21.30.76	3920.73.10	Exact coincidence with CN
29.11.13.11	8408.10(.21+.25+.30)	Aggregation of CN
15.33.25.50	2008 [.20 --- .99]	Aggregation of CN

There are also 330 other Prodcom headings which also have a straightforward relation with the CN, but which are subdivided into over 900 headings that are not harmonised with foreign trade statistics. About 225 headings are related to industrial services and subcontracting. Services are not included in the CN and consequently the relevant Prodcom headings do not have a HS/CN reference. Subcontracting of the manufacture of parts and components occurs in the manufacture of plastic products (Nace 25.24), and foundry products (Nace 27.5), as well as in forging, pressing, stamping, etc. (Nace 28.40) and general mechanical engineering (Nace 28.52).

In the textile industry there are 115 headings incorporating a breakdown by end-use, such as cotton yarns of uncombed fibres distinguishing: .....for carpets,... for other weaving,... for hosiery,... for other uses. Such a breakdown is considered very important for industrial statistics but unsuitable for CN because a custom officer cannot know the intended end-use of the goods on the basis of their custom declaration and their physical attributes.

In the iron and steel industry there are 112 headings which are taken from existing statistics based on the European Carbon and Steel Community Treaty (ECSC) and that are not fully compatible with CN. Almost 30 headings in various sectors (e.g. publishing, manufacture of pesticides, shipbuilding) have a greater level of detail than CN.

Finally, certain CN headings need to be assigned to more than one Nace class. In such cases Prodcom is automatically more detailed than CN.

4. Need to Improve Standardisation by Merging Different Product Classification Sets

In general, the potential for complete or even significant integration of the various nomenclatures is limited because of constraints concerning the variety of their structures, content and intended use. To illustrate this, the Prodcom, being simply a list of products, is not as comprehensive in coverage as the CPA and does not have a hierarchical structure. The CPA, on the other hand, is much too aggregated to be useful for statistical survey purposes.

As a consequence, it is not easy to ascertain whether there are some contradictions between CPA and Prodcom nor is it easy to assign new products to the correct CPA sub-category. The harmonisation of CPA, Prodcom and CN can be improved to allow comparison between production and foreign trade data.

In addition, the terminology adopted by Prodcom and CN is different even when there is correspondence 1:1 between Prodcom and CN codes. So, it is necessary to control the lexico-semantic coherence between CPA headings, Prodcom items as sub-headings and CN detailed items. In this way it is possible to achieve the goal 'One classification, one language' and thus improve the degree of harmonisation between classifications.

It is not easy for the users of economic nomenclatures to navigate through the new European classifications or their predecessors (e.g. Nace-CLIO) and even more difficult is to navigate through the European and the other International economic classifications (e.g. ISIC Rev.3, CPC). A further problem is the burden of form filling on enterprises, particularly where different nomenclatures and coding systems are used. They have to use the Prodcom for giving information about the production and the CN for the INTRASTAT survey concerning the import-export of goods.

Finally, some enterprises or institutions are asked to use the Community Procurement Vocabulary (CPV), which is an expanded 8-digit CPA similar to Prodcom, for public procurements in the EU.

5. An Integrated Classification of Products According to Activity to Improve Comparability of Business Data

The aim of my work is to build an integrated product classification, in other words, a complete product (goods and services) classification to be used as a basis in different surveys and one which provides a framework for the comparison of various kinds of statistics concerning goods and services: production, domestic and foreign trade, prices, etc.

The goal is to create a comprehensive, integrated European handbook or data base of all products-activities to dispose with the need to access or use a multitude of classification data base. An integrated classification of products (goods and services) along with the explanatory notes of Nace Rev.1, can be used as a tool to assign activity codes to statistical units (businesses, institutions, local units).

Since 1993 I have been working progressively towards building an integrated product classification, producing an updated, improved version each year. In a ONU-ECE Seminar held in Geneva on 19-20 October 1995 I presented the draft of integrated product classification: CPATECO 1955 where the CPATECO code was obtained inserting the fifth digit, as it is in the national activity classification (ATECO 1991), in an 8-digit expanded CPA. A correspondence table between CPA, CPC, Nace/CLIO, SITC, NST, CN, CPATECO, 8-digit expanded CPA was prepared as in following example:

CPA	**CPC**	**Nace/ CLIO**	**SITC**	**NST**	**CN 1995**	**CPATECO**	**CPA extended**
012213	02113	010101401	00151	001	01011100	012221310	0122.1310
012213	02113	010101401	00151	001	01011910	012221320	0122.1320
012213	02113	010101401	00151	001	01011990	012221330	0122.1330
012213	02113	010101401	00152	001	01012010	012221340	0122.1340
012213	02113	010101401	00152	001	01012090	012221350	0122.1350
012111	02111	010101402	00111	001	01021010	012101110	0121.1110
012111	02111	010101402	00111	001	01021030	012101115	0121.1115
012111	02111	010101402	00111	001	01021090	012101120	0121.1120
012112	02111	010101402	00119	001	01029005	012101210	0121.1210
012112	02111	010101402	00119	001	01029021	012101220	0121.1220
012112	02111	010101402	00119	001	01029029	012101230	0121.1230
012111	02111	010101402	00119	001	01029041	012101125	0121.1125
012111	02111	010101402	00119	001	01029049	012101130	0121.1130
012111	02111	010101402	00119	001	01029051	012101135	0121.1135
012111	02111	010101402	00119	001	01029059	012101140	0121.1140
012111	02111	010101402	00119	001	01029061	012101145	0121.1145
012111	02111	010101402	00119	001	01029069	012101150	0121.1150
012111	02111	010101402	00119	001	01029071	012101155	0121.1155
012111	02111	010101402	00119	001	01029079	012101160	0121.1160
012111	02111	010101402	00119	001	01029090	012101165	0121.1165

In February 1996, I presented to Eurostat, at a SPC: Nace-CPA Committee meeting, the new draft of CPATECO 1996, based on the new versions of HS/CN 1996, Prodcom 96, CPA 96. At this point my initial approach towards creating an integrated product nomenclature was the incorporation and linkage of CPA 1996 and Prodcom 1996 headings. Following this I reclassified all the CN 1996 (over 10.000 items) according to:

- the 8-digit codes of Prodcom in the case of a 1:1 correspondence between Prodcom and CN items,
- or according to a 10-digit extended Prodcom where the CN items were more detailed with respect to Prodcom.

In order to classify the CN headings that were assigned to CPA fields not covered by the Prodcom (e.g. products of agriculture) an extended 8-digit CPA code was created by emulation of the Prodcom.

Thirdly, the CN 96, recoded and sorted according to the CPA, was incorporated into the CPA-Prodcom set by a matching and merging procedure.

To avoid duplication of items, the sub-set of Prodcom products having an exact 1:1 correspondence with CN products was eliminated and replaced with the corresponding CN 96 sub-set of transportable goods, in order to use the CN terminology. In order to obtain a hierarchical mega-structure of about 18.000 headings this integrated nomenclature was sorted according the 10-digit extended CPA codes. The related Nace Rev.1 and CN 96 codes corresponding to the extended CPA codes were inserted.

Everybody is asking for more detail in services due to their growing importance in the economy. On one hand there is not enough detail in services in the CPA and, on the other hand, the CN only goods are included in Prodcom. Consequently it is only possible to achieve more detail in services from the CPV, from the OECD-Eurostat International Trade in Service classification (ITS) or from some other services nomenclature.

The 10-digit extended CPA draft I made in 1996, which I tentatively named CPATECO 1996 (Suggestions for a proper name are welcome) is structured as a hierarchical file containing about 18000 items. CPA 96, Prodcom 96 and CN 96 are merged and integrated in a mega-structure where:

- CPA items are used like main headings.
- Most of the Prodcom 96 items are used like sub-headings and are distinguished by the symbol (–).

- The Prodcom 96 items which represent a breakdown of a CN 96 item are distinguished by the symbol (..).
- CN 96 items describe products in detail, in fact, they generally represent detailed breakdowns of Prodcom and before the description there is the symbol (.).
- The items of CN 96 that exactly coincide with Prodcom 96 are distinguished by the symbol (=) . With respect to CPATECO codes, the extension of the CPA codes has been made in the following way:
- If the CN 96 products do not belong to Prodcom 96 list, e.g. agricultural products, two extra digits have been added to CPA code, in order to obtain the expanded 8-digit CPA code (emulation of Prodcom). It is shown in the following example:

CPAEXT 1996	**Nace Rev.1**	**HS/CN 96**	**Description**
A		A	Products of agriculture, hunting and forestry
01	01		Products of agriculture, hunting and related services
011	011		Crops, products of market, gardening and horticulture
0111	0111		Cereals and other crops n.e.c.
01111	0111		Cereals
011111	0111		Durum wheat
01111110	0111	10011000	. Durum wheat
011112	0111		Shoft wheat and maslin
01111210	0111	10019010	. Spelt for sowing
01111220	0111	10019091	. Common wheat and meslin seed
01111230	0111	10019099	. Spelt, common wheat and meslin (excl. seed)
011113	0111		Maize (corn)
01111310	0111	10051011	. Double and top cross hybrid maize seed
01111320	0111	10051013	. Three-cross hybrid maize seed
01111330	0111	10051015	. Simple hybrid maize seed
01111340	0111	10051019	. Hybrid maize seed (excl. double, top cross, three-cross and simple hybrid maize seed)
01111350	0111	10051090	. Maize seed (excl. hybrid)
01111360	0111	10059000	. Maize (excl. seed)

If the CN 96 products are considered in Prodcom 96 list, and if one CN product corresponds exactly to one Prodcom product, then the CPA extended code coincides with the Prodcom code. If a group of CN products represent a breakdown of a Prodcom item, two serial digits (from 01 to 99) were added to the Prodcom code, in order to obtain the extended ten-digits CPA code.

These situations are shown in the following example, in which it is very interesting to highlight the role played by the sequence of symbols: (=), (–), (.), (..).

CPATECO 1996	Nace Rev.1	HS/CN 96	Description
14	14		Other mining and quarrying products
141	141		Stone for construction
1411	1411		Stone for construction
14111	1411		Monumental or building stone
141111	1411		Marble and other calcareous monumental or building stone
14111133	1411	25151100	= Marble and travertine, crude or roughly trimmed
14111135	1411		– Marble and travertine merely cut into slabs, <= 25 cm thick
1411113501	1411	25151220	. Marble and travertine, merely cut, by sawing or otherwise, into slabs of a square or rectangular shape, of a thickness <= 4 cm.
1411113502	1411	25151250	. Marble and travertine, merely cut, by sawing or otherwise, into blocks or slabs of a square or rectangular shape, of a thickness of > 4 cm to <= 25 cm
14111137	1411	25151290	= Marble, travertine, merely cut, by sawing or otherwise, into blocks or slabs of a rectangular or square shape, of a thickness > 25 cm
14111150	1411	25152000	= Ecaussine and other calcareous monumental or building stone of an apparent specific gravity of >= 2.5, and alabaster, whether or not roughly trimmed or merely cut, by sawing or otherwise, into blocks or slabs of a square or rectangular shape (excl. in the form of granules, chippings or powder, and marble and travertine.
14111153	1411	25152000p	.. Calcareous building stone,alabaster, crude or roughly trimmed into slabs, > 25 cm thick
14111157	1411	25152000p	.. Calcareous building stone, alabaster, cut into blocks, > 25 cm thick
141112	1411		Granite, sandstone and other monumental or building stone
14111233	1411	25161100	= Granite, crude or roughly trimmed (excl. already with the characteristics of setts, curbstones and flagstones)
14111235	1411	25161210	= Granite, merely cut, by sawing or otherwise, into blocks or slabs of a square or rectangular shape, of a thickness of =< 25 cm (excl. already with the characteristics of setts, curbstones and flagstones)
14111237	1411	25161290	= Granite, merely cut, by sawing or otherwise, into blocks or slabs of a square or rectangular shape, of a thickness of > 25 cm (excl. already with the characteristics of setts, curbstones and flagstones)
14111253	1411	25162100	= Sandstone, crude or roughly trimmed (excl. already with the characteristics of setts, curbstones and flagstones)

CPATECO 1996	Nace Rev.1	HS/CN 96		Description
14111255	1411	25162210	=	Sandstone, merely cut, by sawing or otherwise, into blocks or slabs of a square or rectangular shape, of a thickness of =< 25 cm (excl. already with the characteristics of setts, curbstones and flagstones)
14111257	1411	25162290	=	Sandstone, merely cut, by sawing or otherwise, into blocks or slabs of a square or rectangular shape, of a thickness of > 25 cm (excl. already with the characteristics of setts, curbstones and flagstones)
14111290	1411		–	Other stones for building or freestone.
1411129001	1411	25169010	.	Porphyry, syenite, lava, basalt, gneiss, trachyte and similar hard rocks n.e.s., merely cut, by sawing or otherwise, into blocks or slabs of a square or rectangular shape, of a thickness of =< 25 cm
1411129002	1411	25169090	.	Monumental or building stone, whether or not roughly trimmed or otherwise merely cut into blocks or slabs of a rectangular (incl. square) shape, n.e.s.

The product having 8-digit extended CPA code 14111133 belongs both to Prodcom and to CN (symbol =). The product having 8-digit extended CPA code 14111135 belongs just to Prodcom (symbol –) and in CN it has a breakdown into 2 items: 25151220 and 25151250 (symbol .). The opposite happens for the product having 8-digit extended CPA code 14 111150 that coincides with the CN 25152000 (symbol =) and in the Prodcom has a breakdown in 3 items having codes: 14111153, 14111155, 14111157 (symbol ..).

The Nace Rev.1 codes close to Prodcom codes and to CN codes and descriptions highlight the contradictions between the Nace Rev.1 and CPA fourth digit in the textile area while the CN describes the type of fibre of which each product that could allow the use of the Nace Rev.1 fourth digit as CPA and Prodcom fourth digit is made.

CPAEXT 1996	Nace Rev.1	HS/CN 96	Description
DB	DB		TEXTILES AND TEXTILE PRODUCTS
17	17		TEXTILES
171	171		Textile yarn and thread
1710	1710		Textile yarn and thread
17101	1711		Wool grease (including lanolin)
171010	1711		Wool grease (including lanolin)
17101000	1712		– Wool grease
17101000	1712	15051000	. Crude wool grease
17101000	1712	15059000	. Wool grease and fatty substances derived therefrom incl. lanolin (excl. crude)
17102	1710		Natural textile fibres prepared for spinning
171020	1710		Natural textile fibres prepared for spinning
17102011	1715	50020000	. Raw silk, neither spun nor thrown
17102019	1715	50039000	. Silk waste, incl. cocoons unsuitable for reeling, yarn waste and garnetted stock, carded or combed
17102021	1712		– Clean scoured wool
1710202101	1712	51012100	. Shorn wool, degreased, non-carbonised), neither carded nor combed
1710202102	1712	51012900	. Degreased wool, non-carbonised, neither carded nor combed (excl. shorn wool)
17102023	1712	51013000	. Carbonised wool, neither carded nor combed
17102025	1712		– Noils of wool or fine animal hair
1710202501	1712	51031010	. Noils of wool or of fine animal hair, non-carbonised (excl. garnetted stock) (excl. garnetted stock)
17102027	1712		– Tops and carded sliver of wool of hair
1710202701	1712	51051000	. Wool, carded
1710202702	1712	51052100	. Wool, combed, in fragments open tops
1710202703	1712	51052900	. Wool, combed (excl. that in fragments open tops
1710202704	1712	51053010	. Fine animal hair, carded (excl. wool)
1710202705	1712	51053090	. Fine animal hair, combed (excl. wool)
1710202706	1712	51054000	. Coarse animal hair, carded or combed
17102030	1711	52030000	. Cotton, carded or combed
17102040	1714		– Flax, garnetted but not spun; flax tow and waste...
1710204001	1714	53012100	. Flax, broken or scutched
1710204002	1714	53012900	. Flax, hackled or otherwise processed, but not spun (excl. broken, scutched and retted flax)
1710204003	1714	53013010	. Flax tow
1710204004	1714	53013090	. Flax waste, incl. yarn waste and garnetted stock
17102050	1717		– Vegetal bast fibres, processed but not spun

CPAEXT 1996	Nace Rev.1	HS/CN 96	Description
1710205001	1717	53029000	. Hemp Cannabis sativa , processed but not spun; tow and waste of hemp, incl. yarn waste and garnetted stock (excl. retted hemp)
1710205002	1717	53039000	. Jute and other textile bast fibres, processed but not spun; tow and waste of such fibres, incl. yarn waste and garnetted stock (excl. retted fibres of this kind, flax, hemp and ramie)
1710205003	1717	53049000	. Sisal and other textile fibres of the genus Agave, processed but not spun; tow and waste of such fibres, incl. yarn waste and garnetted stock
1710205004	1717	53051900	. Coconut fibres, raw but not spun; tow and waste of such fibres, incl. yarn waste and garnetted stock
1710205005	1717	53052900	. Abaca Manila hemp or Musa textilis , processed but not spun; tow and waste of these fibres, incl. yarn waste and garnetted stock
1710205006	1717	53059900	. Ramie and other vegetable textile fibres n.e.s., processed but not spun; tow and waste of these fibres, incl. yarn waste and garnetted stock

6. Conclusions

The objective of the integrated nomenclature is that of keeping a watch on all the related product classifications of the European Union, making sure that the different product classifications are consistent, can be linked to CPA and are accurately worded in all languages. The objective is that of providing an useful tool to statisticians and nomenclaturists and not that of having a very detailed product classification that will work for all purposes. Everybody will continue to use each product classification separately.

Prodcom and HS/NC have a particular function in the measurement of markets and trade performance which is different from the needs of the public procurement field, where particular products are of interest in very fine detail and others much less so. The CPA is the common structure which brings all these things together, necessary for general international statistics. I hope I helped users of nomenclature to navigate from the macro-structure towards the micro-structure of the whole set of goods and services.

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COMPARABILITY OF PRODUCTION INDICES: Are Diverging Methods of Index Compilation Compatible with High Quality?

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Statistics are only valid if they allow comparisons, for example comparing prices, wage levels, productivity, investment behaviour, expenses for R&D and many more. Different kinds of comparisons are possible and common practice. Rarely are users aware of the possible, but unfortunately sometimes very real, deficiencies of such comparisons. The paper discusses these questions from the perspective of Eurostat, the Statistical Office of the European Communities.

Key words: International Comparability, Production Index, Practice of Member States.

1. Introduction

Comparisons between industrial activities or between sectors of the economy are already misleading if different concepts are inherent in the statistics used. Comparisons between different points in time, for example the present compared with the situation ten years ago are also very common. This may be problematic: if the underlying nomenclature has changed, or the collection method of the data was altered, or different observation units are used, conclusions of the comparisons may be distorted or even misleading.

Even more problematic may be comparisons between different countries, although this is nowadays common practice and there is certainly a growing necessity for this in a single European market with a forthcoming single currency. In addition to the above mentioned problems there are deeply rooted divergences of practice, both in data collection and in compilation of the statistics. This surely may lead to different results and it is rather difficult for the user to judge the magnitude of these differences.

Is there a political will to remedy this situation? Very little. In fact the conflict between additional costs for statistical offices plus the burden on reporting units on one hand and the user needs for harmonised and truly comparable statistics on the other hand may partially be solved for accuracy and timeliness of the statistics, but not for a harmonisation of concepts since these have often a very long tradition in the different countries and nobody wants to change.....

2. The Production Index

The production index, undoubtedly the most important of all short term indicators and used every day as a key indicator for analysing the business cycle, provides a good example of diversity of methods. The range of potential *conceptual* differences, for instance as regards the formula for the relevant index (Laspeyres, Paasche, Fisher, etc.) is common knowledge. However, the reality of the European situation is such that this diversity goes much farther: not only is there an argument as to which index concept should be applied but there are also different points of departure as far as *basic information* is concerned. The aim of the production index is to provide a quantitative measurement of monthly value added. As we know, this cannot be done in the form of an original exercise, and it is therefore necessary to work with hypotheses which are more or less valid over the short term.

Unfortunately the Member States of the European Union use a wide range of diverging concepts in order to approximate the short term production evolution. This may cause (and probably *does* now and then) more or less severe *misinterpretations*.

This paper will highlight the major differences of methods concerning the production index prevailing in Europe. It will focus also on the consequences these diverging methods have on the outcome, i.e. the values of the production index. It is the aim of this paper to invite users of (short term) statistics to be more cautious when they compare data from different countries and to help Eurostat in its attempt to harmonise the statistics as much as possible.

3. The Ideal

The term "production" has different possible meanings:

⇒ On one hand "production" means the *activity of manufacturing*, that is transforming goods.
⇒ On the other hand "production" is interpreted as the *result* of this activity, i.e. the *output* of manufactured goods in a fixed period.

It is generally accepted that the *ideal* production volume index shows the evolution of value added at factor cost.[1] The formula for this index Q is a standard Laspeyres volume index

$$Q_t^L = \frac{\sum_{i=1}^{N} p_{i,0} \times q_{i,t} - \sum_{j=1}^{M} \alpha_{j,0} \times \delta_{j,t}}{\sum_{i=1}^{N} p_{i,0} \times q_{i,0} - \sum_{j=1}^{M} \alpha_{j,0} \times \delta_{j,0}} \tag{1}$$

with q = quantities
p = prices
α = material prices
δ = material quantities
i = commodities and
j = materials used as input.

This ideal index of net output at constant prices should take account of

- variations in types and qualities of the products and of the input materials,
- changes in stocks of semi finished goods and
- changes in technical input-output relations (processing techniques).

4. Practical Problems

The practical difficulties in realising this are however great. Generally, the outputs q will be confined to final products (in fact only to principal products) and the information on raw material consumption will be limited to the main

1 The common practice of understanding the term "production index" as "evolution of value added" contradicts the exact definition of "production" in the framework of national accounts, but nonetheless the term "value added index" is never used in practice. This convention is therefore followed throughout this text.

materials. In addition, it is rather difficult to take account of changing work in progress or of the use of business services. Even so, the data required for compiling the formula are unlikely to be available except from a census of production or an extensive sample enquiry. In practice, the series may be available *annually*, and after some time lag. It might be approximated crudely on a quarterly basis, but it cannot be expected to be available either promptly or as frequently as monthly.

Even if all elements of the formula are available, problems arise in coping with the three demands mentioned above. Each of these factors affects in different ways the outcome of our compilation.

Firstly, the *quality* or type of product may change without showing up in the physical units (e.g. better cars over time). The solution here turns on using different series for varying qualities and types, i.e. attention should be directed to the definition of the product.

Secondly, there may be changes in the amount of *work in progress* during a reporting period (i.e. the work in progress at the end of the period may differ from that at the beginning) which would not show up in the output series. This will not cause difficulty if the change in one period is the same as that in another. It is not the existence of stock-piling which causes the trouble but *changes* in the rate of stock-piling relative to output. The difficulty is partly overcome, but not completely, by taking "output" data at various points in the production process. This makes possible the inclusion of stock-piling at the selected points but ignores changes in intermediate work in progress. If significant changes in work in progress are to be expected, as in construction, shipbuilding and engineering, then other solutions must be sought.

Thirdly, the amount of *processing* applied to *materials* per unit of product may change quite apart from variations in the quality of type of product. Materials of a greater or lesser degree of fabrication can be used or outside services can be used to a greater or less extent. In the car industry, for example, there is a choice between producing the engine in-house or buying it from suppliers.

5. Possible Approximations

To summarise, volume production in the sense of value added at factor cost cannot be measured directly by the reporting units, but only *approximated.* So the statistical offices must *convert* the information available from the reporting units in a particular industry, using more or less complex calculations. In practice, two types of substitute series are used as basic information:

⇒ *input data*
  a) consumption of typical raw materials (in quantities)
  b) consumption of energy, in particular electricity
  c) employment or hours worked
⇒ *output data*
  d) production of (selected) products in quantity
  e) deflated values of selected commodities
  f) (deflated) sales data.

Whatever kind of basic data is used, the choice of information must ensure a close correlation with the evolution of value added at factor cost, but the **costs** of data collection must be considered as well.

6. Comparison of Different Types of Basic Information

In the following analysis the advantages and disadvantages of different kinds of basic data are presented in detail:

a. Consumption of raw materials

The clear advantage of using material series as a proxy for the production index is that it is easy to measure so that collection costs are low.

To use series of input of materials involves the *assumption* that net output is constant per unit of materials used. This is not plausible where many different materials, together with fuels, packaging and business services have to be taken into account. It can be accepted only for an industry where one homogeneous material (or, at most, a few materials) accounts for the bulk of materials used. The series should represent the amount of the material consumed (not purchased), measured in physical units. A good example is the consumption of paper (in tons) in the printing industry. If several material inputs are used some adjustment needs to be made for changes in the proportions used in production.[1]

The disadvantage of materials input series is that, unlike labour input series, they may be far from a direct representation of work done in an industry. The *timing* of materials input, even if measured as consumption and

1 One possibility would be to take a series of values of all materials used in the industry, deflated with an index of the materials' prices.

not purchase of materials, is not that of work done. Such a series may allow to some extent, but by no means completely, for changing qualities of products. A series of material inputs does not make a correct allowance for changes in work in progress; in fact, while output series err in one direction, input series tend to err in the other direction. For example, if there is a growth in work in progress in a recording period (e.g. stock-pilling of intermediate products) then some part of the materials used is being "locked-up" in partly finished product. In such a case, the materials input series rises more, while an output series rises less, than work done.

Materials input is also an imperfect proxy for work done when there are changes in the amount of processing applied to materials for a given product. For example, if cruder materials or less fabricated components are purchased by an industry and more work done on the materials and components in the industry itself, then more work is done and less materials are used for a given output. Hence, when work done is increasing, it may be found that an output series remains uncharged and a series of materials input actually declines. In addition, material input series will ignore technical substitutions of minor for major materials if it is confined to a few of the more important materials. Changes in the amount of wastage of materials may not be adequately allowed for in a series of materials recorded as used or consumed.

b. Consumption of energy

A series based on consumption of energy would appear to have some advantages. In particular in the most common form of measuring electricity consumption, is easy to measure and thus causes only low collection costs.

Energy series of a single type can be constructed for diverse industry groups and there is a convenient and standard unit of measurement. The timing of the series would be better than materials series though probably not as good as labour series. The energy series used must be total consumption of energy, whether purchases or produced on the spot. There is a difficulty here, since the available data are often confined to purchases.

The main difficulty, however, is that the relation between consumption of energy and output is peculiarly liable to change. The introduction of new machinery, for example, will often have a much greater effect on energy consumed than on labour and material inputs. If no other series is available energy series can be useful in interpolating between quarterly more reliable data. Special care must be taken however to observe and allow for technological changes affecting energy consumption.

c. Employment or hours worked

The most generally available statistics in all countries are labour series such as the number of employees or hours worked. Between these two preference is to be given to a series of man-hours worked, since it takes account of short-time and overtime working. Even if hours worked are used, however, there may be need for some adjustment to allow for changes in the proportions of men, women and juveniles employed.[1]

The advantage of labour input series is that they are fairly direct approximations of work done. In general the timing of labour input and of work done agrees.

The main difficulty, and the one which prevents a general use of labour input series, is that they do not take account of changes in labour productivity (output per hour worked). Such series can only be used as an approximation to a series of work done if it is known that changes in labour productivity in an industry are small.

If labour input series are employed as a proxy of the production index, the index cannot be used for the purpose of assessing changes in the productivity of labour. This is very serious since one of the uses of an index of production is to throw light on this important question. It follows that, as a general rule, limited use of labour input series may be justifiable in the short-run. Over a longer period they would though need to be adjusted for changes in labour productivity.[2]

d. Physical quantities of output (gross production)

In this most classical case, the standard Laspeyres formula is used, without trying to take account of material inputs:

$$Q_t^L = \frac{\sum_{i=1}^{N} p_{i,0} \times q_{i,t}}{\sum_{i=1}^{N} p_{i,0} \times q_{i,0}} \qquad (2)$$

1 In order to overcome lack of hour data, some statistical offices take a series representing the aggregate wage bill in an industry and deflate it with an index of wage rates. This is not of general application, however, since changes in overtime work as a proportion of total hours worked would create distortions in the derived index.

2 For this, first the past productivity evolution is calculated (or approximated) and then extrapolated to the present time.

For an easier application this formula can be transformed to[1]

$$Q_t^L = \sum_{i=1}^{N} w_{i,0} \times \tilde{q}_t \tag{3}$$

with $w_{i,0}$ = the weight (production share) of commodity i in the base year and

$\tilde{q}_t$ = the quantity increase in period t since the base period.

If output is measured in physical terms, there are various alternative units which can be used. A choice can be made quite often between the number of pieces, volume, area or length measure, and the weight. There may be other measures, such as horsepower and engine capacity for machinery or vehicles.

None of these measures is the exact volume series required because they do not take account of *quality changes*. It may be that the output in some cases is so nearly homogeneous and free from quality changes that any physical unit will give the required volume series. In general, the product is so variable in type and quality that no one physical unit can be found to serve as a volume series.

The solution to this difficulty is to separate the different types and qualities and use separate series or (what amounts to the same thing) to devise some quantity index to cover the varying qualities.

If an industry is characterised by a rather long production cycle, for example ship-building, a measure of output is not appropriate as a proxy for changes in value added in a given period.

e. Gross production in value

The alternative is to take the value of various types and qualities of products and to deflate with an index representing changes in the level of prices of output.

The practical difficulty, however, may be to obtain *the necessary price data*. It may be difficult to obtain price quotations completely appropriate to the value series, especially for products intended for export.

The output series used, whether in physical or deflated value terms should represent production or completed items at the end of a stage of production, e.g., production of finished clothing or cars. The figures needed have to represent the result of current production, whether for sale or for stock. Deliveries, however, are made both from current production and from stock and

1 See Appendix 1

they represent the result partly of current and partly of past production. If the timing of production figures is right, then the timing of deliveries is wrong.

f. Sales data[1]

An *alternative* approach if changes in the quality of goods occur or if the combination of products in one group changes (for example a growing share of exports), is to calculate the index based on the value of *sales S* (for all observations v in the activity concerned). This new index includes such changes, while the price index p^L (type Laspeyres) for the deflation of sales values does not (or should not) express qualitative and structural changes.

The corresponding formula is:

$$Q_t = \frac{\sum_{v=1}^{V} \frac{S_{v,t}}{p_t^L}}{\sum_{v=1}^{V} S_{v,0}} \quad . \tag{4}$$

This index Q_t, derived from deflating sales with a Laspeyres price index, is itself a *Paasche* volume index, as can easily be proved.[2]

Paasche and Laspeyres indices show quite different results; in general the level of the Paasche index is *higher* than that of the Laspeyres index. This may cause (even *political)* problems if two Member States are compared, one using a Paasche, the other a Laspeyres type production index. Member States are therefore strongly discouraged from using this approach.

If, instead of the Laspeyres price index, Paasche price indices p^P are used, the deflation of turnover causes no more problem, since the resulting volume production index is of type Laspeyres.[3]

Another problem of deflating turnover (sales) is that price indices used for deflation are in general only available for *domestic* prices[4]. On the other hand, sale also include exports. Therefore export price indices are needed. A more sophisticated method may be derived from values of total domestic sales of an activity S^D and total sales abroad S^E. Using the appropriate price

1 In the context of this paper, the words "sales" and "turnover" are used as synonyms.

2 See Appendix 2

3 See Appendix 3

4 This problem has already appeared for method e. (deflated product values).

indices for domestic and export sales p^D and p^E , the formula for the index calculation becomes:

$$Q_t = \frac{\sum_{v_d=1}^{V_d} \frac{S^D_{v_d,t}}{p^D_t} + \sum_{v_e=1}^{V_e} \frac{S^E_{v_e,t}}{p^E_t}}{\sum_{v=1}^{V} S_{v,0}} \quad . \tag{5}$$

When this formula is applied, changes in the quality of products and changes in the relative importance of markets where the goods are sold are treated like changes in the volume of the production.

What are the advantages of this method? It is surely *easier* and *faster* to collect industry sales than selected individual products. Since speed is a very important priority for short term indicators, this aspects counts to a large extent. As a questionnaire asking for sales is identical for all reporting units, while a product questionnaire has to be adapted for each unit, the method of using sales data as a proxy for the production index is in general also considerably *cheaper* than other methods. In times of tight public budgets this is also an important argument in favour.

Finally, with this method all effects from quality changes are incorporated in the index compilation, including changes of product mix and processing techniques.[1]

The disadvantages of using deflated turnover are also apparent and have already been discussed in part:

- between production and sales may be a considerable time-lag, so that the (so called) production index calculated with this method gives a warning about a turning point in the business cycle several months too late;
- sales from stocks are included, production for stock is ignored; both effects give a false picture of true production;
- merchandise and work of subcontractors is included and might be counted a second time by the true producers of these goods;
- deliveries which are not invoiced (but have been produced) are excluded;

1 Of course this only holds if the price indices used are of high quality.

- all intermediate production of finished or semi-finished goods for subsequent treatment in the same enterprise is ignored;
- possible delocalization of the manufacture of semi-finished products, for example to low wage countries, is not taken account of;
- secondary activities of enterprises are included in the data collection, unless kind of activity units are chosen as the reporting units;
- deflation with price indices might be inappropriate, especially for exported sales and in areas with strong variations of prices;
- the result is a Paasche production index if deflation is done with conventional Laspeyres price indices.

For some of these deficiencies there are remedies: changes of stocks can be taken account of, and this is in fact often done by the statistical offices; care can be invested in using high quality price indices for deflation, approximating Paasche type price indices.

7. Member State Practice

The following table shows the present diversity of methods in most West European countries concerning the production volume index. It highlights the basic information principally used at present. Further details can be checked in the methodological reference data base of Eurostat, called MONA LISA.[1]

Apparently two thirds (10 out of 15) of all EU Member States use quantity information of products or commodity groups as base information for their volume production index.

In Germany also individual product (or commodity group) information is used, but in the form of deflated values. The statistical offices of Denmark, the Netherlands and the United Kingdom use deflated sales of complete industrial activities as their basic input for the production index. Sweden uses at present mainly hours worked (labour input) as basic information. Outside

1 Eurostat disposes of a rich electronic reference database on national methodologies, called MONA LISA (Methods of National Statistical Offices concerning Industrial Short Term Indicators) which is constantly updated. The contents of MONA LISA are also published at regular intervals. This data base allows the user of European short term statistics to check at any time how much the common rules and recommendations are followed. It also allows him to understand to what extent the differences in the data are due to diverging concepts of methods used in the Member States.

Methods used in 1995

Country	Dominant type of basic information	Second type of basic information
Belgium	quantities	
Denmark	deflated sales	
Germany	deflated product values	quantities
Greece	quantities	
Spain	quantities	
France	quantities	
Ireland	quantities	deflated sales
Italy	quantities	
Luxembourg	quantities	deflated product values
Netherlands	deflated sales	quantities
Austria	quantities	
Portugal	quantities	
Finland	quantities	hours worked
Sweden	hours worked	quantities
United Kingdom	deflated sales	quantities
Norway	quantities	
USA	electricity consumption	quantities

of Europe, the United States rely very much on electricity consumption for their estimations of the monthly production index.

It should not be forgotten that the choice of the basic information depends very much on the *specific situation* of a given industrial activity. This may also vary from one Member State to another. In certain cases more than one method might be applied inside a given industry, for example quantities for the large enterprises and deflated sales for the small ones.

8. Conclusion

a. Preferences

After studying the advantages and disadvantages of the different types of basic data and taking into consideration the actual practice of Statistical Offices in many industrialised countries, a list of *preferences* can be established. When doing so, it has to be kept in mind that there is a trade-off between low **costs** on one hand and the *quality* of the final index on the other hand. Neither of these two dimensions can be neglected.

To sum up, information on products or commodity groups in quantity or in value are the most appropriate in order to follow the "true" evolution of production.
Deflated turnover of total industries – which has the advantage of being the least costly – would come next in priority.
Using material, energy or labour input as basic information should only be applied if all other methods fail, since here the disadvantages outweigh the advantages of the methods.

b. Comparability

But this list of priorities does not solve the fundamental problem of *comparability* of series across countries. As we saw above, two major methods predominate:

⇒ information on selected products or
⇒ deflated sales.

Quantity measure of output do not take account of quality changes so the evolution of production is *underestimated*, maybe the true growth rate of value added at constant prices in a country over one year was or even 1 percent higher than measured by the statisticians. Consequently the derived productivity index is equally underestimated.

Sales, deflated with Laspeyres price indices, give a Paasche measure at constant prices, which generally *overestimates* the true evolution.

Thus an analyst compares country A (which uses product quantities) with a productivity growth of 2% with country B (which uses deflated sales) with a productivity growth of 4% and concludes: "Country B performed significantly better than country A". Far from the truth.....

In addition we saw that sales lag production. An analyst who concludes that country B shows its tuning points always later than county A and thus the economy of country B is clearly influenced in its performance by country A is again mistaken.

Thirdly we saw that often in sales secondary activities are included in the measurement. This will again lead to wrong conclusions in detailed analysis of activities, if countries that apply different methods are compared.

c. Other Examples

Many more examples for diverging methods for other short term indicators can easily be found.

For the variable of *employment,* the denominator in productivity indices, *data sources* and *definitions* vary considerably among the Member States.

Three very different sources can be identified:

- Direct industry collection, where enterprises are asked to give information on these labour input variables. This is the most common source in the area of short term indicators.
- The labour force survey (LFS), where households are asked (by direct interviewers of via the telephone) to give the appropriate information. This source is for example the base for our labour input variables in Spain, Sweden and Finland.
- A third source is used in the Netherlands: administrative data available in connection with the social security system. This source allows a rich set of variables and poses no additional burden on enterprises.

For obvious reasons the results differ substantially depending on the source: While the LFS surely has deficiencies concerning the identification of the industrial activity in which the interviewed person works (who is not familiar with the 4-digit level of Nace Rev.1), it allows accurate information on true hours worked. In the direct industry survey it can be assumed that not true hours worked are given, but the (theoretical) hours foreseen in the contract. Administrative sources often follow a different concept of data definition which can not be controlled by the statistician. They also often arrive rather late in comparison to direct data collection.

A further example in the domain of short term indicators is *seasonal adjustment* (which would easily fill another 20 pages). The list is not yet closed......

d. Outlook

Statistical offices will certainly not change very rapidly their methods. My experience over the past years of tough negotiations proves this.

It is therefore all the more important that analysts are informed about meta-information, i.e. on the background methodologies used in different countries, if they do not want to be mislead in their conclusion.

9. Appendix: Formulae

1. Transformation

Starting with the classical Laspeyres-formula, with the quantities q of commodities i in period t being weighted with the prices p of the base year 0, we obtain the volume index Q_t^L

$$Q_t^L = \frac{\sum_{i=1}^{N} p_{i,0} \times q_{i,t}}{\sum_{i=1}^{N} p_{i,0} \times q_{i,0}} \quad .$$

Multiplying the numerator by the vector $\sum_{i=1}^{N} \frac{q_{i,0}}{q_{i,0}}$ (=1) the formula is transformed to

$$Q_t^L = \frac{\sum_{i=1}^{N} p_{i,0} \times q_{i,t} \times {}^{q_{i,0}}\!/\!_{q_{i,0}}}{\sum_{i=1}^{N} p_{i,0} \times q_{i,0}} \quad .$$

This equals to

$$Q_t^L = \sum_{i=1}^{N} \frac{p_{i,0} \times q_{i,0}}{\sum_{i=1}^{N} p_{i,0} \times q_{i,0}} \times {}^{q_{i,t}}\!/\!_{q_{i,0}} \quad .$$

Now the formula consists of summing up

a) the base year production share of commodity I:
$\frac{p_{i,0} \times q_{i,0}}{\sum_{i=1}^{N} p_{i,0} \times q_{i,0}}$, i.e. the weight $w_{i,0}$, multiplied by

b) the quantity increase in period t since the base year ($\tilde{q}_t$), so that
This form of the production volume index can be applied in practice

$$Q_t^L = \sum_{i=1}^{N} w_{i,0} \times \tilde{q}_t$$

without major difficulties.

2. Deflation of Sales

If the production volume index Q_t is defined as deflated sales S (for all observations $\mathbf{v}$ in the activity concerned) and the deflator is of type Laspeyres (p^L), i.e. the formula is:

$$Q_t = \frac{\sum_{v=1}^{V} \frac{S_{v,t}}{p_t^L}}{\sum_{v=1}^{V} S_{v,0}}$$

it can easily be shown that this index is itself a *Paasche* volume index.

If we use again $\mathbf{i}$ as a symbol for the commodities in the activity concerned, we have for the Laspeyres price index:

$$p_t^L = \frac{\sum_{i=1}^{N} p_{i,t} \times q_{i,0}}{\sum_{v=1}^{V} S_{v,0}}$$

substituting this formula in the formula for the production index Q_t we obtain:

$$Q_t = \frac{\sum_{v=1}^{V} S_{v,t} \Bigg/ \left(\frac{\sum_{i=1}^{N} p_{i,t} \times q_{i,0}}{\sum_{v=1}^{V} S_{v,0}} \right)}{\sum_{v=1}^{V} S_{v,0}}$$

eliminating $\Sigma S_{v,0}$ gives:

$$Q_t = \frac{\sum_{v=1}^{V} S_{v,t}}{\sum_{i=1}^{N} p_{i,t} \times q_{i,0}} \quad .$$

Since the sum of sales is equal to the sum of all quantities multiplied by their prices, we can express this equation also as:

$$Q_t = \frac{\sum_{i=1}^{N} p_{i,t} \times q_{i,t}}{\sum_{i=1}^{N} p_{i,t} \times q_{i,0}} \quad .$$

So we have quantity changes q_t/q_0 weighted with the prices in period t instead of the base period 0, i.e. a Paasche volume index.

3. Deflating with Paasche price indices

If, instead of the Laspeyres price index, Paasche price indices p^P are used

$$p_t^P = \frac{\sum_{i=1}^{N} p_{i,t} \times q_{i,t}}{\sum_{i=1}^{N} p_{i,0} \times q_{i,t}} \equiv \frac{\sum_{v=1}^{V} S_{v,t}}{\sum_{i=1}^{N} p_{i,0} \times q_{i,t}}$$

then the deflation of turnover S_v causes no more problem:

$$Q_t^L = \frac{\sum_{v=1}^{V} \frac{S_{v,t}}{p_t^P}}{\sum_{v=1}^{V} S_{v,0}} \quad .$$

Here Q_t^L is the *Laspeyres* volume index in period t, since the formula can be rewritten to

$$Q_t^L = \frac{\sum_{v=1}^{V} S_{v,t} \Bigg/ \left(\frac{\sum_{v=1}^{V} S_{v,t}}{\sum_{i=1}^{N} p_{i,0} \times q_{i,t}} \right)}{\sum_{v=1}^{V} S_{v,0}}$$

which after elimination of $\Sigma S_{v,t}$ gives

$$\frac{\sum_{i=1}^{N} p_{i,0} \times q_{i,t}}{\sum_{v=1}^{V} S_{v,0}} \equiv \frac{\sum_{i=1}^{N} p_{i,0} \times q_{i,t}}{\sum_{i=1}^{N} p_{i,0} \times q_{i,0}} \quad .$$

So this time the quantity changes q_t/q_0 are weighted with the prices in period 0, the volume index is of type Laspeyres.

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STATISTICAL ANALYSIS OF BALANCE-SHEET RATIOS TO EVALUATE THE PERFORMANCES OF ENTERPRISES: A Comparison Between Steel and Food Sector

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In order to arrive at a complete evaluation of enterprise performance, which is indispensable for effective and appropriate company management planning, it is of fundamental importance to conduct a critical examination of balance-sheet items and the calculation of relevant ratios, accompanied by their careful, critical evaluation, supported by statistical techniques. These techniques aim at synthesising these ratios together with the description of their potential functional relations. In this way we are able to express judgements and form opinions about the dynamics and the determinants of enterprise performance both in time and space.

The increase in availability of ever more detailed and reliable information about company behaviour allows us to conduct further investigation aimed at an analytical description of distribution of ratios of which the mean value, the measures of dispersion, of skewness and kurtosis only give information of a limited kind, restricted to certain specific aspects. This analytical description involves a comparison between an empirical distribution and a suitable theoretical distribution and often this analysis provides a useful instrument for research into the nature of the causes which influence the manifestation of the phenomena.

In this work an attempt to meet this objective was made, with reference to the manufacturing sector. In particular, this work focuses on a comparison of two sectors, the steel and the food sectors, through the delineation of the most appropriate theoretical function with reference to the ratio Value Added/Turnover. This research deals with an homogeneous set of companies in terms of sector and size in that the reference data base is constituted by the Balance-Sheet for steel and food companies which in 1993 and 1994 declared a turnover of over 25 billion lire (source Mediobanca).

Key words: Distribution of Balance-Sheet Ratios, Theoretical Distribution, Pearson's System of Frequency Curves.

1. Introduction

In order to arrive at a complete evaluation of enterprise performance, which is indispensable for effective and appropriate company management planning, it is of fundamental importance to conduct a critical examination of balance-sheet items. This provides us with information about economic, financial and patrimonial aspects of company management, as a whole, as well as furnishing information about the results achieved in specific areas of company activity. In particular, an analysis of balance-sheet items should consist of transforming 'data' into 'information' (as Rizzo reminds us, 1993); this means that the calculation of relevant ratios should be accompanied by their careful, critical evaluation, supported by statistical techniques. These techniques aim at synthesising these ratios together with the description of their potential functional relations. In this way we are able to express judgements and form opinions about the dynamics and the determinants of enterprise performance both in time and space.

With these aims in mind there has been widespread recourse to traditional statistical techniques for the construction and interpretation of ratios for various sectors of production (see e.g., Alberici 1975; Favotto 1981; Appetiti 1984; Vincenzini 1984; Altman and La Fleur 1985; Previti Flesca 1986; Rizzo 1993). These analyses generally consist of a comparison of the values obtained for ratios under review for each company or company type with the average for the sector:

- the definition of the main characteristics of the distribution of the ratios;
- the research into the potential functional associations between ratios;
- the construction of models for the description of company critical points.

In addition, with reference to the study of ratios distribution, more often than not, the analyses are directed at the calculation of a range of statistics, synthesis of the ratios under exam, namely: the mean value, the measures of dispersion or spread, the measures of skewness and kurtosis.

The increase in availability of ever more detailed and reliable information about company behaviour allows us to conduct further investigation aimed at an analytical description of distribution of ratios of which the mean value, the measures of dispersion, of skewness and kurtosis only give information of a limited kind, restricted to certain specific aspects. This analytical description involves a comparison between an empirical distribution and a suitable theoretical distribution and often this analysis provides a useful instrument for research into the nature of the causes which influence the manifestation of the phenomena. The traditional procedure considers normal distribution as the theoretical distribution of reference, furnishing, however, only measures of distance (such as those of skewness and kurtosis) between normal and the empirical distribution. It is possible to overcome the information limits of this procedure by interpolation which allows us to isolate analytically the functional form which best fits the empirical distribution.

In a previous work (Santini 1996) an attempt to meet this objective was made, with reference to the banking sector, through the delineation of the most appropriate theoretical function for some of the most important ratios, to describe enterprises behaviour (cross-section) and providing, at the same time, an effective and immediate instrument to evaluate company performance.

In this work the analysis, which was extended to manufacturing sector, focuses on a comparison of two sectors, the steel and the food sectors, through the analysis of their performances with reference to the ratio Value Added/Turnover (from now on termed VAT)[1] . This research deals with an homogeneous set of companies in terms of sector and size in that the reference data base is constituted by the Balance-Sheet for steel and food companies which in 1993 and 1994 declared a turnover of over 25 billion lire (source Mediobanca).

2. Statistical Method

One of the main objectives of company performance analysis is that of determining the position of a company relative to its competitors by means of considering one or more relevant aspect: turnover potential, liquidity, solvency, etc. The result is usually arrived at by determining, for a specified group of

1 The choice to analyse the ratio Added Value/Turnover was determined by, essentially, two factors: 1) the ratio shows a notable capacity to indicate the economic position of a company, irrespective of the sector chosen for analysis; 2) the ratio is calculated with reference to flow aggregates and therefore both with high level of comparability.

companies and relative to each ratio derived from the balance-sheet, the key salient values which render a comparison of the performance of each individual company possible.

In company practice these values are held to be the mean value, the percentiles, arrived at using the empirical distribution (whether it refers to a sample or to the population). These indices, even if they characterise and define the relative position of a company within a particular group, do not make reference to any ideal standards to which a company, possessing certain structural and operative characteristics, should refer.

The techniques of interpolation try to go further, in certain circumstances, in so far as they refer to a theoretical model which fits better to empirical distribution and which can offer more information than that provided by the statistical indices derived from the distribution under review. In this way it is possible to arrive at a study of the characteristics of empirical distribution and their comparisons in time and space.

Very often the decision on a system of curves for describing frequency distributions is based on knowledge which has already been acquired for the phenomenon under review but, in some cases, such as this one, for example, the complexity of the phenomenon together with the shortage of elements on the suitable form of the theoretical model which best adapt to the empirical distribution, prompts more sophisticated analyses.

Given the fact that a distribution is wholly determined by its moments (Shapiro and Gross 1981), one possible method to decide the functional theoretical form of the empirical distribution can justly be based on a calculation of central moments, in particular the third and the fourth central standardised moment. The procedure for the identification of the model consists of three distinct but complementary phases:

i the measurement of the degree of skewness of the distribution;

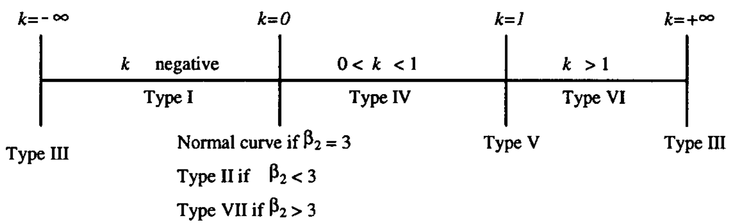
ii the measurement of kurtosis which in general shows which aspect of the form of symmetrical distribution belongs to the flattening or rising of central frequencies. Traditionally this characteristic comes to the fore when we take as terms of reference the normal distribution which has the same mean and the same standard deviation of distribution under examination;

iii the joint use of measures under i) and ii) to arrive at the delineation of the theoretical function which best represents the empirical distribution.

The measures of skewness and kurtosis, both proposed by Pearson come to be designated respectively by the following formulae: $\sqrt{\beta_1} = \frac{\bar{m}_3}{\bar{m}_2^{3/2}}$ and $\beta_2 = \frac{\bar{m}_4}{\bar{m}_2^{2}}$ where $\bar{m}_2$, $\bar{m}_3$ and $\bar{m}_4$ are respectively the second, the third and the fourth central moment[1]. By using jointly the two indices it is possible not only to test the hypotheses of normality[2] of the distribution under review, but also, as Pearson suggests, to identify the functional form which best adapts to empirical distribution when the 'criterion' k is calculated[3]:

$$\kappa = \frac{\beta_1(\beta_2+3)^2}{4(2\beta_2-3\beta_1-6)(4\beta_2-3\beta_1)} \quad .$$

κ can take any value between $-\infty$ and $+\infty$ and from the following diagram it will be seen how the curves cover all the possible values of the criterion and do not overlap (Elderton and Johnson 1969):



1 In the case of a noticeably positive skewness, the result is $\sqrt{\beta_1} > 0$ while if is noticeably negative, $\sqrt{\beta_1} < 0$. If the distribution shows a high rising of central frequencies β_2 takes values greatr than 3 while in the case of high flattening its values are lower than 3.

2 The test, proposed by Pearson, is based on the observation that the normal distribution results as being symmetrical ($\sqrt{\beta_1} = 0$) and with $\beta_2 = 3$. Tables are provided to test, for specific sample dimensions and levels of significance, the normality of distributions. For large sample asymptotic test can be used. In fact, for large samples, $\sqrt{\beta_1}$ is asymptotically normal with zero mean and variance equal to 6/n, while $\beta_2 - 3$ is asymptotically normal with zero mean and variance equal to 24/n.

3 See Elderton and Johnson (1969) and Leti (1983), for a detailed description of Pearson's system of frequency curves. Alternatively, it is possible to delineate the function by representing the indices β_1 and β_2 in the graph, where the family of Pearson's Curves is represented (see Biometrika Tables for Statisticians, edited by Pearson and Hartley, Cambridge University Press).

It is opportune to point out that the method proposed by Pearson has an essentially descriptive use and not an interpretative one in so far as the curves, as Boldrini (1968) reminds us, are not able to provide information about the influential circumstances which determine the phenomenon under investigation. However, even if, it always remains extremely difficult, if not impossible, to isolate the exact probability associated with the outcome of any specific single event, an adequate functional representation of empirical distribution allows us to form a more precise opinion about the ideal result to which companies should move towards.

3. An Analysis of the Characteristics of the Distribution of the Ratio Value Added/Turnover for the Steel and the Food Sector

Table 1 brings together the main characteristics of the distributions analysed. As far as we can see the measures of skewness and kurtosis[1], using Pearson's test, do not allow us to verify the hypothesis of normality. The criterion k, which takes a negative value, shows that Type I best adapts to empirical distributions[2]

1 The measures of skewness and kurtosis, and the parameters of the curves have been calculated with reference, as Pearson suggested, to the central moments adjusted according to Sheppard when the curve has high contact at both ends. In particular if $\overline{m}_i$ is the generalised central moment of the empirical distribution, the adjusted central moments $\overline{\mu}_i$ will be equal to: $\overline{\mu}_2 = \overline{m}_2 - \frac{1}{12}; \overline{\mu}_3 = \overline{m}_3 ; \overline{\mu}_4 = \overline{m}_4 - \frac{1}{2}\overline{m}_2 + \frac{7}{240}$.

2 This type of curve takes the following form:

$$y = y_0(1+\frac{x}{a_1})^{m_1}(1-\frac{x}{a_2})^{m_2}$$

It has five parameters (y_0, a_1, a_2, m_1 & m_2), with $-a_1 < x < a_2$ and shows a maximum in correspondence with $\mu - \frac{1}{2}\frac{\overline{\mu}_3}{\overline{\mu}_2}\frac{r+2}{r-2}$. The parameters take the following values:

1) $a_1 + a_2 = \frac{1}{2}\sqrt{\overline{\mu}_2(\beta_1(r+2)^2 + 16(r+1))}$ $(r = \frac{6(\beta_2 - \beta_1 - 1)}{(6+3\beta_1 - 2\beta_2)})$;

2) m_1 & m_2 take the value $\frac{1}{2}((r-2) \pm r(r+2)\sqrt{\frac{\beta_1}{\beta_1(r+2)^2 + 16(r+1)}})$ (when $\overline{\mu}_3$ is positive m_2 is the positive root of the previous expression; in addition, the following relation exists $m_1/a_1 = m_2/a_2$);

3) $y_0 = \frac{N}{a_1 + a_2} \cdot \frac{m_1^{m_1} m_2^{m_2}}{(m_1+m_2)^{m_1+m_2}} \cdot \frac{\Gamma(m_1+m_2+2)}{\Gamma(m_1+1)\Gamma(m_2+1)}$

Table 1. **Characteristics of the distribution of ratio: Value Added/Turnover.**

	Steel Sector 1993
Numer of companies	136
$\sqrt{\beta_1}$	0.90
β_2	3.65
k	–0.6472
Function	Type I
	$y = 24.0067(1+\frac{x}{2.15666})^{0.7826}(1-\frac{x}{18.6558})^{6.7708}$
Mode	13.35
P	0,1818

	Steel Sector 1994
Numer of companies	146
$\sqrt{\beta_1}$	0.80
β_2	3.50
k	–0.6121
Function	Type I
	$y = 26.7226(1+\frac{x}{2.7972})^{1.3439}(1-\frac{x}{18.4632})^{8.8701}$
Mode	15.13
P	0.0921

	Food sector 1993
Numer of companies	169
$\sqrt{\beta_1}$	0.53
β_2	.97
k	–0.2534
Function	Type I
	$y = 31.9874(1+\frac{x}{3.7415})^{2.1609}(1-\frac{x}{12.6832})^{7.3255}$
Mode	15.03
P	0.2782

Table 1. Cont.

	Food sector 1994
Numer of companies	168
$\sqrt{\beta_1}$	0.48
β_2	2.76
k	–0.1583
Function	Type I
	$y = 31.7913(1 + \frac{x}{3.2530})^{1.4654}(1 - \frac{x}{9.6702})^{4.3566}$
Mode	15.03
P	0.2782

The high level of goodness of fit of the curves, verified using the 2 test, whose results are included in the last line of the Table 1[1]. Allows us to construct Tables 2a, 2b, 3a and 3b. These provide for both sectors and for two years, the probability F(x) that the ratio VAT (in %) assumes a value no greater than x[2].

Graphically F(x) is represented by the dotted area in the figures of the tables under examination. The tables 2a, 2b, 3a and 3b prove to be particularly useful for a comparison of the relative position of a company in terms of the ratio Value Added/Turnover (in %) with respect to a particular year

1 P shows the probability that χ^2_v is higher than the value obtained using the statistic $\sum \frac{(f_3 - f_t)^2}{f_t}$, where f_e represents the observed frequencies, f_t the expected frequencies, v=k-r-1, where k is the number classes in which distribution is shown, r the number of parameters of the theoretical distribution. A value of P greater than α=0.05 shows a good fit between theoretical and empirical distribution.

2 In order to render the reading of the tables simpler the probability F(x), associated with values x situated at both ends have not been included: in particular values of x which show F(x) lower than 0.5‰ or greater than 99.95% have been excluded. Only values F(x) for entire values of x have been calculated also for the purposes of simplifying the description of the procedure adopted. It is evident however that it is possible to determine F(x) in correspondence with any fractional value of x relatively quickly.

and the dynamic of its position over time. In fact. the tables give us the relative frequency of companies with a ratio lower than or equal to the value examined (VAT=x). This relative frequency, in so far as it results from a theoretical distribution, can be interpreted in terms of probability. One example can help to clarify the modality of the correct reading of the tables. With reference to Table 2a, when x=VAT=14%, F(x)=0.308483; this result indicates that 30.8% of steel companies with a turnover greater than 25 billion lire reveal a ratio lower than 14%; or expressed in another way, that the probability company's registering a ratio lower than 14% is equal to 30.8%. Moving on to Table 2b, instead, it is shown that in correspondence with a value x=VAT=14%. F(x)=0.294506, so that in 1994 the probability is reduced to 29.5%. This result permits us to describe two important aspects:

1 the relative position of a company with respect to its competitors;

2 the improvement or deterioration of its position over time. In practice. the company would have to improve its result in order to maintain its position.

If we compare Tables 2a and 3a, which refers to food sector, we can see that if we still limit the analysis to companies with a turnover of over 25 billion lire, the same level of ratio VAT has, in 1993, a value of F(x) equal to 0.356505. This is noticeably higher than that shown by the steel sector. We can thus conclude that the food sector has performed worse, overall, than the steel sector. Furthermore the tables allows us to determine the relative frequency (and so the probability) for specific intervals of interest of the ratio examined. Another example will clarify this second approach to a reading of the tables. If we were interested in steel companies with a ratio VAT in 1993 of between 20 and 25% we would have to use the following procedure: in correspondence with $x_{(1)} = 20\%$, we read $F(x_{(1)}) = 0.510296$, while in correspondence with $x_{(2)} = 25\%$, we read $F(x_{(2)}) = 0.652025$. Keeping in mind that $F(x_{(1)})$ represents the relative frequency of companies with a ratio VAT (in %) lower than 20% and that by extension $F(x_{(2)})$ represents the relative frequency of companies with a ratio lower than 25%, the difference $F(x_{(2)}) - F(x_{(1)}) = 0.142$ shows that 14.2% of companies reveal a VAT of between 20 and 25 %. The practical utility of the use of these tables is clear, therefore in that we are able to achieve a more complete evaluation of company performance, both in time and space, and across sectors.

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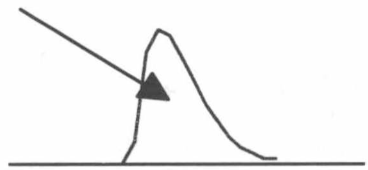
Table 2a. Value Added/Turnover (in %). Shortened Distribution function. Pearson Curves Type I. Steel industries 1993

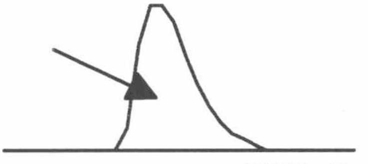
$$F(x)=\int_{2.5667}^{x} 24.0067\ (1+\frac{x}{2.1566})^{0.7826}\ (1-\frac{x}{18.6558})^{6.7708}\ dx$$



x	F(x)	x	F(x)	x	F(x)
3	0.001429	38	0.884453	73	0.990301
4	0.011560	39	0.895245	74	0.999440
7	0.076331	42	0.922895		
10	0.169191	45	0.944334		
11	0.203214	46	0.950288		
14	0.308483	49	0.965102		
15	0.343612	50	0.969140		
19	0.478630	54	0.981635		
20	0.510296	55	0.983986		
21	0.540927	56	0.986079		
24	0.626035	59	0.991033		
25	0.652025	60	0.992310		
26	0.676795	61	0.993429		
29	0.743809	64	0.995997		
30	0.763758	65	0.996635		
31	0.782548	66	0.997185		
35	0.846755	70	0.998687		
36	0.860250	71	0.998929		
37	0.872802	72	0.999132		

Table 2b. Value Added/Turnover (in %). Shortened Distribution function. Pearson Curves Type I. Steel industries 1994

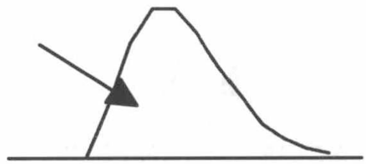
$$F(x) = \int_{1.1420}^{x} 26.7726 \ (1 + \frac{x}{2.7972})^{1.3439} \ (1 - \frac{x}{18.4632})^{8.8701} \ dx$$



x	F(x)	x	F(x)
2	0.001046	37	0.894380
3	0.006035	38	0.905657
4	0.015616	39	0.915949
8	0.096040	43	0.948463
9	0.124582	44	0.954713
10	0.155539	45	0.960320
11	0.188441	46	0.965337
14	0.294506	49	0.977317
15	0.331041	50	0.980434
19	0.474986	54	0.989537
20	0.509289	55	0.991135
21	0.542574	56	0.992519
24	0.635209	59	0.995615
25	0.663424	60	0.996362
26	0.690230	61	0.996997
29	0.762057	64	0.998362
30	0.783154	65	0.998676
31	0.802866	66	0.998937
35	0.868643		
36	0.882062		

Table 3a. Value Added/Turnover (in %). Shortened Distribution function. Pearson Curves Type I. Food industries 1993

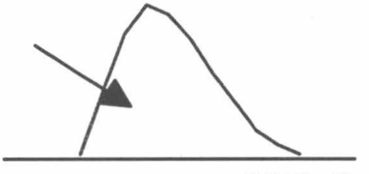
$$F(x) = \int_{-3.6797}^{x} 31.9874 \left(1 + \frac{x}{3.7415}\right)^{2.1609} \left(1 - \frac{x}{12.6832}\right)^{7.3255} dx$$



x	F(x)	x	F(x)
–1	0.002665	34	0,911077
0	0.006778	35	0.923121
1	0.013521	36	0.933881
3	0.036211	38	0.951893
4	0.052456	39	0.959319
8	0.148513	43	0.980474
9	0.179195	44	0.984026
10	0.211938	45	0.987032
11	0.246395	46	0.989556
14	0.356505	49	0.994824
15	0.394304	50	0.995983
19	0.542818	54	0.998699
20	0.578017	55	0.999050
21	0.612037	56	0.999316
24	0.705634		
25	0.733681		
26	0.760050		
29	0.828919		
30	0.848498		
31	0.866445		

Table 3b. **Value Added/Turnover (in %). Shortened Distribution function. Pearson Curves Type I. Food industries 1994**

$$F(x) = \int_{-2.3912}^{x} 31.7913 \left(1 + \frac{x}{3.2530}\right)^{1.4654} \left(1 - \frac{x}{9.6702}\right)^{4.3566} dx$$



x	F(x)	x	F(x)
-1	0.001924	34	0,926150
0	0.006966	35	0.937295
1	0.015696	36	0.947171
3	0.044575	38	0.963452
4	0.064493	39	0.970027
8	0.174308	43	0.987902
9	0.207574	44	0.990681
10	0.242436	45	0.992939
11	0.278538	46	0.994748
14	0.390908	49	0.998113
15	0.428690	50	0.998732
19	0.574535		
20	0.608648		
21	0.641501		
24	0.731393		
25	0.758211		
26	0.783379		
29	0.848874		
30	0.867409		
31	0.884351		

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STATISTICAL METHODS AND MODELS FOR THE ANALYSIS OF CROSS-CULTURAL DATA

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Comparison of regions, countries and cultures can be a useful method to gain insight into societal structures and processes. Typically, such comparisons have been based on aggregate data. Through the collection of multiregional and multicultural data sets on the individual level it is now possible to gain deeper insight by analysing whether complex multivariate associations that are found in one region or culture also hold for other regions and cultures, or in what ways these associations differ across regions and cultures. A special problem occurs in the analysis of individual data from questionnaires because the data are often measured on a dichotomous or ordinal level as opposed to a metric level. Consequently, this paper treats statistical models for mean and covariance structures with metric and /or non-metric dependent variables. These models allow for comparisons of means, variances, covariance matrices, regression coefficients and factor structures for purely metric dependent variables and, in addition, comparisons of threshold models for dichotomous and ordinal dependent variables across different regions and cultures. Only the comparison of cross-sectional data across regions and cultures is considered. Comparisons of longitudinal data are deferred to another paper. While the comparison of mean and covariance structure models for metric dependent variables may be implemented with standard software such as LISREL fairly easily, it is rather tricky to implement comparisons for threshold models for non-metric dependent variables. In this case, newly developed software such as the programs LISCOMP and MECOSA should be employed.

Key Words: Multicultural Data, MECOSA, LISREL.

1. Introduction

Societal structures and processes are often understood by comparing different regions, countries and cultures. The accumulation of data bases for the same (or at least partially overlapping) variables in different regions and cultures gives social scientists the opportunity to probe much deeper into the societal similarities and differences of different regions and cultures than ever before. However, this requires the extension of the commonly used models for use in analysing multiple data sets from different cultures.

In this paper I focus on the comparison of cross-sectional data sets for different cultures where data have been obtained on the same variables. I do not consider at all the analysis of panel data from different cultures although it can be treated within the same framework. The analysis of data sets where the sets of variables are not identical but only partially overlapping is mentioned only in passing; however, the relevant literature is cited.

In particular, I consider the use of the analysis of means, variances, covariances, regression coefficients and factor structures for cross cultural comparisons. Models are formulated first for metric dependent variables and then for dichotomous and other limited dependent variables. Data requirements, estimation methods and software are discussed briefly. The analysis of contingency tables using loglinear or related models is also omitted from this discussion. Treatment of this issue merits a separate paper.

2. Mean and Covariance Structure Models for Cross Cultural Comparisons

The following model is based primarily on the LISREL model for multiple groups (Jöreskog and Sörbom, 1988, chapter 10). An observed outcome y^* in the form of a vector of metric variables, is considered for an individual from region or culture (g):

$$\eta^{(g)} = \alpha^{(g)} + B^{(g)}\eta^{(g)} + \Gamma^{(g)}x^{(g)} + \zeta^{(g)} \tag{1}$$

where

$$y^{*(g)} = \nu^{(g)} + \Lambda^{(g)}\eta^{(g)} + \varepsilon^{(g)} \quad , \tag{2}$$

(g) is the group index ranging from $1, \ldots, G$. It denotes that the model is formulated for the region or culture indexed by g. The simplest case is the comparison of $G = 2$ cultures, for instance, of Germany and Japan.

$\eta^{(g)}$ is a vector of metric dependent but possibly latent variables that cannot be observed directly. These variables are regressed onto themselves in the form of a simultaneous equation model and onto the independent variables $x^{(g)}$. A typical example for such a latent dependent variable is *general satisfaction with life* which may constructed using observed variables found for instance in the questionnaire of the German Socio-economic Panel (SOEP, Hanefeld, 1984).

$x^{(g)}$ is a vector of observed independent variables with expected value $E(x) = \xi^{(g)}$ and covariance matrix $V(x^{(g)})$. Te values of x vary across individuals. The vector x may include dummy variables to deal with non-metric variables such as sex and occupation. Continuing the example of general life satisfaction as the dependent latent variable, x may include income, sex, occupation, job characteristics and the like.

$\alpha^{(g)}$ is the vector of regression constants for $\eta^{(g)}$.

$B^{(g)}$ is the matrix of regression coefficients of $\eta^{(g)}$ on $\eta^{(g)}$. It is assumed that $(I - B)^{-1}$ exists, where I is the identity matrix.

$\Gamma^{(g)}$ is the matrix of regression coefficients of $\eta^{(g)}$ on $x^{(g)}$.

$\zeta^{(g)}$ is a vector of disturbances with expected value $E(\zeta^{(g)}) = 0$ and covariance matrix $V(\zeta^{(g)})$. $\zeta^{(g)}$ varies across individuals, but is assumed to be uncorrelated with $x^{(g)}$.

$y^{*(g)}$ is a vector of metric variables. The variables of $y^{*(g)}$ are directly observed. They are connected with the latent variables $\eta^{(g)}$ through a factor analytic model. If the dependent latent variable is again *general satisfaction with life*, then the observed variables $y^{*(g)}$ typically include such variables *as satisfaction with health, household income, flat or house, professional work, household work* and *spare time*. In the SOEP all of these variables are measured on a *10* point Likert scale (which we consider to be metric although it is in reality only an ordinal scale). In this example, we also treat these variables as metric indicators of general satisfaction with life.

$\nu^{(g)}$ is the vector of regression constants in the factor analytic model $\eta^{(g)}$.

$\Lambda^{(g)}$ is the matrix of regression coefficients in the regression of $y^{*(g)}$ onto $\eta^{(g)}$. It is usually called the matrix of factor loadings.

$\varepsilon^{(g)}$ is a vector of measurement errors that varies across individuals with expected value $E(\varepsilon^{(g)}) = 0$ and covariance matrix $V(\varepsilon^{(g)})$. Note that the diagonal elements of this covariance matrix give the error variance in the factor analytic measurement model. The measurement errors are assumed to be uncorrelated with the latent variables $\eta^{*(g)}$.

Only the vectors $x^{(g)}$ and $y^{*(g)}$ are observed. Note that, in contrast to the usual LISREL formulation, the model described by (1) and (2) does not incorporate a measurement model for $x^{(g)}$. This is not a restriction, since explanatory variables that are measured with error can always be included in the vector $\eta^{*(g)}$ (see for instance Jöreskog and Sörbom, 1988, chapter 6.1). This is seen immediately by collecting the usual LISREL vectors $\eta^{(g)}$ and $\zeta^{(g)}$ into $\eta^{(g)}$ of equation (1) and the LISREL vectors $y^{(g)}$ and $x^{(g)}$ into $y^{*(g)}$ of equation (2). In equation (1) $x^{(g)}$ denotes only the exogenous variables of the system.

In the most general model, the following vectors and matrices are estimated separately for each region or culture:

$$\alpha^{(g)}, B^{(g)}, \Gamma^{(g)}, \xi^{(g)}, V(x^{(g)}), V(\zeta^{(g)}), \nu^{(g)}, \Lambda^{(g)}, V(\varepsilon^{(g)})$$

Note that $\zeta^{(g)}$ and $V(x^{(g)})$ can be estimated directly from the data $x_h^{(g)}$, $h = 1,...,H_g$ by computing the empirical mean vector and the empirical covariance matrix. The question of selecting a sample will be discussed later. By restricting certain parameter vectors or matrices cross-cultural comparisons are easily made. Some of the typical comparisons of interest include:

1 The comparison of means across different groups, e.g., testing the hypothesis $H_0 : E(y^{*(1)}) =...= E(y^{*(G)})$ against $H_1 : E(y^{*(1)}) =...\neq E(y^{*(g)})$. This null hypothesis may be tested by setting $\alpha^{(g)}$, $B^{(g)}$, $\Gamma^{(g)}$, $V(\zeta^{(g)})$ and $\Lambda^{(g)}$ to 0 and setting $\nu^{(1)} =...= \nu^{(G)}$. The covariance matrices $V(\varepsilon^{(g)})$ need not be unrestricted. In our example with the variables satisfaction with different aspects of life, this null hypothesis would imply that the mean satisfaction with each aspect of life is equal for all G cultures. If this null hypothesis is rejected more specific hypotheses about the mean differences between variables and cultures may be formulated.

2 The comparison of covariance matrices across different groups, for instance testing the hypothesis $H_0 : V(y^{*(1)}) =...= V(y^{*(G)})$ against $H_1 : V(y^{*(1)}) =...\neq V(y^{*(G)})$. The null hypothesis may be tested by setting $\alpha^{(g)}$, $B^{(g)}$, $\Gamma^{(g)}$, $V(\zeta^{(g)})$ and $\Lambda^{(g)}$ to 0 and setting $V(\varepsilon^{(1)}) =...= V(\varepsilon^{(G)})$. The mean vectors $v^{(g)}$ are assumed to be unrestricted. For our example, this null hypothesis means that the means of the different satisfaction variables are allowed to be different for each country, but the association between the satisfaction variables is the same in all cultures. That is, the average level of satisfaction may differ across countries, but the spread of the variables, as measured by the standard deviation and the correlations between the variables, is the same for all cultures. Note that especially in cross-cultural comparisons one is usually not only interested in the levels of a variable but also in the spread, as the latter measures homogeneity of a population with regard to the variable of interest.

3 The comparison of regression constants across different groups. Consider the model $y^{*(g)} = \gamma^{(g)} + \Pi^{(g)}x^{(g)} + \delta^{(g)}$ where $\gamma^{(g)}$ is the vector of regression constants, $\Pi^{(g)}$ is the matrix of regression coefficients and $\delta^{(g)}$ is the disturbance vector with $E(\delta^{(g)}) = 0$ and covariance matrix $V(\delta^{(g)})$. The hypothesis H_0: $\gamma^{(1)} =...= \gamma^{(G)}$ may be tested by setting $B^{(g)}$, $v^{(g)}$ and $V(\varepsilon^{(g)}) = 0$, $\Lambda^{(g)} = I$ and $\alpha^{(1)} =...= \alpha^{(G)}$. $\Gamma^{(g)}$and $V(\zeta^{(g)})$ remain unrestricted. The vector $\alpha^{(g)}$ then corresponds to $\gamma^{(g)}$, $\Gamma^{(g)}$ to $\Pi^{(g)}$ and $V(\zeta^{(g)})$ to $V(\delta^{(g)})$. For the case of the satisfaction variables, this null hypothesis implies that the mean levels of satisfaction are equal in all cultures, given that the independent variables have the value 0.

4 The comparison of regression coefficients across different groups. In the model above $\alpha^{(g)}$ and $V(\zeta^{(g)})$ are allowed to remain unrestricted while $\Gamma^{(1)} = \Gamma^{(2)} =...=\Gamma^{(g)}$. This model is especially important since it allows the regression constants and the error covariance matrices to vary across region or cultures while the regression coefficients are restricted to be equal. This model implies that regions or cultures may be on different levels in y^* expressed by the variations in $\alpha^{(g)}$, but that the independent variables work in the same way on y^*, i.e. the hypothesised mechanisms are identical in each country. For the satisfaction variables, this null hypothesis implies that independent variables such as income, occupation and job characteristics, have the same influence in all cultures under consideration.

5 The comparison of the coefficients in a simultaneous equation model across different groups. If $\Lambda^{(g)} = I$ and $\nu^{(g)} = 0$ and $V(\varepsilon^{(g)}) = 0$ then $y^{*(g)} = \eta^{(g)} = \alpha^{(g)} + B^{(g)}\eta^{(g)} + \Gamma^{(g)}x^{(g)} + \zeta^{(g)}$. The equality of the simultaneous equation structures may be tested by setting $B^{(g)} =...= B^{(G)}$ and $\Gamma^{(1)} = \Gamma^{(2)} =...= \Gamma^{(G)}$.

6 The comparison of factor loadings across different groups. By setting $\alpha^{(g)}$, $B^{(g)}$ and $\Gamma^{(g)}$ to 0 one obtains the model $\eta^{(g)} = \zeta^{(g)}$ with $V(\eta^{(g)}) = V(\zeta^{(g)})$ and $y^{(*g)} = \nu^{(g)} + \Lambda^{(g)}\eta^{(g)} + \varepsilon^{(g)}$. The equality of factor loading matrices may be tested by setting $\Lambda^{(1)} = \Lambda^{(2)} =...= \Lambda^{(G)}$ while $\nu^{(g)}$, $V(\eta^{(g)})$ and $V(\varepsilon^{(g)})$ remain unrestricted. Of course, these parameters may also be restricted to be equal to test the full equality of the factor analytic model across the different groups. This null hypothesis is of key interest when variables are used as indicators for latent variables. If we think of the satisfaction variables as indicators for the variable *general satisfaction with life*, then the equality of factor loadings implies that the relationship between $\eta^{*(g)}$ and $y^{*(g)}$ does not change across cultures. If the latent variable is defined by the indicators and cannot be measured in any other way it is essential that the factor loadings are the same. Otherwise the latent variable can take on a different meaning in each culture. An important exception occurs when the items that have been selected as indicators are different for each culture, and only partially overlap. This is taken up in the next point.

7 The comparison of simultaneous equation models while the factor loadings are different. In this case, $B^{(1)} = B^{(2)} =...= B^{(G)}$ and $\Gamma^{(1)} = \Gamma^{(2)} =...= \Gamma^{(G)}$ while all other parameter are allowed to remain unrestricted. This formulation of the general model corresponds to the substantive hypothesis that the causal mechanisms for $\eta^{(g)}$ in the different region or cultures are equal while the levels expressed in $\alpha^{(g)}$ and $\xi^{(g)}$ are different and the indicators collected in $y^{*(g)}$ are related to $\eta^{(g)}$ in different ways for the individual cultures. This is the case when the items $y^{*(g)}$ used for measuring $\eta^{(g)}$ have different connotations in each culture or if different items are selected to measure the same latent variables. If the items partially overlap then restrictions may be imposed on certain coefficients of $\Lambda^{(g)}$, g=1, ..., G. What happens if a latent variable $\eta_i^{(g)}$is measured by 4 indicators in group 1 and by 5 indicators in group 2 where only the first two indicators overlap? Even this case can be handled by writing the matrices $\Lambda^{(1)}$ and $\Lambda^{(2)}$ in the following way:

$$\Lambda^{(1)T} = (\lambda_1^{(1)}, \lambda_2^{(1)}, \lambda_3^{(1)}, \lambda_4^{(1)}, 0, 0, 0)$$

$$\Lambda^{(2)T} = (\lambda_1^{(2)}, \lambda_2^{(2)}, 0, 0, \lambda_5^{(2)}, \lambda_6^{(2)}, \lambda_7^{(2)}) .$$

The parameters $\lambda_1^{(1)}$ and $\lambda_2^{(1)}$ are set equal to $\lambda_1^{(2)}$ and $\lambda_2^{(2)}$ and because the same items are used in both groups. $\lambda_3^{(1)}$ and $\lambda_4^{(1)}$ indicate the items 3 and 4 are used in group 1 while the zeros for $\lambda_3^{(2)}$ and $\lambda_4^{(2)}$ show that these items are not used in group 2. Items 5, 6, 7 are not used in group 1 but are used in group 2. For technical reasons, i.e. to ensure estimation, the variances $V(\varepsilon_j^{(g)})$ of the variables j that have not been observed in group (g), g=1,2 must be set to 1. The covariances with all other variables are set to 0. Details of this procedure are found in Allison (1987) and Arminger and Sobel (1990). However, at present, this method is restricted to metric dependent variables.

These examples suffice to show that the model is general enough to deal with the typical research questions encountered in cross-cultural research. Of course, much more elaborate and subtle question may be adressed by taking into account not only the mean structures parameterized in $\alpha^{(g)}$, $B^{(g)}$, $\Gamma^{(g)}$ and $\Lambda^{(g)}$ but also the covariance structures $V(\zeta^{(g)})$ and $V(\varepsilon^{(g)})$.

We now expand the model of equations (1) and (2) into a more general mean and covariance structure model to treat estimation more easily and to include the case of non-metric dependent variables. Substitution of equation (1) into equation (2) yields the reduced form of the system:

$$y^{*(g)} = \nu^{(g)} + \Lambda^{(g)}(I - B^{(g)})^{-1}\,\alpha^{(g)} + \Lambda^{(g)}(I - B^{(g)})^{-1}\,x^{(g)} + \Lambda^{(g)}(I - B^{(g)})^{-1}\,\zeta^{(g)} + \varepsilon^{(g)} . \qquad (3)$$

After the substitutions

$$\begin{aligned}\gamma^{(g)} &= \nu^{(g)} + \Lambda^{(g)}(I-B^{(g)})^{-1}\,\alpha^{(g)},\\ \Pi^{(g)} &= \Lambda^{(g)}(I-B^{(g)})^{-1}\,\Gamma^{(g)},\\ \delta^{(g)} &= \Lambda^{(g)}(I-B^{(g)})^{-1}\,\zeta^{(g)} + \varepsilon^{(g)}\end{aligned}$$

the last equation may be written as

$$y^{*} = \gamma^{(g)}(\upsilon) + \Pi^{(g)}\,(\upsilon^{(g)}) + \delta^{(g)} \qquad (4)$$

with $E(\delta^{(g)}) = 0$ and

$$V(\delta^{(g)}) = \Sigma^{(g)}(\delta) = \Lambda^{(g)}(I - B^{(g)})^{-1}\, V(\zeta^{(g)})(I - B^{(g)})^{-1T}\, \Lambda^{(g)T} + V(\varepsilon^{(g)}).$$

The vector υ in equation (4) denotes all parameters in $\alpha^{(g)}$, $B^{(g)}$, $\Gamma^{(g)}$, $V(\zeta^{(g)})$, $\nu^{(g)}$, $\Lambda^{(g)}$ and $V(\varepsilon^{(g)})$ that have to be estimated from the data. Of course the usual identification restrictions have to be fulfilled. However, if restrictions are imposed across groups, many of the usual identification restrictions for one group can be alleviated.

The parametrization of υ that is implied by equation (1) and (2) is by no means the only one; other parametrizations that come from much more complicated models have been proposed by McDonald (1978), Küsters (1987) and Arminger and Sobel (1990). The common denominators of all these models is the reduced form of the mean and the covariance structure of $y^{*(g)}$ given $x^{(g)}$ parameterized by the vector υ:

$$E(y^{(*g)} \mid x^{(g)}) = \gamma^{(g)}(\upsilon) + \Pi^{(g)}(\upsilon)x^{(g)} \tag{5}$$

$$V(y^{(*g)} \mid x^{(g)}) = \Sigma^{(g)}(\upsilon)\ . \tag{6}$$

The model is second order identifiable if the equalities $\gamma^{(g)}(\upsilon_1) = \gamma^{(g)}(\upsilon_2)$, and $\Pi^{(g)}(\upsilon_1) = \Pi^{(g)}(\upsilon_2)$ and $\Sigma^{(g)}(\upsilon_1) = \Sigma^{(g)}(\upsilon_2)$ for all g=1, ..., G imply that $\upsilon_1 = \upsilon_2$.

3. Estimation of Mean and Covariance Structures for Metric Dependent Variables

To estimate the parameter vector υ from data bases from G different regions or cultures we assume that in each region a sample $(y_h^{*(g)}, x_h^{(g)})$, $g=1,\dots,G$; $h=1,\dots,H_g$ of observations has been collected. The sample sizes H_g need not be equal. Usually the samples will be random samples in each country. However, this is necessary only for the purpose of prediction. If the main interest of the study is not prediction but the comparison of causal mechanisms then it is not necessary that a sample is random in the sense that it is representative for the distribution of (y^*, x); it is only assumed that the individuals in the sample are drawn independently. However, consistent estimation of is only achieved if the model is correctly specified, i.e. $\zeta^{(g)}$, $\varepsilon^{(g)}$ are uncorrelated with $x^{(g)}$ and with each other. Finally, we note that the samples from different regions and cultures will be drawn independently of each other.

The parameter vector υ is estimated from the data sets of all groups jointly. Estimation is performed by using the maximum likelihood (ML), the pseudo ML (PML) or the weighted least squares (WLS) method. In the ML method one assumes that the errors $\delta^{(g)}$ are normally distributed $\delta^{(g)} \sim N(0, \Sigma^{(g)}(\upsilon))$. The joint second order moment matrix of the unconditional vector y^* and x is inferred from equations (5) and (6). It is given by

$$\Omega^{(g)} = \begin{pmatrix} E(y^{*(g)} y^{*(g)T}) & E(y^{*(g)} x^{*(g)T}) \\ E(x^{(g)} y^{*(g)T}) & E(x^{(g)} x^{(g)T}) \end{pmatrix} \tag{7}$$

where $E(x^{(g)} x^{(g)T})$ is the second order moment matrix of $x^{(g)}$. The other submatrices are given by the following equation (the group index (g) is left out for notational convenience):

$$E(y^* y^{*T}) = \gamma\gamma^T + \Pi\xi\gamma^T + \gamma\xi^T\Pi^T + \Pi E(xx^T)\Pi^T + \Sigma \tag{8}$$

$$E(y^* x^T) = \gamma\xi^T + \Pi E(xx^T) \tag{9}$$

$$E(xy^*\gamma^T) = \xi\gamma^T + E(xx^T)\Pi^T. \tag{10}$$

The empirical second order moment matrix of $(y^{*(g)}, x^{(g)})$ is:

$$M^{(g)} = \frac{1}{H_g} \begin{pmatrix} \sum_h y_h^{*(g)} y_h^{*(g)T} & \sum_h y_h^{*(g)} x_h^{(g)T} \\ \sum_h x_h^{*(g)} y_h^{*(g)T} & \sum_h x_h^{(g)} x_h^{(g)T} \end{pmatrix}.$$

In the ML-method the loglikelihood function of all samples jointly is maximised where each sample is weighed by its sample size H_g. The sum of all sample sizes is denoted by H.

$$l(\upsilon) = -\frac{1}{2H} \sum_{g=1}^{G} H_g (\ln|\Omega^{(g)}(\upsilon)| + tr M^{(g)} \Omega^{(g)}(\upsilon)^{-1}) . \tag{11}$$

If the assumption of multivariate normality conditional on $X^{(g)}$ is violated, the ML method still yields consistent estimates $\hat{\upsilon}$ of υ, but the estimate $\hat{V}(\hat{\upsilon})$ *of* *the asymptotic covariance matrix* $V\hat{\upsilon}$ will not be consistent for all the parameters of the model. Alternatively, one can use the PML method. This method maximises the same loglikelihood function as above, but computes a consistent estimate of $V(\hat{\upsilon})$. The PML method for mean and covariance structures is discussed in Arminger and Schoenberg (1989) and Arminger and Sobel (1990). If the sample size for each region is rather large, say $H_g = 1000$ or more, one can also use the weighted least squares (WLS) method discussed by Shapiro (1986). This method also yields a consistent estimate of $V(\hat{\upsilon})$ if the residuals are non-normal.

The ML and the WLS method for multiple groups are implemented in the program packages LISREL (Jöreskog and Sörbom 1988) and LISCOMP (Muthén 1988). The estimation methods and the programs are fairly robust and large numbers of groups, i.e. more than *100*, can be handled with LISREL.

4. Mean and Covariance Structures with Non-metric Dependent Variables

Basic ideas

We use essentially the same model as before, but instead of considering only metric dependent variables we extend the model to dependent variables that may be metric and/or censored metric and/or ordinal. These cases cover the typical measurement levels in empirical social and economic research. This section is based on Schepers, Arminger and Küsters (1991).

The vector $y^{*(g)}$ is now assumed to be a vector of (usually) unobserved propensities or dispositions which is modelled as before under the additional assumption of multivariate normality conditional on $x^{(g)}$:

$$y^{*(g)} \,\Big|\, x^{(g)} \sim N(\gamma^{(g)}(\upsilon) + \Pi^{(g)}(\upsilon)x^{(g)}, \Sigma^{(g)}(\upsilon)) \,. \tag{12}$$

Here, N denotes the multivariate normal density function, $\gamma^{(g)}(\upsilon) + \Pi^{(g)}(\upsilon)x^{(g)}$ is again the mean structure and $\Sigma^{(g)}(\upsilon)$ is the conditional covariance structure. Each disposition $y_i^{*(g)}$ is connected to an observed metric, censored metric or ordered categorical variable y_i through a threshold model explained below. Note that an ordered categorical variable includes a dichotomous variable as a special case. The assumption of multivariate conditional normality is used to generate the marginal tobit and probit models discussed below. The vector υ is again the collection of all free parameters for all groups $g=1,\ldots, G$. Furthermore, the thresholds for ordinal variables for each group are added to υ.

The threshold relations

Each observed variable y_{hi} is connected with y^*_{hi} by one various measurement relations. For convenience of notation, the case index $h=1, \ldots, H_g$, is omitted. The following measurement relations are considered:

- y_i is metric (identity relation). There are no thresholds.

$$y_i = y_i^* \tag{13}$$

- y_i is ordered categorical with unknown thresholds $\tau_{i,1} < \tau_{i,2} < \ldots < \tau_i$, K_i and categories $y_i = 1, \ldots, K_i + 1$ (ordinal probit relation, McKelvey and Zavoina 1975):

$$y_i = k \Leftrightarrow y_i^* \in \left[\tau_{i,K-1}, \tau_{i,k}\right) \tag{14}$$

$$\text{with } \left[\tau_{i,0}, \tau_{i,1}\right) = \left(-\infty, \tau_{i,1}\right) \text{ and } \tau_{i,K_i+1} = +\infty.$$

The thresholds are parameters that must be estimated from the data. To identify the model, threshold $\tau_{i,1}$ is set to 0 and the variance of the reduced form error term $\sigma_i^2(\upsilon)$ is set to 1. Note that the case of a dichotomous variable is included under this formulation. In this case, the threshold is equal to 0. The model generated by equation (14) is (besides the identity relation) probably the most important one for social scientists since many of their variables are ordered categorical. Typical examples from the SOEP include questions about the comparison of working conditions now and one year before. Questions are asked about type of work, income, career opportunities, job security and the like. In all questions the possible answers are ordered categories, i.e. there was a positive change, no, change or a negative change. Although these categories can be numbered as 1, 2 and 3, such numbers implying equal distance between the categories would be meaningless. Hence, we consider these questions in the SOEP as ordinal without a meaningful average and scale. Hence, the threshold and variance restrictions must be made.

- Classified metric variables may be treated analogously to the ordinal probit case with the difference that the class limits are now used as known thresholds (Stewart 1983).
- y_i is one-sided censored with a threshold value $\tau_{i,1}$ known a priori (tobit relation, Tobin 1958).

$$y_i = \begin{Bmatrix} y_i^* & \text{if } y_i^* > \tau_{i,1} \\ \tau_{i,1} & \text{if } y_i^* \leq \tau_{i,1} \end{Bmatrix} \tag{15}$$

- y_i is double-sided censored with threshold values $\tau_{i,1} < \tau_{i,2}$ known a priori (two-limit-probit relation, Rosett and Nelson 1975).

$$y_i = \begin{Bmatrix} \tau_{i,1} & \text{if } y_i^* \leq \tau_{i,1} \\ y_i^* & \text{if } \tau_{i,1} < y_i^* < \tau_{i,2} \\ \tau_{i,2} & \text{if } \tau_{i,2} \leq y_i^* \end{Bmatrix} \tag{16}$$

For the case where y_i is dichotomous, the probit relati on also arises as a special case of the random utility maximisation principle (Nelson 1976).

Marginal likelihood estimation

The estimation of the parameter vector υ in a general mean and covariance structure with endogenous non-metric variables is performed in three stages. This three stage method was originally devised by Muthén (1979, 1984). It has been implemented in LISCOMP by Muthén (1988) for the linear models of equations (1) and (2) and in MECOSA by Schepers (1991) for the linear and/or non-linear models of equations (5) and (6). The use of LISREL is not advised because the thresholds and polychoric correlation coefficients are not conditioned on x. Consequently, all independent variables are supposed to come from a multivariate normal distribution, which is certainly not true for dummy variables.

1 In the first stage the threshold parameters τ, the reduced form coefficients γ and Π of the regression equation, and the reduced form error variance σ_i^2 of the i-th equation are estimated using marginal maximum likelihood. Note that in this first stage the mean structure is estimated without the restrictions of equation (12). The parameters to be estimated in the i-th equation are the thresholds denoted by the vector τ_i, the regression con-

stant denoted by γ_i, the regression coefficients, i.e. the i-th row of Π denoted by Π_i and the variance denoted by σ_i^2. The loglikelihood function that is maximised with respect to $\{\tau_i, \gamma_i, \Pi_{i,} \sigma_i^2\}$ of the i-th equation is given by

$$l_i\,(\tau_i, \gamma_i, \Pi_i, \sigma_i^2) = \sum_{t=1}^{T} \ln P(y_{ti}|x_t) \; . \tag{17}$$

The formulation of $P(y_{ti} \mid x_t)$ depends on the measurement level of the observed variable y_i. If y_i is metric then $P(y_{ti} \mid x_t)$ is the univariate normal density with expected value $\gamma_i + \Pi_{i.}\, x_t$ and variance σ_i^2, i.e.,

$$P(y_{ti}|x_t) = \varphi(y_{ti} | \gamma_i + \Pi_{i.} x_t, \sigma_i^2)\,, \tag{18}$$

in which $\varphi(y \mid \mu, \sigma^2)$ denotes the univariate normal density. Another example is the ordinal probit model that is applied if y_i is an ordinal variable. In this case the probability that $y_{ti} = k$ must be computed as:

$$P(y_{ti} = k | x_t) = \int_{\tau_{i(k-1)}}^{\tau_{i(k)}} \varphi(y^* | \gamma_i + \Pi_{i.} x_t, 1) dy^* \, . \tag{19}$$

The probability of the last equation is the basis of the likelihood used in the ordinal probit model (McKelvey and Zavoina 1975). If other models are used such as the tobit model (Tobin 1958) for dependent variables censored on one side only or the two limit probit model (Rosett and Nelson 1975) for dependent variables censored on two sides then the probabilities $P(y_{ti} \mid x_t)$ have to modified accordingly.

A solution to the likelihood equations obtained by setting the first derivatives of $l_i\left(\tau_i, \gamma_i, \Pi_i, \sigma_i^2\right)$ to 0 is computed in MECOSA by applying a Quasi-Newton algorithm proposed by Polak (1971) using analytical first derivatives. The second order derivatives are approximated by computing the crossproduct of the first order derivatives. The first estimation stage yields strongly consistent estimates of τ_i, γ_i, $\Pi_{i.}$ and σ_i^2. Regularity conditions and the proof of strong consistency are given in Küsters (1987).

2 In the second stage the problem is to estimate the covariances of the error terms in the reduced form equations. Note that in this stage the covari-

ances are estimated without parametric restrictions. Since the errors are assumed to be normally distributed and strongly consistent estimators of the reduced form coefficients have already been obtained in the first stage the estimation problem reduces to maximising the loglikelihood function

$$l_{ij}(\sigma_{ij}) = \sum_{t=1}^{T} \ln P(y_{ti}, y_{tj} \mid x_t, \hat{\tau}_i, \hat{\gamma}_i, \hat{\Pi}_i, \hat{\sigma}_i^2, \hat{\tau}_j, \hat{\gamma}_j, \hat{\Pi}_j, \hat{\sigma}_j^2, \sigma_{ij}), \tag{20}$$

in which $P(y_{ti}, y_{tj} \mid x_t, \hat{\tau}_i, \hat{\gamma}_i, \hat{\Pi}_i, \hat{\sigma}_i^2, \hat{\tau}_j, \hat{\gamma}_j, \hat{\Pi}_j, \hat{\sigma}_j^2, \sigma_{ij})$ is the bivariate probability of y_{ti} and y_{tj} given x_t and the reduced form coefficients. A typical example of this bivariate probability is the case when y_i and y_{tj} are both ordinal. Then the probability that $y_{ti} = k$ and $y_{tj} = l$ is given by:

$$P(y_{ti} = k, y_{tj} = l \mid x_t) = \int_{\tau_{i,(k-1)}}^{\tau_{i,(k)}} \int_{\tau_{j,(l-1)}}^{\tau_{j,(l)}} \varphi(y_i^*, y_j^* \mid \hat{\mu}_{ti}, \hat{\sigma}_i^2, \hat{\mu}_{tj}, \hat{\sigma}_j^2, \sigma_{ij})\, dy_j^* dy_i^* \tag{21}$$

in which $\hat{\mu}_{tj} = \hat{\gamma}_i + \hat{\Pi}_i x_t$, $\hat{\mu}_{tj} = \hat{\gamma}_j + \hat{\Pi}_j x_t$ and $\varphi(y_i^*, y_j^* \mid \mu_{ti}, \sigma_i^2, \mu_{i,} \sigma_j^2, \sigma_{ij})$ is the bivariate normal density function. Note that in the ordinal case $\hat{\sigma}_i^2 = \hat{\sigma}_j^2 = 1$. Hence, σ_{ij} is a correlation coefficient, called the polychoric correlation coefficient (Olsson 1979). The loglikelihood function $l_{ij}(\sigma_{ij})$ has to be modified accordingly if variables with other measurement levels are used.

The objective function $l_{ij}(\sigma_{ij})$ is maximised using the regula falsi algorithm with analytical first derivatives. The resulting estimates $\hat{\sigma}_{ij}$ are strongly consistent estimators σ_{ij}. Note that these covariances are the covariances of the error terms in the equations conditional on x_t.. In contrast to LISREL, we do not assume that the variables y_{ti}^* and y_{tj}^*, which depend on x_t, are normal. We only assume that the errors are normal.

The estimated thresholds $\hat{\tau}_i$, the reduced form coefficients $\hat{\gamma}_i$ and $\hat{\Pi}_i$, the variances $\hat{\sigma}_i^2$ and the covariances $\hat{\sigma}_{ij}$ from all equations are then collected in a vector $\hat{\kappa}_H$ which depends on the sample size H. For the final estimation stage, a strongly consistent estimate of the asymptotic covariance matrix W of $\hat{\kappa}_H$ is computed. This estimate is denoted by $\hat{W}_H$. The asymptotic covariance matrix W is difficult to derive since the estimates of $\hat{\sigma}_{ij}$ of the second stage depend on the estimated coefficients $\hat{\tau}_f, \hat{\gamma}_f, \hat{\Pi}_f, \hat{\sigma}_f^2, f = i,j$ of the first stage. The various elements of the asymptotic covariance matrix W are given in Küsters (1987). The estimate $\hat{W}_H$ is computed in MECOSA by using analytical first order and numerical second order derivatives of the first and second stage loglikelihood function.

3 In the third stage the vector of thresholds, the reduced form regression coefficients and the reduced form covariance matrix are written as a function of the structural parameters of interest, collected in the parameter vector υ. The parameter vector υ is then estimated by minimising the quadratic form

$$Q_H(\varphi) = (\hat{\kappa}_H - \kappa(\upsilon))^T \hat{W}_H^{-1} (\hat{\kappa}_H - \kappa(\upsilon)) \tag{22}$$

which corresponds to a weighted least squares approach. The vector $\hat{\kappa}_H$ is asymptotically normal with expected value $\kappa(\varphi)$ and covariance matrix W. Since $\hat{W}_H$ is a strongly consistent estimate of W the quadratic form $Q_H(\upsilon)$ is centrally χ^2 distributed with $p-q$ degrees of freedom if the model is specified correctly and the sample size is sufficiently large. The number p indicates the number of elements in $\hat{\kappa}_H$ while q is the number of elements in υ.

The parameter vector υ itself may be thought of as a continuously differentiable function of a vector υ^* of fundamental parameters. Hence, the υ's may be restricted in a very general way. Typical examples are the restriction that must be positive, that the υ's are ordered or that the υ^*'s lie within given intervals. All of these restrictions are easily formulated in terms of the υ^*'s and are easily implemented in MECOSA.

Estimation in multiple groups

The estimation of υ from G data sets from different regions or cultures is based as in the metric case on the assumption that G independent samples with sample sizes H_g are available. In the first stage, univariate regression, tobit and probit models are estimated for each dependent variable in each group. In the second stage, the correlations and covariances are estimated in each group depending on the measurement levels. In the third stage, a weighted least squares estimation is performed where the weight matrix $\hat{W}^{(g)}$ depends on the sample size. The following function is minimised:

$$Q(\upsilon) = \sum_{g=1}^{G} (\hat{\kappa}^{(g)} - \kappa^{(g)}(\upsilon))^T \hat{W}^{-1(g)} (\hat{\kappa}^{(g)} - \kappa^{(g)}(\upsilon)) \ . \tag{23}$$

In analogy to the matrices $\Lambda^{(g)}$ of factor loadings one has to estimate the threshold parameters $\tau^{(g)}$ in the different groups. If one believes that for instance the categories of the trichotomous variables about changes in the working conditions mean the same in all regions or cultures the thresholds must be restricted to $\tau^{(1)} =,..., \tau^{(G)}$. Otherwise the meaning of the categories is assumed to be different across cultures and comparisons may be without meaning.

A special problem in the construction of the parameter υ arises because the variances of the error term in probit models is restricted to *1*. However, if the thresholds are set equal across cultures, these variances can vary across groups in a meaningful way in comparison to the first culture which is taken as a reference group. Consequently, the variances for some groups can be unrestricted. This must be considered in the third stage of the estimation procedure of section Marginal Likelihood Estimation. The same problem comes up in the analysis of panel data and is treated in greater detail in Arminger (1987).

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Part C

Frames and Sampling

Biffignandi, Butti and Schionato

... administrative registers contain one or more dimensional variables (such as number of employees and self-employed workers, total sales, wages, number of local units, consumption etc.). Therefore it is necessary to define methodologies and procedures for improving the lack of information through their integration and the analysis of the relationships among variables contained in different registers.

Teikari

An important feature of business surveys is the definition of the sampling units in the frame and the elements that constitute the population. After the definition of population elements the frame units must be determined. If we are interested in income, outlay or financial statistics the Institutional Unit (Enterprise) is generally the preferable one otherwise Kind-of-Activity Unit or Establishment could be one to be preferred. The reporting unit is not always the same as the statistical unit either in business surveys.

The frame most often used in business surveys is the Business Register. This is the frame which directly identifies the individual elements of the population. The devices for making contacts and some important auxiliary variables of the elements are also included in business registers. Naturally there are also some frame imperfections. For example, the rapid changes in small businesses creates under- and overcoverage in the frame.

Ballin and Falorsi

The main concern of this work is to describe the sampling strategy adopted in the 1995 survey with a detailed analysis of: (i) the sample selection method that aims the maximum overlap with the previous survey, (ii) the calculus of inclusion probabilities of first and second order, (iii) the determination of sampling weights and sampling errors.

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Statistics Finland

STRATIFICATION VARIABLES AND CRITERIA FOR DETECTING THE ACTIVE STATUS OF A BUSINESS*

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The statistical register of businesses is built according to the standards of the European Community, Act n. 2186/93. This Act requires, for each active business and local unit, the inclusion of those variables by which it is possible to measure the size of the economic units. The variables are obtained from administrative registers. The following variables are requested explicitly: the number of employees and self-employed workers, the total sales, the net profits.

The analysis of the connections existing among the above-mentioned variables is a subject of great interest because it is relevant to the designing of models for the detection of outliers and incorrect data and for missing data estimation. Moreover, it is by these dimensional variables that it is possible to determine the active status of an economic unit and consequently its inclusion in the register which contains only active units. In our research, we initially apply an original procedure for clearing the data set from anomalous kinds of businesses and from those businesses which are likely to be closing down. As a second step of analysis, we apply both an "a priori" and an "analytical" approach for the determination of the threshold total sales values which allow to define a unit as active, that is which corresponds at a minimum amount of work; this problem arises when microdata on employment is unknown. The "a priori" approach is based on the rules proposed by the European Community which establish the active status of a business on the basis of a minimum amount of total sales. The "analytical" approach is based on the links between total sales and number of employees and self-employed workers; these relations are empirically detected after suitable cleaning of anomalous microdata and adequate stratification.

Key words: Statistical Register of Businesses, Administrative Register, Microdata, Total Sales, Stratification Variables, Missing Data, Dormant Businesses.

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1. Introduction

The increasing use of administrative registers for statistical analysis generates the problem of finding appropriate methodologies for missing data estimation or for the checking of register data. This paper makes the assumption that the integration of registers permits the joint use of the juridical form of a business, class of age, electrical consumption, total sales, class of total sales, employees and self-employed workers.

We propose procedures for the evaluation of the status of a business, in particular: 1) for "fictitious" and "closing down" businesses; 2) for the determination of the active status, when microdata on employment are lacking.

The first topic is an important and preliminary one, since its use in the economic analysis of data sets containing "fictitious" businesses, that is anomalous from the point of view of business management, created for administrative or fiscal reasons, or containing businesses that are "closing down" or "dormant", distorts and obscures the search for economic behaviour. Therefore, before starting the analysis, it would be appropriate to clean the data set from statistically detected anomalous microdata.

As regards the second topic, it should be observed that in the context of the wider topic of methodologies for missing data estimation, the need for employment and total sales data estimation is connected with the necessity to assess whether an economic unit is active or not. In fact, European Community Act no. 2186/93 requires that, in the statistical register of businesses, only active units[1] are to be included and the inclusion, for each business and local unit, of those variables by which it is possible to measure their size as economic units (the number of employees and self employed workers, the total sales, the net profits...). As the above cited law requires that the statistical register of businesses is to be built with the information coming from the national administrative registers, it might happen that the administrative registers contain missing data or units that do not correspond to active businesses.

Generally speaking, the analysis of the relations among dimensional variables is therefore a subject of interest, whose study might lead to the designing of models for outliers and incorrect data detection, for missing data

1 Paragraph n. 2 in the Act 2186/93 specifies that the juridical units which carry on, totally or partially, a productive activity must be part of the register. Therefore, all units created for mere adminitstrative or formal purposes ("convenience companies" or "fictitious" business) are excluded; moreover, by paragraph 3.1, are excluded the production of families for self-consumption and the services of real estate renting

estimation and for the search of criteria that can ascertain active units. The creation of a reliable and complete data set containing dimensional data constitutes a reference point essential to the arranging of a reliable territorial and sectoral statistical framework, as well as for the definition of appropriate stratification criteria to be employed in sample surveys[1]. In Italy, there are several administrative registers that can be employed for this purpose. They are: the business register of the Chambers of Commerce (RD), the social security register (INPS), the compulsory insurance register (INAIL), the tax register, the electrical and telephone company registers.

There are also some projects and experiments for the integration of administrative registers to be used in economic analysis. The ASPO and ASIL projects, concerning the provinces of Lombardia and Lazio respectively, the Excelsior project, the Informative System and the Economic Observatory for Handicrafts (SIOE). According to what has been requested by the European Community, the National Statistical Institute (ISTAT) has started the construction of the statistical register of businesses called ASIA (statistical register of active businesses) which will be based on the crossing of microdata coming from the existing administrative files, and where necessary checked and integrated with surveys.

This paper is based on the fact that, in Italy, administrative registers contain one or more dimensional variables (such as number of employees and self-employed workers, total sales, wages, number of local units, consumption etc.). Therefore it is necessary to define methodologies and procedures for improving the lack of information through their integration and the analysis of the relationships among variables contained in different registers. This paper is divided in two parts: the first (section 2) describes briefly the characteristics of administrative registers and shows that no source is able to cover totally the information on the dimensional aspects of a business. The second part proposes an empirical analysis dealing with the possible lack of correct data on employment in administrative registers and with the search of procedures for the utilisation of the variable "total sales" as an indicator of the active status and of the size of a business. Chapter Identification of Anomalous Data presents a correction procedure for identifying anomalous businesses within anonymous microdata coming from administrative registers; this is useful for the creation of a "statistically rectified" database on which it is possible to base some form of functional analysis. In the following sections, a simulation of the application to the Italian context of the "a

1 The role of total sales among the dimensional variables is discussed in various contexts (see for instance, Gambale 1993; Petska 1985; Zinger, Chan and Mc Cann 1985, Czajka).

priori" approach based on the proposals coming from Eurostat and concerning the evaluation criteria of a minimum threshold in total sales for an active business are discussed. As this approach does not seems to fit well in the Italian economic situation, an "analytical" approach is suggested. It is built on the functional relationships between total sales and number of employees and self-employed workers; regression analysis is applied to the database which has been rectified by the ad hoc procedure (given at section 3.2) and suitably stratified.

2. Dimensional Variables of Administrative Registers

As the European Community requests that the statistical register of businesses must be supplied by administrative and juridical registers, it is therefore fundamental to find the criteria by which a unit from those registers is to be considered an economic unit and thus must be included in the business register.

The recommendation manual on repertories deals with this problem and it underlines that, to consider an entity "an organising unit of goods and services", that is, a business, it is necessary to find a minimum amount of "labour" among the production factors. Therefore, a determining element for the solution of our problem is the evaluation of the amount of that production factor (labour); the convention proposed in the VI book of the recommendation manual on repertories says that a business must employ at least one person, paid or unpaid, dependent or independent, at least part-time; this represents the minimum dimension of a business.

A real problem is that it is necessary to define the criteria by which it is possible to pass from a set of positions contained in administrative files and concerning the same juridical unit[1] to a business which, as such, must be included in the statistical register. In this way it is possible to recognise the units economically significant (active units) on the basis of the directions given in the Community regulations.

For this purpose the dimensional data found in the administrative sources must be examined so as to define the juridical units that are believed to employ the minimum amount of labour necessary for them to be considered as businesses.

1 The set of positions concerning the same juridical unit is generally obtained through linkage of fiscal codes made on the records of the administrative files

In fact, though it is almost certain that, except for the phenomenon of the "submerged economy", all the businesses might be found in at least one of the registers listed below, not all the record units of the registers listed above refer to economically active businesses at a given time; in those registers, there are several units created for mere administrative or formal purposes ("convenience companies" or "fictitious" business); which, therefore, do not need the use of work. There are also several cases in which, because of delays in communication and registration, in some registers there are positions referring to ceased businesses or to "dormant" businesses that have not yet started or have temporarily interrupted their activity. Other critical situations, for the correct determination of the number of active businesses at a given time, arise with take-overs or transformations of businesses; in such cases, there can often be a double registration in administrative files, which contain at the same time the business taken over (business "falsely ceased") and the business taking over (business "falsely born").

In Italy the administrative and juridical registers containing dimensional information on businesses and/or local units are: the business register of the Chambers of Commerce (RD), the tax register of the Ministry of Finance, the National Institute for Social Security (INPS) register, the National Institute for Compulsory Insurance on Work Accidents (INAIL) register, the telephone company (TELECOM) register, the electrical company (ENEL) register.

Among the above-mentioned six registers, there are several dimensional data that can be used to determine whether or not a juridical unit must be considered a business.

It is evident that the first source that can be used to determine whether or not a unit from an administrative file must be considered a business is the archive of the INPS (National Institute for Social Security). In this archive, there are all the units that employ personnel. For those units it is easy to quantify the factor "labour" and to determine whether a business exceeds the threshold of half a unit of work. However, the businesses that employ dependent work correspond approximately to one third; it is therefore fundamental to make use of other sources for almost all the small businesses, in which the productive activity is run only by self-employed workers (the entrepreneur and his assistants).

From this point of view, also the archive of the INAIL is relevant. This archive refers to businesses with an obligation for insurance against accidents. This archive does not contain additional information on dependent labour when compared to the INPS database because occupational data refer only to the personnel that must be insured against accidents, which is a subset of the personnel belonging to the INPS archive. The data from the branch of handicrafts are of great interest which the compulsory insurance is extended to the owner and his assistants. So, unlike the INPS archive, it is possible to obtain some information, in this branch on the units actually active and on the dimensional class, taking also into account the number of self-employed workers.

Another register that might contain some useful information for the recognition of businesses is the business register of the Chambers of Commerce (RD), which contains data on employees and self-employed workers separately, for about 50% of the registered units. These data are collected through the declarations found on the payment notes for the annual registration fee in the Chamber of Commerce is asked this information with reference to December 31 of the previous year.

The three above-mentioned sources enable us to dispose of direct information on the amount of employed in the labour; their joint use allows to determine whether a business is active and the dimension of about 60%–70% of the total number of businesses.

From Table 1 it is evident that there is a number of businesses for which there is no sure information available on employees, which makes it unavoidable to make use of other dimensional variables for ascertaining the active status and of the number of employees. There are sources that contain dimensional variables on businesses other than the number of employees, but all the same useful to determine both if a record unit can be economically relevant and its occupational size.

Table 1. **Coverage of dimensional data by branch and source. (Businesses with correct data on employees).**

	Source			
Branch	**RD**	**INPS**	**INAIL**	**Total**
Manufacturing	57.2%	44.1%	68.2%	85.3%
Construction	56.7%	29.5%	63.1%	79.7%
Commerce	62.1%	18.3%	22.6%	68.1%
Services	56.7%	27.3%	64.2%	78.6%
Professionals	0.0%	2.5%	3.1%	4.0%
Total	**54.7%**	**26.1%**	**48.6%**	**72.4%**

N.B. Only the budinesses for which at least one source gives correct and reliable data are included in the total column.

Among these sources there is the tax register of the Ministry of Finance, which contains information on the annual tax declarations on value added. This permits to gather figures on "total sales", from which, by making suitable hypotheses, it is possible to deduce whether or not such units are businesses. The electrical company ENEL and the telephone company TELECOM registers complete the framework of administrative files that can be used for the recognition of active businesses. The information on electrical and telephone consumption contained in these two registers can be especially useful for the recognition of cases of recent "closing down" of a business, not readily detected by the other registers.

3. Empirical Analysis

Data

The analysis, with the goals explained in paragraph 1, was conducted in three Italian provinces: one from the North (in the following: province N), one from the Centre (province C) and one from the South (province S). The variables included in the analysis, obtained from administrative registers, are: branch of economic activity (four branches have been considered: manufacturing, construction, commerce, services), juridical form, class of age, amount of electrical consumption in the year t, total sales of the last available year, number of employees in the year t and $t-1$.

Among the businesses belonging to the three provinces, we consider all the businesses with a number of employees less than 50 because there is already a number of statistical surveys concerning medium or large size businesses aimed at producing correct dimensional data. Besides, these businesses prove to be atypical, with reference to relations among dimensional variables, due to their structural complexity. The branch of agriculture has been excluded from this analysis because it is marginal to the others.

Identification of anomalous data

The first part of our empirical analysis is aimed at proposing a methodology for "cleaning" the matrix of anonymous microdata coming from administrative registers from those records which are likely to be referred to anomalous businesses as, for example, "convenience companies" or "fictitious" businesses. It means that preliminarily to the main part of the analysis (par. 3.3), outliers have been detected, of the kind that we will call "proper outliers". This name is due to the fact that they represent anomalous businesses and are elements of disturbance and not relevant to our analysis of economic behaviour. In fact, the records identified as such outliers were characterised by a very high level of total sales compared to the number of employees, which is indeed a sign of an atypical economic behaviour; their proportion of the total was less than 3%. In particular, the "proper outliers" were detected and removed when observations on the variable "total sales per employee" (FATTPC) were outside the range of twice the standard error:

$$\text{FATTPC} \notin (\mu_{FATTPC} - 2\sigma_{FATTPC}, \mu_{FATTPC} + 2\sigma_{FATTPC}) \ .$$

As a result of this, the statistical analyses that followed saw a considerable improvement in their quality.[1]

As a second step, cluster analysis[2] was applied to the "cleaned" data matrix in order to detect "closing down" businesses. A subset of the available variables was chosen for inclusion in the clustering procedure, which was devoted to generate homogeneous groups of observations and especially the group containing "closing down" businesses. As there are many differences with respect to the dimensional variables among the four branches that we have studied, cluster analysis was conducted separately for each branch.

The hypothesis made for the identification of "closing down" businesses was that, from the point of view of employment, they are passing through a recessive phase, thus leading to the acceptance of the following equation:

$$\text{Number of employees (year } t\text{–1)} - \text{Number of employees (year } t) > \delta \ ,$$

where δ is a positive threshold.

The above-mentioned hypothesis on the recessive trend in employment is taken into account in the clustering variables choice, leading to the certain inclusion of the variables "number of employees in the year t–1" and "number of employees in the year t". Subsequently, other variables of the data matrix were selected for the analysis and, through the examination of the results of the trials, the final subset of clustering variables was formed. This subset included the following variables: the number of employees in the year

1 A more sophisticated method for the detection of outliers is based on the Tietjen-Moore statistics. The results obtained by this method do not differ significantly from our simpler formula.

2 The method of aggregation "average" was employed (Anderberg 1973).

t, the number of employees in the year t–1 and the juridical form of the business, all of them not previously standardised[1]. For each branch and province, the significant number of clusters has been determined by statistical tests typical of cluster analysis (for a detailed analysis of the results, see Biffignandi, Butti and Schionato 1995). By cluster analysis, the aim of identifying records referred to "closing down" businesses was reached through the analysis of small clusters of businesses, characterised by a sudden decrease in the number of employees, from the year t–1 to the year t. We have called the observations belonging to these clusters, "improper outliers" because, though not referring to anomalous businesses (like "proper outliers"), their behaviour is different from the rest of the businesses, for which the occupational trend does not show a phase of recession.

The limited number businesses that our analysis detected as "closing down" suggested that they should not be removed from the data set before applying the statistical analyses proposed in the following paragraphs.

Recognition of active units and of their size.

As already pointed out, for a businesses to be considered as active and therefore included in the statistical register of businesses, it is necessary that it employs at least one person, paid or unpaid, dependent or independent, at least part-time; this represents the minimum dimension of a business. When reliable data on employment are lacking, a hypothesis is made that a minimum quantity of labour is necessary in order to yield some production and therefore determine a minimum threshold of total sales, corresponding to "half a worker" per year, that permits to assess whether an economic unit is active. In this case, also the value of the variable "number of employees" of a business might be obtained through a simple proportion.

The "a priori" approach

The "a priori" approach for the determination of the active status of a business, when reliable data on workers are lacking, was discussed in the context of the European Community. It is based on some relational hypotheses among those business variables that permit the determination of the minimum threshold of total sales.

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1 A standardization of the three variables, in fact, would have assigned them equal weight, reducing the strength of the hypothesis on the behaviour of the variable "number of employees".

The Eurostat working group on business repertories has put forward a first proposal in order to define a minimum threshold for the amount of total sales of an active business according to an "a priori" approach. The estimation is based on hypotheses concerning the following links among business variables:

$$\text{VA (Value Added)} = 1/3 \text{ CA (Total Sales)} \tag{3}$$

$$\text{RGL (Labour payment)} = 1/2 \text{ VA} \tag{4}$$

$$\text{RLO (Gross payment of personnel)} = 2/3 \text{ RGL.} \tag{5}$$

From these relations, it is possible to obtain the link between gross payment of personnel and total sales, which is given by:

$$\text{RLO} = 1/9 \text{ CA.} \tag{6}$$

Keeping in mind that the criterion to establish whether a record unit (in this case, a fiscal unit) corresponds to a business is that of at least one person employed part-time, it follows that the gross payment of personnel (dependent and not dependent) must exceed half of the annual minimum gross salary (SML). Therefore, a fiscal unit corresponds to a business if:

$$\text{CA} > 9/2 \text{ SML.} \tag{7}$$

Such hypotheses could be checked on data from several areas, even if it is evident that the minimum threshold of total sales calculated by this rule is, for the Italian productive structure, definitely high. In fact, supposing that the annual gross minimum salary amounts to L.18.200.000[1] it is possible to determine a corresponding minimum total sales which amounts to L.81.900.000, a sum that, in a sample of definitely active businesses, is not reached by about 25% of them.

The "analytical" approach

The "a priori" approach examined in the previous section seems not to fit well in the Italian productive reality and might generate distorted results depending on the productive characteristics of the different territorial areas and of the

1 Gross minimum salary for a person employed full time.

branches of economic activity. It seems therefore necessary to find and to apply an "analytical" approach based on a model that describes the relationship between total sales and the number of employees (or between several variables such as electrical consumptions, telephone consumption and number of employees). On the basis of the relation found for those businesses for which all the dimensional variables are known, it is then possible to estimate the thresholds used to determine whether a business is active even when only the variable "total sales" (and not the number of employees) is available.

Our experiment was carried out on three different territorial areas so as to verify if the hypotheses made were valid throughout all the territories. From a functional point of view, we assumed a linear relation between total sales and the number of employees[1]. The data were processed for each province separately, after having been cleaned from the "proper outliers". Regression analyses were implemented with simulations aimed at determining the best stratification criterion. In fact, it has been found that, without stratification, no relation between total sales and the number of employees appears. In order to observe relationships between the two variables, the determination of the features of the strata, within which the regression analyses are applied, is of fundamental importance. In fact, the homogeneity of the businesses belonging to each stratum has to be ensured. In particular, within each stratum, there must be a good correlation and reduced variability in the relation between total sales and the number of employees. Beside that, the number of strata cannot be excessively large. For the determination of the best stratification for our analysis, we used both the "direct"[2] and the "indirect"[3] approach. The choice of the variables was restricted to those presented in section 3.1.

By applying the "direct" approach, the simulations carried out in the search for the best stratification criterion indicated that the regression coefficients generally show higher values for the provinces of the North and of the Centre, than of the South. For this reason, the location (expressed as province) was chosen as the stratification variable. Furthermore, the stratification for the branch of economic activity combined with the juridical form of the

1 Preliminary analyses have shown that the variable "total sales" is the most significant from a dimensional point of view.

2 The "direct" approach is based on the comparison of coefficients of determination obtained by alternative stratification procedures.

3 The "indirect" approach takes into account the role that the variables has assumed in the cluster analysis (for details, see Biffignandi, Butti and Schionato 1995).

business has gave a better explicit power than did the class of age of the business.

In conclusion, the linear relation between total sales and the number of employees is best described when applied to a stratification scheme made of 12 strata, obtained by crossing the values of the variables "branch of economic activity" and "juridical form of the business".

The determination coefficients resulting from the above-mentioned twelve strata are reported in the following tables separately for each province.

Table 2. **Coefficients of determination of the province N *).**

Juridical form	Branch			
	Manufacturing	**Construction**	**Commerce**	**Services**
Individual business	0.69	0.74	0.50	0.60
Company of people	0.55	0.74	0.66	0.51
Company of capitals	0.31	0.35	0.57	0.28

*) The analysis was carried out on the data set that was cleaned from "proper outliers".

Table 3. **Coefficients of determination of the province C.**

Juridical form	Branch			
	Manufacturing	**Construction**	**Commerce**	**Services**
Individual business	0.47	0.53	0.40	0.67
Company of people	0.73	0.58	0.67	0.52
Company of capitals	0.50	0.54	0.29	0.41

Table 4. **Coefficients of determination of the province S.**

Juridical form	Branch			
	Manufacturing	**Construction**	**Commerce**	**Services**
Individual business	0.51	0.68	0.51	0.62
Company of people	0.55	0.61	0.58	0.48
Company of capitals	0.26	0.18	0.62	0.32

In order to assess the usefulness and the validity of the procedure for the deletion of the outliers (of the kind "proper") described at the beginning of section 3.2, the linear model was applied also to the raw data (not previously cleaned of from outliers). Table 5 presents the comparison between the average value of the determination coefficients before and after deletion of the outliers; the improvement in their value is a proof that it is necessary to detect anomalous data contained in administrative registers and to remove them before applying functional models.

Table 5. **Coefficients of determination before and after the removal of "proper outliers".**

Province	Average R^2	
	With outliers	**Without outliers**
North	0.40	0.54
Centre	0.35	0.53
South	0.36	0.50

Now it is possible to make some remarks on the results shown in the Tables. The group of the company of capitals is more critical than the other juridical forms, for which the determination coefficients are higher than 0.50. Nevertheless, for more than 95% of the observations (percentage of businesses with juridical form different from company of capitals), the linear relation, within the strata, shows a fairly good quality and therefore might be used, with enough reliability, in the determination of the number of employees, knowing the variable "total sales".

As an example we consider province S, Tables 6 and 7 display the regression coefficients of the relation between total sales (in annual m. liras) as the dependent variable and number of employees as the independent variable (after deletion of "proper outliers").

Table 6. **Province S: regression coefficients.**

Juridical form	Branch			
	Manu-facturing	**Construction**	**Commerce**	**Services**
Individual business	56.7	106.0	185.6	89.4
Company of people	90.3	105.5	251.5	72.4
Company of capitals	216.4	165.0	461.0	204.8

Table 7. **Province S: intercept of the linear regression equations.**

Juridical form	Branch			
	Manu-facturing	Construction	Commerce	Services
Individual business	1.3	–98.8	–99.1	–69.4
Company of people	–76.8	–96.1	–311.1	–24.2
Company of capitals	48.6	644.2	–312.5	–321.1

On the basis of these values it is possible, for each stratum, to calculate the value of total sales that corresponds to a given number of employees. Thus, the active status of a business might be established by determining in advance a conventional threshold for the number of employees which corresponds to a level in the total sales by which it is possible to divide "suspected active" from "suspected not active" businesses.

The choice of this conventional value must depend on the nature of the data available on personnel in each country; the hypothesis of the European Community law that sets "half a worker" per year as the threshold, might not immediately be applied to the above described model because the data on employees refer to a stock value (that is, to the number of employees on December 31 of a year) while the Community law refers to "annual units of work" that is a the flow value. The latter is systematically lower than the former because of difficulty in evaluating part-time or seasonal workers.

This remark leads to the use of a threshold value higher than "half a worker" in the application of the model (Table 8 shows, as an example, total sales values corresponding to an employee for the province S).

Table 8. **Total sales values corresponding to "an employee": province S.**

Juridical form	Branch			
	Manu-facturing	Construction	Commerce	Services
Individual business	58.0	7.2	86.5	20.0
Company of people	13.5	9.4	–59.6	48.2
Company of capitals	265.0	809.2	148.5	–116.3

The values of Table 8 might be used as conventional thresholds in order to assign an indicator of a critical situation to those businesses for which the active status is unknown and total sales are lower than the total sales thresholds written in the Table.

This indicator might be improved by considering, instead of a single threshold, a set of possible values obtained on the basis of the variability of the model. Beside the intercept of the linear function previously determined, we can consider the interval estimates calculated at 95% confidence level by using the standard error of the intercept.

This way, total sales intervals are defined (see Figure 1) and on their basis it is possible to identify alternative total sales values which can be linked to a qualitative indicator of the active status of a business. The total sales values are defined according to the criteria indicated in Table 8. Table 9, as an example, lists total sales values for individual businesses in the province S.

Table 9. **Indicator the active status of a business and corresponding total sales.**

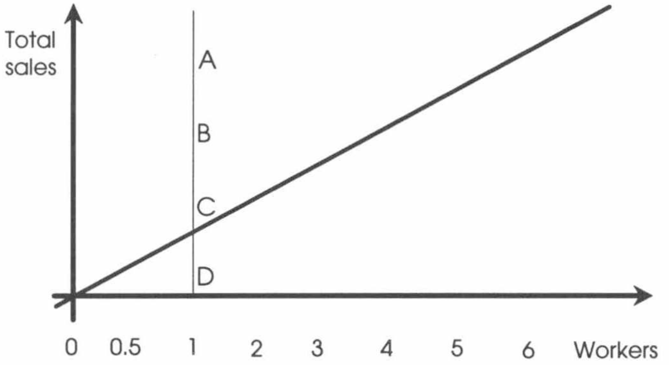
Active Status	Total Sales
a) Almost certainly active	$F > b + (a + 1.96 s_a)$
b) Probably active	$b + a \leq F \geq b + (a + 1.96 s_a)$
c) Probably not active	$b + (a - 1.96 s_a) \leq F < b + a$
d) Almost certainly not active	$F < b + (a - 1.96\ s_a)$

Table 10. **Values for total sales of individual businesses linked to the qualitative indicator of active status: province S.**

Business	Branch			
	Manufacturing	Construction	Commerce	Services
a) Almost certainly active	>68.9	>36.6	>102.3	>28.4
b) Probably active	58.0–68.9	7.2–36.6	86.5–102.3	20.0–28.4
c) Probably not active	47.1–58.0	0–7.2	70.7–86.5	11.6–20.0
d) Almost certainly not active	<47.1	n.s.	<70.7	<11.6

N.B.: negative values have been replaced by 0; n.s.= not significant.

Figure 1. Interval for total sales.



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SPECIAL FEATURES IN SAMPLING DESIGNS OF BUSINESS SURVEYS

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Surveying businesses has many special features at the same time as it has many common features with social surveys. In my presentation I will concentrate on the special features. One of the most interesting features in business surveys is the very skewed distribution with many small businesses and very few large businesses. The Simple Random Sampling is hardly ever a good procedure for surveying businesses, because the large businesses contribute generally much greater to estimates than small businesses. The Probability Proportional-to-Size Sampling and the Stratified Sampling according to the size measures are the most suitable schemes in business surveys.

Another important feature of business surveys is the definition of the sampling units in the frame and the elements that constitute the population. After the definition of population elements the frame units must be determined. If we are interested in income, outlay or financial statistics the Institutional Unit (Enterprise) is generally the preferable one otherwise Kind-of-Activity Unit or Establishment could be one to be preferred. The reporting unit is not always the same as the statistical unit either in business surveys.

The third feature I will present is the response burden which is distributed unevenly when surveying businesses randomly in the longitudinal and the cross section samplings. When the greater part of samples are drawn from a single frame it is possible to co-ordinate the business samples and so to make Response burden more even. The use of permanent random numbers is a recommended method in co-ordinating business samples. When a panel study is needed we can use constant shift rotation methods in sampling. In the business register of Statistics Finland we are preparing the co-ordination system by which it is possible to co-ordinate both longitudinal survey samples and cross sectional samples.

The frame most often used in business surveys is the Business Register. This is the frame which directly identifies the individual elements of the population. The devices for making contacts and some important auxiliary variables of the elements are also included in business registers. Naturally there are also some frame imperfections. For example, the rapid changes in small businesses creates under- and overcoverage in the frame.

Through this paper it is supposed that we can carry out the direct element sampling (Särndal et al. 1992). This means that there is a frame as a direct listing of population elements. I will not handle the cases where the frame is the list of sets of elements as is the case of area frames

Key words: Business Surveys, Co-ordination of Business Sampling, Response Burden, Rotation of Sampling Units.

1. The Frame Units

The frame units are shortly called units. The units in business surveys are in general enterprises and their establishments, local units or activity units. In Business Register an enterprise is an institutional unit which is an economic transactor with the autonomy, authority, and has an ability to allocate resources for the production of goods and services. The establishments, the local units and the activity units are entities at which or from which the enterprise undertakes the economic activity of producing goods and services.

In a small enterprise the economic activity generally takes place mostly in one activity and in one place. Then it is easy to collect information geographically and on more detailed activity level. In large and complex enterprises the economic activity takes place in units which are grouped for management, administrative and decision-making purposes into hierarchical structures. This means that we cannot get geographically or industrially detailed information in enterprise level. So we must use units which are sensible parts of enterprises. The most usable are units the definition of which is internationally standardised such as establishments, local units and kind of activity units. For the homogeneous use in international statistics the U.N. Statistical Office has given a recommendation for harmonising the use of economic activity units internationally. According this recommendation the enterprise is suitable unit in financial research and corresponding research where the unit must have autonomy in financial decisions. The kind of activity units are suitable for activity classification in the production statistics.

Whereas local units and establishments are suitable units in regional statistics.

Business survey statisticians are often interested in how Business Register links survey units over time, what changes are reported etc. The treatment of changes is linked to what is registered in Business Registers at any point in time. In other words, whatever events in the outside world are deemed relevant to consider, their consequences for registration in Business Register should be described between units. The base of Business Registers in general is the files of tax authority. So it often happens that it leaves in the administrative world and cannot correctly reflect the events in outside world. However the differences in purpose of observation do not necessarily result in incompatible measurement of reality. Most often the business in reality very well is reflected in the Business Register as an enterprise and at the same time in the files of the tax administration as a taxable unit. So the administrative legal unit is the "building block" of the enterprise. It often occurs that a corporation owns many different legal units which are created for reasons of convenience or as tax shelters or for liability reasons. When this relates to entities that perform ancillary activities, they should be merged with producing unit they serve into one institutional unit (ISIC rev. 3).

The target population in business surveys has an continually changing structure. Business Register should reflect these changes but unfortunately it is never perfect. So it often happens that not all events in the target population are updated in the frame. There is for example undercoverage if new births are not updated and overcoverage if some deaths are not updated. Also due to the administrative nature of Business Register there are administrative creates and disclosures of enterprises which are not real births and deaths. This topic has taken up in session 'Enterprise, Demography, Job Creation.'

Even if Business Register was perfect it should be note that comparing enterprises or the lower level units after a number of years, would in many cases lead to the conclusion that they have changed considerably implying changes of identity. But if the same units are compared every week it is very probable that in no single week any changes happened big enough to change identity of unit.

2. Stratification

A very special character in business population is the very *skew distribution* according to any size measure. There are few very large firms and a very large number of small firms. This means that good estimates for population total could be got even surveying the largest enterprises as the take all part and only few using some sampling scheme. This method does not reflect the changes in population very well but is usable when we are estimating the totals only.

The skewness of population means that Simple Random Sampling hardly ever gives good estimates for business population. The Simple Random Sampling can be used when stratifying the population according to some size measure. Otherwise it should be used sample designs that relates the inclusion probability of units to the size measure.

Using stratification by size we should define the size-classes. Most frequently the choice falls on employment. Then we must decide if we use the number of paid employees or the number of all employees. Using the number of paid employees we exclude the self-employed persons from the target population. If we use all employees including the self-employees it is difficult to define the threshold between households and enterprises. The other possible choices for the size measure are turnover and value-added. The value-added is sometimes the better measure for the scale of production than is the employment. The problem is that the information of value-added is often missed in Business Registers. The turnover is often a good measure for size of unit within one activity class but is often invalid between activity classes.

When we have chosen the good measure of size we must decide what is the suitable sample scheme for our purposes. If we select the stratified sampling we must decide how to determine the strata. The stratum can be determined as some fixed definition such as micro enterprises, small enterprises, medium size enterprises and large enterprises. Another way is to find the optimal thresholds for the strata which are derived in terms of an auxiliary variable that is highly correlated with the information being collected by the sample and applied to the population that has this auxiliary information.

The extreme case is to divide the population into two strata: a take-all stratum and a take-some stratum as was mentioned in the beginning of this chapter. The take-all stratum contains the largest elements in the population. They are surveyed entirely. The take-some stratum contains the rest of elements. They are surveyed by a Simple Random Sampling.

Approximate cut-off rules for stratifying a population into the take-all and the take-some universes have been given by Dalenius (1952) and Glasser (1962). Hidiroglou (1986) presented cut-off rules for a desired level of precision of estimation. This method is shortly presented below.

Consider a finite ordered population of N units. There are t large units in the take-all universe and $N–t$ small units in take-some universe. The total of the variable y which is the size measure is then

$$Y = \sum_{i=1}^{N-t} y_{(i)} + \sum_{i=N-t+1}^{N} y_{(i)}, \qquad \text{where } y_{(1)} \le y_{(2)} \le \ldots \le y_{(N)} .$$

The sample size $n(t)$ is selected so that t units are selected with inclusion probability one and the small units are selected without replacement, using Simple Random Sampling from the remaining small units in the take-some universe $N–t$. The estimator of the total Y is then

$$\hat{Y} = \frac{N-t}{n(t)-1} \sum_{i=1}^{n(t)-1} z_i + \sum_{i=N-t+1}^{N} y_{(i)} , \quad \text{where } y_{(i)} \le z_i \le y_{(N-1)} .$$

Assume that the desired level of precision for the estimated total is specified by c, the desired coefficient of variation. Than after calculating the variance of $\hat{Y}$ and substituting $V(\hat{Y}) = c^2\hat{Y}^2$ we can solve the equation for $n(t)$, which is the overall sample size obtained by adding to the number of take-all units the required take-some sample size.

$$n(t) = t + \frac{(N-t)S^2_{(N-t)}}{c^2\hat{Y}^2 + (N-t)S^2_{(N-t)}} .$$

For c, Y and N fixed, there exist a minimum for $n(t)$ which is the minimum size of sample. This gives the minimum sample size stratifying the universe to take-all stratum and to take-some stratum. It also gives the optimal size of take-all part. When distribution of population is very skew we can get a good total estimate with a small sample size including most units into the take-all part.

If we want to stratify the population into L strata it is desired to avoid underrepresentativeness in small strata when large discrepancies exist in the strata sizes. Bankier (1988) suggested to determine stratum samples sizes n_h such that the loss function for a given constant power q

$$F = \sum_h (x_h^q \, CV(\hat{Y}))^2$$

is minimised subject to the constraint,

$$\sum_h n_h = n$$

where $CV^2(\hat{Y})$ is the coefficient of variation of variable y, x_h is some measure of size and q is a constant in the range $0 \le q \le 1$.

The total of the variable of interest in stratum h is

$$Y_h = \sum_{i}^{N_h} y_{h_i}$$

and the estimate of Y_h is

$$\hat{Y}_h = N_h \sum_{i}^{n_h} y_{h_i}/n_h \ .$$

Function F is minimised if

$$n_h = n \frac{S_h X_h^g / \bar{Y}_h}{\sum_h S_h X_h^g / \bar{Y}_h} = n \frac{X_h^g / CV(Y_h)}{\sum_h X_h^q / CV(Y_h)}$$

where $S_h = \sqrt{\sum_{i}^{N_h} (y_{h_i} - \bar{Y}_h)^2/(N_h - 1)}$ and $\bar{Y} = Y_h/N_h$.

The choice of q results in significantly different allocations. Setting $q = 1$ and letting $X_h = Y_h$ results the well known Neyman allocation. Alternatively setting q = 0 results in an allocation where the coefficients of variation are almost equal from stratum to stratum assuming that the coefficients of variation vary little between the strata and that the strata sampling fractions are small. In practise a suitable choice of the power q may be 1/2 or 1/3. Power allocation often makes it possible to increase the precision of estimate in the small strata.

3. Use of Permanent Random Number in Rotation – Poisson Sampling

If the study variable y is approximately proportional to a known auxiliary variable x, there is some merit in selecting the elements with probability to the size measure x. However it is not easy to devise a fixed-size probability proportional to size sampling scheme without replacement having all the desirable properties (Särndal et al. 1992):

1 The actual selection of the sample is relatively simple

2 The first order inclusion probabilities π_k are strictly proportional to x_k

3 The second order inclusion probabilities satisfies $\pi_{kl} > 0$ for all $k \neq 1$

4 The second inclusion probabilities π_{kl} generated by the scheme can be computed exactly without very heavy calculations

5 $\pi_{kl} - \pi_k\pi_l < 0$ for all $k \neq l$ which guarantees that the variance estimator takes always non-negative values.

A large number of sampling schemes have developed but most of them are relevant only when sample size is one or two. When the sample size is increased above two the calculations of second order inclusion probabilities becomes often very complex.

In this situation it is also interesting to observe one special character in business sampling. When sampling randomly some business population the distribution of response burden will be uneven. This may lead to sample fatique which can be avoided only by changing the sample elements so often as possible. When a number of samples are drawn from one frame it is possible to control response burden. This means that we must add the 6th desirable property to the list above.

6 The sampling scheme must be carried out so that it is possible to control the overlap between the samples. This is easy to carry out if we use the sampling schemes which are based on the use of permanent random numbers.

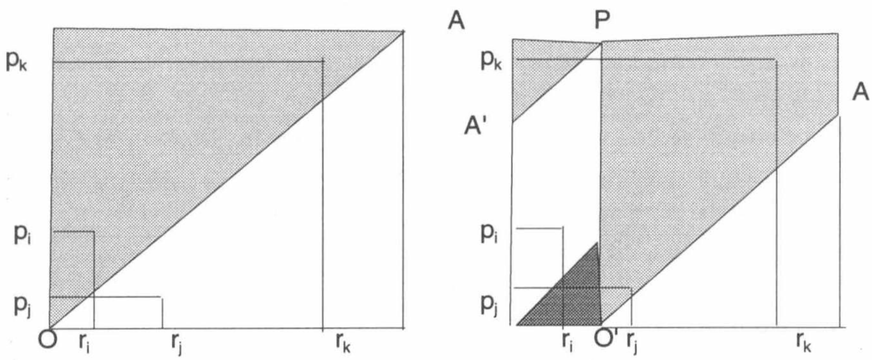
As the 7th desirable property should also be added because in the business population continually happens births and deaths.

7 The changes in business population should be possible to control between samples. This is easy to carry out if we use the sampling schemes which are based on the use of permanent random numbers.

The Poisson sample owns the most of desirable properties listed above. Poisson sampling is defined by Hajek (1964). We give every frame units the random number which is drawn from the Unif(0,1) distribution and order the units in ascending order according these random numbers. Then we give each unit the inclusion probability which is strictly proportional to the size measure of this unit. Subsequently I will suppose that we have adjusted these inclusion probabilities so that none of them is greater than one. Then we go through the list of units item by item and choose those units which have the inclusion probability greater than its random number.

Poisson sampling is easy to carry out and it is easy to control the overlap between samples if we keep the random numbers, given the frame units, permanent. The rotation can be handled easily with the permanent random number technique. Brewer et al (1972, 1984) developed so called constant shift method for Poisson sampling. This method has a good property including the great units which have the great contribution to estimates very extensively in successive samples. The smaller units who mostly suffer from the response burden are included very seldom in panel. Figures 1 and 2 represent the constant shift method.

Figure 1. First draw *Figure 2. Second draw*



We shift the start of sample area from point O (Figure 1) to point O' (Figure 2). In the first draw is included the units above the line OA. As we can see the units $p_k r_k$ and $p_i r_i$ are included in the first sample. Unit $p_i r_i$ is not included in the first sample. When we rotate we change the sample area to point O'. This means that all units that lie above the lines $O'A$ and $A'P$ are included in the second sample. The second sample includes a small unit $p_i r_i$ as a new unit in panel. Unit $p_i r_i$ is freed and unit $p_k r_k$, which is rather large is included in both successive samples. Thus constant shift rotation using Poisson sampling happens so that the smallest units are included only once or not at all (as happens in the strongly shaded area in figure 2) in the every rotation round. The greatest units with inclusion probability one are always included in panel. The number of inclusion of units between these extreme cases in successive samples is dependent of the size of unit and the length of constant shift.

The random sample size is a drawback in Poisson sampling. Because the sample size is variable it follows that sometimes ratio estimator is undefined because of an empty sample (in stratum). *Modified Poisson sampling* is one procedure which ensures that empty sample is never selected. It was first suggested by Ogus and Clarc (1971). An ordinary Poisson sample is drawn first. If some stratum is empty, a second Poisson sample is drawn and so on repeatedly until a non-empty sample is achieved. The advantage is the smaller variance than in ordinary Poisson sample and that it ensures the non-empty samples. But it does not ensure a stable sample size. Inclusion probability includes the multiplicative term of probability of selecting an empty sample (in stratum) in each lap. So the variance term will be rather complicated.

The Collocated sampling is a procedure by Brewer, Early and Joyce (1972) and later developed by Brewer, Early and Hanif (1984). It reduces the variation in sample size by manipulating the random numbers so that they are uniformly spaced instead of uniformly distributed over the interval (0,1). It means that the random numbers used in selection are distributed at equal intervals instead of distributed randomly over the interval (0,1).

The Sequential Poisson sampling is a procedure by Ohlsson (1990). It generalise sequential Simple Random Sampling (SRS) to Poisson sampling. We introduce the normed random number which depend both on the random number of unit and the size measure of unit. The units are then ordered according normed random numbers and desired number of successive units are selected from the sorted list.

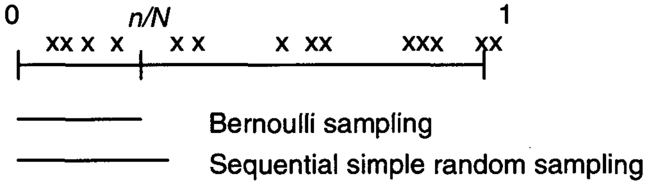
According to Ohlsson the drawback in Sequential Poisson sampling is that it is not a strict probability proportional to size-procedure. Exact expression for the inclusion probabilities of sequential Poisson sampling are not readily obtained. So the exact Horvitz-Thompson estimator can not be used. However approximately unbiased estimators have found to be good in simulation studies.

4. Use of Bernoulli Sampling and Simple Random Sampling in Co-ordination of Sampling

Bernoulli sampling is the special case of Poisson sampling. The inclusion probability is constant n/N where n is the expected sample size and N is the size of population. The co-ordination of Bernoulli samples can be carried out as follows. The units are ordered in ascending order according their permanent random numbers. From beginning are then drawn the units until we have unit whose random number is greater than n/N.

The Sequential Simple Random Sampling is carried out as follows. The units are ordered in ascending order according their permanent random numbers. From the random or the fixed point are then drawn n units to the right or to the left. The Sequential Simple Random Sampling is based on the technique described by Fan et al. (1962). Using this technique Atmer et al. (1975) introduced a Permanent Random Number technique for Simple Random Sampling at Statistics Sweden.

The differences between Bernoulli sampling and sequential Simple Random Sampling is described in the figure below.



The sample size in Bernoulli sampling is dependent on how the random numbers are distributed over the interval (0,1). Sequential Simple Random Sampling gives exactly n sampling units.

5. Bernoulli-Poisson sampling

Poisson rotation has the drawback to pass some units in every rotation round. This drawback can be reduced or even avoid with the combined Bernoulli-Poisson sample.

We give every unit a Permanent Random Number, r, which is realisation of a uniform distribution Unif(0,1). Then we give a size measure Q to every unit. We assume here that the size measure is normed so that there is not negative values and not the values that exceeds 1. Now we have the two-dimensional area where one dimension is the random number, r, and the other dimension is the normed size measure Q (Figure 1).

We divide the sampling area into the Bernoulli part Ob_0 where the inclusion probability $b_0 = \frac{n_{be}}{N}$ is equal for each unit and into the Poisson part where inclusion probability is dependent of size measure Q_k. The units included in the sample lies in the area above lines OB_0 and b_0A (Figure 1).

Assume we will rotate units in four years period. We draw a sample ones a year. Then we have a constant shift of 1/4 to the right in every sample. In

Figure 1. **The first draw**

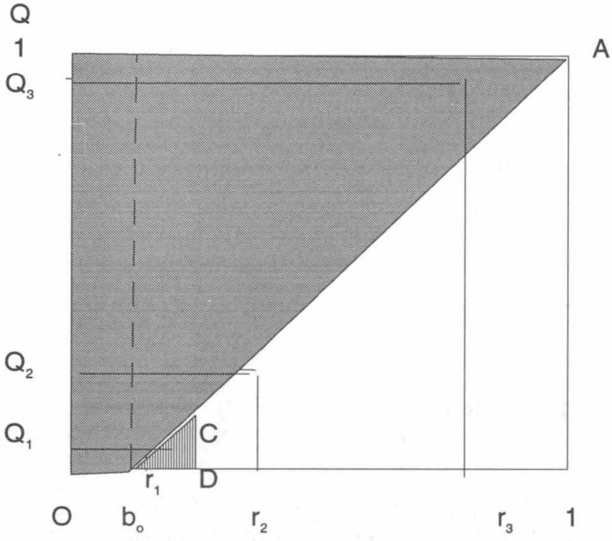
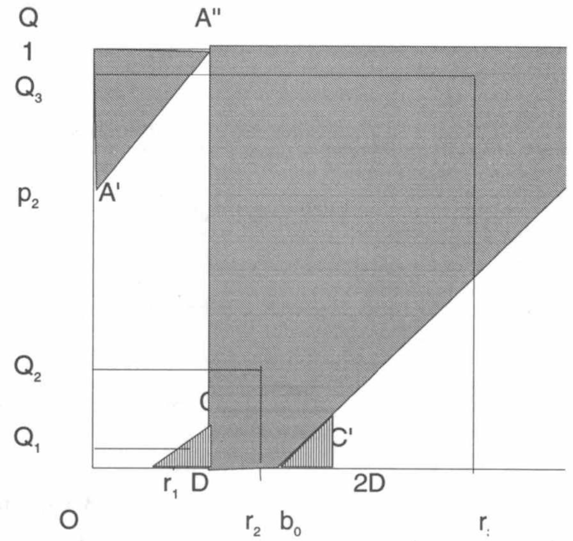


Figure 2. **The second draw**



Ficures 1 and 2 this constant shift is D. The Bernoulli part begins in the first draw from point O, in the second draw from point D, in the third draw from point $2D$ and so on. The unit r_1Q_1 lies then in the area where units have probability zero to be included in neither of successive samples. The size of this area depends on the difference between the size of Bernoulli part and the constant shift. When Bernoulli part is greater than or equal to the constant shift the triangle vanishes. Putting $b_o = n$ where n is the overall expected sample size we get Bernoulli sampling as a special case. The other special case which is the Poisson sampling we get putting $b_o = 0$. In this case the triangle has the length of constant shift D.

6. OTKO

Statistics Finland is developing application for purposes of sample co-ordination of enterprises and establishments. It is called OTKO which comes from the Finnish name 'Otantojen Koordinointi' (Sample co-ordination). In OTKO all units have their own Permanent Random Numbers, which gives the opportunity to use sequential selection methods. All units have also their own Response Burden Rate, Which tells when they are overburdened and need some rest. OTKO calculates more

Response Burden for small units than big units for the same questionnaire. The size of unit is measured by number of all employees.

OTKO has several methods for sampling, including complete new Combined Bernoulli-Poisson sampling procedure. It has also many ways to stratify population.

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SAMPLING WEIGHTS WITH MAXIMUM OVERLAP AND DIFFERENT STRATIFICATION CRITERIA
The Case of the Italian Survey on the Structure of Agricultural Enterprises

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This paper describes the main aspects of the sample methodology and strategy adopted in the 1995 survey on the structure of agricultural enterprises performed by National Statistical Institute of Italy (Istat).

The Survey, aiming to estimate the size and evaluate the structure of agricultural enterprises according to criteria that are consistent with those adopted by other countries within the European Economic Community, is the second of three to be carried out by Istat on a biennial basis within the context of agricultural surveys planned by the EEC for the 1993–97 period. In the two sampling occasion, 1993 and 1995, have been used different criteria of stratification. Furthermore in the 1995 survey the sample statistical units have been selected using a simple and very easy to implement method that assures the maximum overlap with the 1993 survey.

The main concern of this work is to describe the sampling strategy adopted in the 1995 survey with a detailed analysis of: **1** the sample selection method that aims the maximum overlap with the previous survey, **2** the calculus of inclusion probabilities of first and second order, **3** the determination of sampling weights and sampling errors.

Key words: Agricultural Surveys, Sample Selection with Maximum Overlap, Inclusion Probabilities, Sampling Weights.

1. Introduction

This paper describes the main aspects of the sample methodology and strategy adopted in the 1995 survey on the structure of agricultural enterprises performed by National Statistical Institute of Italy (Istat). Reference was made to the following *Community regulations: 571/88* dated 29.02.88 published in the Official Gazette (O.G.) No. L 56 on 02.03.88, *807/89* dated 20.03.89 published in the O.G. No. L 86 on 31.03.89, *837/90* dated 26.03.90 published in the O.G. No. L 88 on 03.04.90, *959/93* dated 05.04.93 published in the O.G. L 98 on 24.04.93, *94/432, 94/433, 94/434* dated 30.05.94 published in the O.G. No. L 179 on 13.07.94. The preceding regulations were established by the EEC and are in accordance with decisions taken by the *93/156/EEC* Commission on 09.02.93 published in the O.G. No. L 65.

The purpose of the survey is to estimate the size and evaluate the structure of agricultural enterprises according to criteria that are consistent with those adopted by other countries within the European Economic Community (EEC).

This survey is the second of three to be carried out by Istat on a biennial basis within the context of agricultural surveys planned by the EEC for the 1993–97 period. The distinguishing feature of the previous survey, conducted in 1993, was that for the first time the Institute gathered statistical information concerning both surface area and production using the same survey model. This same approach was followed with further refinements when performing the 1995 survey.

In the two sampling occasion, 1993 and 1995, have been used different criteria of stratification. Furthermore in the 1995 survey the sample statistical units have been selected using a method that assures the maximum overlap with the 1993 survey. The main concern of this work is to describe the sampling strategy adopted in the 1995 survey. A detailed analysis is developed for the calculus of the sampling weights.

Before describing the sampling strategy adopted for the 1995 survey, brief comments will be made on the sampling strategy used in the 1993 survey.

These are the aspects covered by this paper. Section 2 gives a brief description of the universe to be observed. Section 3 describes the main features of the sampling plan and estimating techniques adopted in the 1993 survey, whereas Section 4 covers these same features relative to the 1995 survey.

2. Brief Description of the Universe

The reference universe or sampling list used both during the 1993 and 1995 surveys is based on the results of the 4th General Census on Agriculture carried out in 1990. This list indicates all agricultural enterprises that are identifiable by means of corresponding codes, giving the names of managers with the relative addresses. The size of this universe is 3,023,344 enterprises. A breakdown of the universe by region is given in Appendix 1.

Statistical units contained in the list have the following characteristics:

- use of land for agricultural, forestry and/or livestock production, where land is intended as meaning one or more areas that are either contiguous or non-contiguous, located within the same commune or extending over a number of communes;
- existence of a technical-economic production unit headed up by a manager, intended as meaning either an individual, a company or other body assuming the risk of the enterprise.
- The list also includes agricultural enterprises that do not possess land.

These are defined as:

- livestock enterprises that raise animals without recourse to agricultural land;
- livestock enterprises that raise animals using grazing land belonging to communes, other public bodies or private individuals where such land does not form a constituent of the enterprise.

3. The Sampling Design and Estimating Techniques Used for the 1993 Survey

In order to meet requirements regarding constraints for accuracy expressed in terms of variance coefficient, a stratified sampling plan was envisaged for each of the relevant variables (indicated in Appendix 2).

Agricultural enterprises were therefore subdivided into strata, defined by combining the categories of the following variables: geographical region, Size of Agricultural land Utilised (SAU) and technical-economic sector (OTE).

The geographical region variable comprised 21 subsets: *Italy's 19 administrative regions plus two autonomous provinces* (Trento and Bolzano).

The SAU variable, expressed in hectares (ha^2), was defined as *the set comprising areas of arable land, family vegetable gardens, permanent grassland and grazing land, forestry and agricultural crops and edible chestnut woods*; these represent the area effectively covered and utilised for agricultural purposes. Nine categories were adopted in the 1993 survey as listed in Table 1.

The OTE variable was introduced as a basic parameter to define the classification types for agricultural enterprises. The introduction of an agricultural enterprise typology at both the Community and national level became necessary because of the need to classify such enterprises in defined sets based on their productive structure. For the survey in question this variable was subdivided into the nine categories defined by O.G. EEC/85/377.

Table 1. Categories of SAU variable in terms of ha^2 for the 1993 survey.

SAU=1	0	SAU=6	[5,10)
SAU=2	(0,1)	SAU=7	[10,20)
SAU=3	[1,2)	SAU=8	[20,50)
SAU=4	[2,3)	SAU=9	[over 50).
SAU=5	[3,5)		

A total of 1,701 strata were defined as a result of this stratification. The size of these strata in terms of the number of enterprises they include will be indicated hereafter by the symbol N_h where h = 1,...,1701 is the stratum index. The Neyman procedure (for description see Cicchitelli et al 1992, 317–322) was used to determine the sample size with reference to each of the 21 variables concerned. Appropriate constraints were introduced to ensure a minimum sample size to be assigned to each stratum. By using this procedure, 21 sample sizes subdivided into the various strata were defined. Then the largest sample size was selected for each stratum from among the 21 possible which led to a final sample that included 83,204 enterprises. The sample size for each stratum will hereafter be indicated by n_h, (h = 1,...,1701).

This set of enterprises formed what was referred to as the *basic list* which was accompanied by a second, *supplementary list*. Certain units were extracted from the latter to substitute units from the basic list that did not participate in the survey, either because they were not available or refused to participate in the interview.

Units to be included in the two lists were selected in a strictly random manner in accordance with sampling principles for finite populations. The specific procedure adopted was as follows:

1 a random number was attributed to each of the enterprises included in the sampling list;

2 within each region, enterprises were then sorted according to the SAU, OTE variables and the random number associated with them;

3 the first n_h enterprises were selected for each stratum based on the sorted order obtained previously. These enterprises then formed the basic list;

4 following the same sorted order, the next $5*n_h$ enterprises were selected. The latter then constituted the supplementary list.

The estimating procedure adopted for the totals concerned was in essence based on a separate ratio estimator that can be expressed by the general formula

$$\tilde{Y} = \sum_{h=1}^{1701} \frac{\tilde{Y}'_h}{\tilde{X}'_h} X_h \quad ,$$

where $\tilde{Y}'_h$ is the direct (or Horvitz-Thompson) estimate of the total concerned for the h-th stratum, X_h represents the known total for auxiliary variable X in the h-th stratum and $\tilde{X}'_h$ is the direct estimate of X_h.

In the case under consideration the known auxiliary variable X_h is represented by the size of the stratum and therefore the above-mentioned estimator can be expressed as follows

$$\tilde{Y} = \sum_{h=1}^{1701} \frac{\tilde{Y}'_h}{\tilde{N}'_h} N_h \quad .$$

The explicit expressions for quantities involved in the preceding formulae are given by:

$$\tilde{Y}'_h = \sum_{r=1}^{n'_h} Y_{hr} \pi_h^{-1} = \frac{N_h}{n_h} \sum_{i=1}^{n'_h} Y_{hr} \qquad \text{and} \qquad \tilde{N}'_h = \sum_{r=1}^{n'_h} \pi_h^{-1} = n'_h \frac{N_h}{n_h} \, ,$$

where, with reference to stratum h: Y_{hr} denotes the value of variable of interest Y in the r-th unit, is the number respondents and π_h denotes the inclusion probability. After little algebra the estimator can be expressed as

$$\tilde{Y}_h = \frac{N_h}{n'_h} \sum_{r=1}^{n'_h} Y_{hr} \ .$$

The purpose of using this estimator is to reduce the impact of inefficiencies caused either by non-response or non-availability of certain statistical units.

The same result can also be reached by modifying the direct sample weights (expansion coefficients) by incorporating the probability of response, ξ_h, for each unit in the estimating procedure. In particular, under the hypothesis that probability of response for each unit included in the sample is constant within each stratum, an appropriate estimate for this is provided by n'_h/n_h. Therefore, the estimate covering the joint probability for the inclusion and participation of each unit in the h-th stratum is, under opportune conditions, is given by the result of $\varphi_h = \pi_h \xi_h. = n'_h/N_h$. Consequently the expansion coefficient for the universe, defined as the inverse of φ_h, is

$$K_h = 1/\varphi_h = N_h/n'_h \ .$$

It can be immediately verified that the estimator obtained using the latter expansion coefficient coincides with that described previously.

Assuming that the estimator is linearized, it can be demonstrated that its variance is approximately given by the formula

$$var(\tilde{Y}) = \sum_{h=1}^{1701} N_h^2 \frac{(1-f_h)}{n_h \xi_h} S_h^2$$

the latter can be estimated utilising the relative sampling quantities.

In order to facilitate interpretation of the uncertainty connected with the estimator, it is opportune to resort to the relative error or variance coefficient. This is obtained by dividing the estimate variance by the total for the variable. Therefore the expected relative error will be calculated using the expected estimate variance and the total established by the census. On the other hand, the observed relative error will be calculated using the estimates obtained from the sample effectively observed. These values are shown in Appendix 2 and, as can be immediately noted, they are all less than the pre-established threshold (Ferrante 1995).

4. Sampling Design for the 1995 Survey

The main characteristics of the 1995 survey in terms of objectives, definition of statistical units, variables surveyed and estimate domains remain substantially the same as those established for the 1993 survey. However, significant modifications were made with regard to the sampling design.

These changes involved both the type of stratification used and also the selection procedure for units to be included in the sample.

Stratification was changed in order to increase both the overlapping between the sampling strata and the domains for which the EEC explicitly requested processing reports and for reasons of comparability and integration with various surveys carried out by Istat.

Instead, the selection procedure was modified in order to ensure that there was considerable commonality, that is overlapping, between the samples used in the 1993 and 1995 surveys.

These modifications are described below; there is also a brief description of the estimating technique referred to as the *constrained weight estimate* (Falorsi and Falorsi 1995).

Stratification

The difference between the 1993 and 1995 sampling plans in essence regards the stratification variables utilised.

In the 1995 survey, strata were defined based on the combinations arising from the subsets established for the variables region, SAU, number for head of cattle, number for head of pigs, number for head of sheep and goats.

Table 2. **Categories of SAU variable in terms of ha^2 for the 1995 survey**

Categories	Size	Categories	Size
SAU=1	0	SAU=5	[10,50)
SAU=2	(0,1)	SAU=6	[50,100)
SAU=3	[1,5)	SAU=7	[over 100)
SAU=4	[5,10)		

Table 3. **Categories for head of cattle in the 1995 survey**

Categories	Sizes	Categories	Sizes
1	0	3	[10,50)
2	[1,10)	4	[over 50).

The *region* variable was not modified, remaining as defined in the 1993 survey.

Categories for the *SAU* variable were reduced (the new categories are given in table 2).

The size brackets and other variables are shown in Tables 3, 4 and 5.

The above led to a total of 3,257 strata that contained at least one agricultural enterprise.

Table 4. **Categories for head of sheep and goats in the 1995 survey**

Categories	Size	Categories	Size
1	0	3	[250,500)
2	(0,1250)	4	[over 500).

Table 5. **Categories for head of pigs in the 1995 survey**

Categories	Sizes	Categories	Sizes
1	0	3	[500,1000)
2	[1,500)	4	[over 1000).

Sample size

The sample size for each of the strata defined in accordance with the above was established based on a process taking into account the following factors:

1 based on financing received from the EEC it was possible to envisage an overall sample size of about 84,000 units – in substance this conforms to the sample size used in the 1993 survey;

2 expected accuracy for the main variables covered in the survey was defined in EEC regulations cited in the introduction. As already mentioned these accuracy levels are given in Appendix 2;

3 for organisational reasons significant changes were not made to the sample sizes previously defined for each region in the 1993 survey;

4 a minimum sample size was established providing for at least 4 units in each stratum. In cases where a stratum contained less than 4 units, it was surveyed in total. This condition was established in order to avoid that an inordinate number of strata remained empty – that is cases where no unit responded – as a result of nonresponse non-availability of units selected.

Based on the above conditions the problem was mainly that of reallocating the overall sample size among the new strata defined for the survey. From a computation standpoint this was achieved by means of successive attempts made according to the following procedure:

a an overall sample size was fixed at a national level equal to $\tilde{n}$

b this sample was allocated to strata according to the specific nature of each of the 21 variables shown in Appendix 1. The Neyman allocation procedure used, based on the formula

$$n^*_{lk} = \tilde{n} \frac{n_l S_{lk}}{\sum_{r=1}^{3257} N_r S_{rk}} \quad , l=1,....,3257, \ k=1,..,21$$

where S^2_{lk}, indicates the variance of the k-th variable in the l-th stratum and evaluated on the census data;

c the choice from among the 21 possible sizes for each sample stratum was made using the function

$$n^*_{+1} = \max_{k=1}^{21} \left[n^*_{lk}, \min(4, N_l) \right] .$$

d finally, but solely in cases where the overall size for each region varied significantly from that established for the 1993 survey, the procedure was repeated from step a, defining a new $\tilde{n}$.

After a number of attempts it was held that the regional sizes shown in Appendix 1 were satisfactory. The result was an overall sample size of n^*=84,048.

Appendix 2 shows the expected variance coefficients calculated by means of the formulae indicated in section 3 and using the new stratification and allocation.

Sample selection and inclusion probabilities

Sample selection

The sampling selection has been done looking for the maximum overlap with the 1993 survey. In this way it is possible a better use of the auxiliary information gathered by the previous survey. Furthermore it is possible to think about the two survey as a *panel survey*. The main concern of these surveys is the estimation of net changes. The overlapping permits the observation of some *gross changes* (Kalton and Citro 1993).

In order to describe the selection method, consider the symbols given in Table 6.

The selection method is the following:

- if $N_{+l} \leq 4$, all units are surveyed;
- if $N_{+l} > 4$, two case are considered:
  - **a** when $n_{+1} \leq n^*_{+1}$, all units of old sample are included in the new one. Furthermore $n^*_{+1} - n_{+1}$ units are selected among the N_{+l}-n_{+l} not included in the old sample;
  - **b** when $n_{+1} > n^*_{+1}$, the n^*_{+1} units of the 1995 sample are selected among the n_{+l} units selected in the old sample.

Table 6. **Symbols used for population and sample in the 1993–95 surveys.**

Strata				1995				
1993	1	2	.....	l	.....	L=3257		
1	n_{11} N_{11}	n_{12} N_{12}		n_{1l} N_{1l}		n_{1L} N_{1L}	n_1	N_1
2	n_{21} N_{21}	n_{22} N_{22}	.....	n_{2l} N_{2l}	.....	n_{2L} N_{2L}	n_2	N_2
....	....	....	.....	....	.....	....	.....	.....
h	n_{h1} N_{h1}	n_{h2} N_{h2}	.....	n_{hl} N_{hl}	.....	n_{hL} N_{hL}	n_h	N_h
....		....	.....	....	.....	....	.....	.....
H=1708	n_{H1} N_{H1}	n_{H2} N_{H2}	.....	n_{Hl} N_{Hl}	.....	n_{HL} N_{HL}	n_H	N_H
'93 sample size in '95 strata	n_{+1}	n_{+2}	.....	n_{+l}	.....	n_{+L}	n	
'95 stratum size	N_{+1}	N_{+2}	.....	N_{+l}	.....	N_{+L}		N
'95 stratum sample size	n^*_{+1}	n^*_{+2}	.....	n^*_{+l}	.....	n^*_{+L}	n^*	

n_{hl} denotes the number of units selected in the '95 survey and belonging to stratum h of '93 survey and stratum l of '95 survey;
n_{+1} denotes the sum over h of n_{hl};
N_{hl} denotes the population size of cross classification of stratum h ('93) and stratum l ('95);
N_{+1} denotes the sum over h of N_{hl};
n^*_{+1} denotes the sample size allocated in stratum l ('95).

First order inclusion probabilities

In order to compute the inclusion probabilities for each unit belonging to the generic stratum l of '95 survey it is useful to consider the following random variable (r.v.):

- $A_{+1} = \{$ *number of units of old sample belonging stratum* $l\}$
  its sample space is $\{a_l, ..., b_l\}$ where
  $$b_l = \sum_{h=1}^{H} inf(N_{hl}, n_h) \quad \text{and} \quad a_l = sup(0, n - \sum_{r \neq l}^{L} b_l) \qquad l=1,...,L$$
  the observed value of A_{+l} is n_{+l};

- $B_r = \begin{cases} 1 \text{ if } unit\ r-th\ was\ included\ in\ the\ 1993\ survey \\ 0\ otherwise\ , \end{cases}$

  note that $Pr\{B_r = 1\} = \pi_{lr}$ is the inclusion probability for the 1993 survey

- $C_r = \begin{cases} 1 \text{ if } unit\ r-th\ was\ included\ in\ the\ new\ sample \\ 0\ otherwise\ . \end{cases}$

Note that the unknown probabilities $Pr\{C_r = 1\} = \pi_{2r}$ $r = 1,..., N$ are the quantities which we have to determine. They are the probabilities of inclusion for the 1995 survey.

The quantities π_{2r} can be obtained marginalizing the joint distribution of the previous r.v.

$$\pi_{2r} = \sum_{m=a_l}^{b_l} \sum_{k=0}^{1} Pr\{C_r = 1, A_{+l} = m, B_r = k\}. \tag{1}$$

The joint distribution can be obtained as product of some conditional distributions. Denoting with

$$\begin{aligned} \lambda_{r(m,k)} &= Pr\{C_r = 1 | A_{+l} = m, B_r = k\} \\ \eta_m &= Pr\{A_{+l} = m | B_r = k\} = Pr\{A_{+l} = m\} \end{aligned} \tag{2}$$

the expression (1) can be write as

$$\pi_{2r} = \sum_{m=a_l}^{b_l} \lambda_{r(m,1)} \eta_m \pi_{1r} + \lambda_{r(m,0)} \eta_m (1 - \pi_{1r}) \tag{3}$$

Note that formula (2) assumes the independence between A_{+l} and B_r.
Since π_{1r} in known for each units we have to determine only $\lambda_{r(m,k)}$ and η_m.

For $\lambda_{r(m,k)}$ three cases must be considered

1) $n^*_{+l} \leq a_l$ **2)** $n^*_{+l} \geq b_l$ **3)** $a_1 < n^*_{+l} < b_l$.

- **Case 1.** Since n^*_{+l} units are selected among n_{+l}, we have

$$\lambda_{r(m,0)} = 0 \qquad \lambda_{r(m,1)} = \frac{n^*_{+l}}{m} .$$

- **Case 2.** In this case the sample is formed by the n_{+l} old units (selected in 1993) and $n^*_{+l} - n_{+1}$. Selected among those not selected in 1993. Therefore

$$\lambda_{r(m,0)} = \frac{n^*_{+l} - m}{N^*_{+l} - m} \qquad \lambda_{r(m,1)} = 1.$$

- **Case 3.** In this case the previous two cases must be considered simultaneously. Therefore

$$\lambda_{r(m,0)} = \begin{cases} \dfrac{n^*_{+l} - m}{N^*_{+l} - m} & \text{if m} \leq \text{n}^*_{+l} \\ 0 & \text{if m} > \text{n}^*_{+l} \end{cases} \qquad \lambda_{r(m,1)} = \begin{cases} 1 & \text{if m} \leq \text{n}^*_{+l} \\ \dfrac{n^*_{+l}}{m} & \text{if m} > \text{n}^*_{+l} \end{cases} .$$

In order to determine η_m it is useful to note that A_{+l} can be expressed as sum of the A_{hl} random variables

$$A_{+l} = \sum_{h=1}^{H} A_{hl}$$

where A_{hl} denotes the r.v. which determine the number of units of old sample that fall in the cell (h,l) of Table 6.

The joint distribution of A_{hl} conditionally to n_h, is multinomial; Therefore it is possible to write, for each of the '93 strata the following

$$Pr\left\{ A_{hl} = n_{hl}; l = 1,\dots,L \middle| \sum_{l=1}^{L} n_{hl} = n_h \right\} = \frac{n_h!}{\prod_l n_{hl}!} \prod_l \left(\frac{N_{hl}}{N_h} \right)^{n_{hl}} \qquad h=1,\dots,H.$$

Since each marginal distribution is binomial we have

$$Pr\{A_{hl} = n_{hl}\} = \binom{n_h}{n_{hl}} \left(\frac{N_{hl}}{N_h} \right)^{n_{hl}} \left(1 - \frac{N_{hl}}{N_h} \right)^{n_h - n_{hl}} \qquad l=1,\dots,L, \quad h=1,\dots,H;$$

This distribution can be approximated with a Poisson distribution characterised by the parameter $\upsilon_{hl} = n_h \dfrac{NH_{hl}}{N_h}$. Therefore

$$Pr\{A_{hl} = n_{hl}\} \cong e^{-\upsilon_{hl}} \frac{\upsilon_{hl}^{n_{hl}}}{n_{hl}!} \ .$$

Since the sum of Poisson distributions is a Poisson distribution with parameter given by the sum of the parameters, it follows

$$Pr\{A_{+l} = m\} \cong e^{\sum_{h=1}^{H} \upsilon_{hl}} \frac{\left(\sum_{h=1}^{H} \upsilon_{hl}\right)^m}{m!} = e^{-\upsilon_{+l}} \frac{\upsilon_{+l}{}^m}{m!} \ .$$

At least, it is possible to condition each distribution to the range of m; Therefore

$$Pr\{A_{+l} = m | a_l \le m \le b_l\} = \eta_m \cong \frac{\frac{\upsilon_{+l}^m}{m!}}{K_l} = \frac{\upsilon_{+l}^m}{m!\,K_l} \ .$$

where $K_l = \sum_{\nu=a_l}^{b_l} \frac{\upsilon_{+l}^{\nu}}{\nu!}$ is the normalising constant used for the conditioning.

Using the previous formulas the expression (3) takes the forms:

in the case 1), since $\lambda_{r(m,0)} = 0$ and $\lambda_{r(m,1)} = \frac{n_{+l}^*}{m}$

$$\pi_{2r} = \sum_{m=a_l}^{b_l} \lambda_{r(m,1)} \eta_m \pi_{1r} = \pi_{1r} \frac{1}{K_l} \sum_{m=a_l}^{b_l} \left(\frac{n_{+l}^*}{m}\right)\left(\frac{\upsilon_{+l}^m}{m!}\right)$$

in the case 2) the inclusion probabilities assumes the form

$$\pi_{2r} = \sum_{m=a_l}^{b_l} \lambda_{r(m,0)} \eta_m \, (1 - \pi_{1r}) + \lambda_{r(m,1)} \eta_m \pi_{1r}$$

$$= \frac{1}{K_l} \sum_{m=a_l}^{b_l} \left(\frac{n_{+l}^* - m}{N_{+l}^* - m}\right)\left(\frac{\upsilon_{+l}^m}{m!}\right)(1 - \pi_{1r}) + \pi_{1r} \frac{\upsilon_{+l}^m}{m!}$$

at least in the case 3) the inclusion probabilities assumes the form

$$\pi_{2r} = \sum_{m=a_l}^{n^*_{+l}} \lambda_{r(m,1)}\eta_m\pi_{1r} + \lambda_{r(m,0)}\eta_m(1-\pi_{1r}) + \sum_{m=n^*_{+l}}^{b_l} \lambda_{r(m,1)}\eta_m\pi_{1r} + \lambda_{r(m,0)}\eta_m(1-\pi_{1r})$$

$$= \left\{ \frac{1}{K_l}\left[\sum_{m=a_l}^{n^*_{+l}} \left(\frac{n^*_{+l}-m}{N^*_{+l}-m} \right) \left(\frac{\upsilon^m_{+l}}{m!}\right)(1-\pi_{1r}) + \pi_{1r}\frac{\upsilon^m_{+l}}{m!} \right] \right\} + \pi_{1r}\frac{1}{K_l}\sum_{m=n^*_{+l}+1}^{b_l}\binom{n^*_{+l}}{m}\left(\frac{\upsilon^m_{+l}}{m!}\right).$$

It is easy to show that $\pi_{2r} = 1$ when $N_{+l} \leq 4$.

Second order inclusion probabilities

In order to obtain the variances of the estimates it is necessary to determine the second order inclusion probabilities.

Denote with π_{2rs} the joint inclusion probability of the r-th and s-th units for the 1995 survey. Using the following symbology

$$\lambda_{rs(m,m',k,u)} = Pr\{\, C_r = 1,\, C_s = 1 \,|\, A_{+l} = m,\, A_{+l'} = m',\, B_r = k,\, B_s = u \,\},$$

$$\eta_{m,m'} = Pr\{\, A_{+l} = m, A_{+l'} = m' \,|\,, B_r = k,\, B_s = u \,\} = Pr\{\, A_{+l} = m,\, A_{+l'} = m' \,\},$$

$$\pi_{1r(k)s(u)} = Pr\{\, B_r = k,\, B_s = u \,\}, \quad k,u = 0,1$$

where l and l' respectively denote the strata of units r-th and s-th in the 1995 survey, we have:

$$\pi_{2rs} = \sum_{m=a_l}^{b_l}\sum_{m'=a_{l'}}^{b_{l'}}\sum_{u=0}^{1}\sum_{k=0}^{1}\lambda_{rs(m,m',k,u)}\eta_{m,m'}\pi_{1r(k)s(u)} \qquad (4)$$

Since the quantities $\pi_{1r(k)s(u)}$, are known from the 1993 sample design, we have to determine the expression of the two remaining factors of the expression (4).

For the first factor it is useful to consider the cases $l \neq l'$ and $l = l'$. Since the selection are independent, when $l \neq l'$ we have:

$$\lambda_{rs(m,m',k,u)} = \lambda_{r(m,k)}\,\lambda_{s(m',u)}\ .$$

Instead, when $l = l'$ there are three different cases:

1) $n^*_{+l} \leq a_l$ 2) $n^*_{+l} \geq b_l$ 3) $a_l < n^*_{+l} < b_l$.

In the first case we have:

$$\lambda_{rs(m,0,0)} = \lambda_{rs(m,1,0)} = \lambda_{rs(m,0,1)} = 0.$$

$$\lambda_{rs(m,1,1)} = \left(\frac{n^*_{+l}}{m}\right)\left(\frac{n^*_{+l}-1}{m-1}\right).$$

where, being $m'=m$, we have dropped m'.

In the second case we have:

$$\lambda_{rs(m,0,0)} = \left(\frac{n^*_{+l}-m}{N^*_{+l}-m}\right)\left(\frac{n^*_{+l}-m-1}{N^*_{+l}-m-1}\right),$$

$$\lambda_{rs(m,1,0)} = \lambda_{rs(m,0,1)} = \frac{n^*_{+l}-m-1}{N^*_{+l}-m-1},$$

$$\lambda_{rs(j,1,1)} = 1 .$$

At least, we have

$$\lambda_{rs(m,0,0)} = \begin{cases} \left(\frac{n^*_{+l}-m}{N^*_{+l}-m}\right)\left(\frac{n^*_{+l}-m-1}{N^*_{+l}-m-1}\right) & \text{if } m \leq n^*_{+l} \\ 0 & \text{if } m > n^*_{+l} \end{cases},$$

$$\lambda_{rs(m,1,0)} = \lambda_{rs(m,0,1)} = \begin{cases} \frac{n^*_{+l}-m-1}{N^*_{+l}-m-1} & \text{if } m \leq n^*_{+l} \\ 0 & \text{if } m > n^*_{+l} \end{cases},$$

$$\lambda_{rs(m,1,1)} = \begin{cases} 1 & \text{if } m \leq n^*_{+l} \\ \left(\frac{n^*_{+l}}{m}\right)\left(\frac{n^*_{+l}-1}{m-1}\right) & \text{if } m > n^*_{+l} \end{cases}.$$

Consider now the second factor of the right hand side of formula (4). There are two different cases: $l=l'$ and $l \neq l'$.

When $l=l'$ we have

$$\eta_{m,m'} = \eta_m;$$

when $l \neq l'$, since in our context the dependence between the random variables A_{+l} and $A_{+l'}$ may be considered negligible, we have:

$$\eta_{m,m'} = \eta_m \eta_{m'} \; .$$

In order to determines π_{2rs} it is now possible to utilise the just defined quantities.

Constrained weight estimation

The Institute has a software package written in SAS language that can be used directly by the end user to estimate totals by means of this procedure.

In describing this procedure it is assumed that certain information is available with regard to the total of M auxiliary variables, both $\underline{X}_{(d)}$ the vector of the M known totals for estimate domain d and, furthermore, $\underline{X}_r$ the vector of the auxiliary variables surveyed for the r-th unit (the software available allows for the use of auxiliary information also at the estimate domain level; for a detailed description of the methodology and calculation procedure, see Falorsi and Falorsi (1995).

In general the estimate obtained using the constrained weight method for the total of a relevant variable (in a specific domain d) takes the form:

$$\tilde{Y}_{(d)w} = \sum_{r \in S(d)} Y_r w_r \, ,$$

where $S(d)$ is intended as the set of all sample elements corresponding and belonging to that domain and w_r indicates the *final weight* attributed to the r-th unit.

The final weights used in the procedure are obtained in the form of the result of a constrained minimum problem. In particular

$$min\left\{ \sum_{r \in S} G\left(\pi_{2r}^{-1}, w_r\right) \right\} \; ,$$

with the following constraints

$$\sum_{r \in S_{(d)}} w_r \, \underline{X}_r = \underline{X}_{(d)} \, ,$$

where $S_{(d)}$ is the set of the responding sample units in the d-th domain and $G(\pi_{2r}^{-1}, w_r)$ is a general distance function.

The objective, therefore, is to identify a final weight vector $\underline{w}$ which is consistent with information already available for the population and that at the same time ensures the least possible number of modifications to the set of direct weights characterising the sampling design.

In this survey, the possible set of auxiliary information is represented by the total at the moment of the census for the 21 variables listed in Appendix 2, by each of the relevant domains. Moreover, a further element of auxiliary information can be the size of each domain at the moment of the census.

It is shown (Falorsi and Falorsi 1995) that with regard to the generic unit r, the form of the final weight is:

$$w_r = \pi_{2r}^{-1} g^{-1}\left(\underline{X}_r^T \underline{\lambda}\right) = \pi_{2r}^{-1} F\left(\underline{X}_r^T \underline{\lambda}\right) ,$$

where

$$F(\cdot) = g^{-1}(\cdot),\ g(\cdot) = \frac{\delta G(\pi_{2r}^{-1}, w_r)}{\delta w_r} ,$$

and $\underline{\lambda}$ indicates the dimensional M vector for the Lagrange multipliers while the apex T indicates the transposition operation. As this is typically a non-linear problem this solution is obtained by means of numerical-type algorithms.

The expression for the variance estimator $\hat{Y}_{(d)w}$ is obtained using the Deville and Särndal (1992) asymptotic result. They demonstrated that all constrained weight estimators tend towards the non-specific regression estimator. Therefore, based on this result, the variance for the estimator $\hat{Y}_{(d)w}$ can be approximated by the expression

$$\tilde{V}\left(\tilde{Y}_{(d)w}\right) \cong \sum_{r,s \in S(d)} \left(\frac{\pi_{2rs} - \pi_{2r}\pi_{2s}}{\pi_{2rs}}\right)\left(w_r \tilde{\varepsilon}_r\right)\left(w_s \tilde{\varepsilon}_s\right) ,$$

where

$$\tilde{\varepsilon}_r = Y_r - \underline{X}_r^T \underline{\tilde{B}}_{(d)}$$

is the residual and

$$\underline{\tilde{B}}_{(d)} = \left[\sum_{r \in S(d)} w_r \underline{X}_r \underline{X}_r^T\right]^{-1} \sum_{s \in S(d)} w_s \underline{X}_s Y_s$$

is the sample estimate of the regression coefficient in the d-th domain.

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Appendix 1

Number of enterprises in the population and in the surveys by geographical region

Region	Region code	Number of enterprises in the population	Number of enterprises in the 1993 survey	Number of enterprises in the 1995 survey
Piemonte	1	194 078	4 153	6 059
Valle d'Aosta	2	9 180	966	410
Lombardia	3	132 160	4 338	6 227
Veneto	5	224 913	10 118	8 061
Friuli Venezia Giulia	6	57 848	1 402	1 419
Liguria	7	72 479	557	583
Emilia Romagna	8	150 736	3 563	4 913
Toscana	9	149 741	4 052	4 587
Umbria	10	58 551	1 559	2 026
Marche	11	80 832	2 767	2 998
Lazio	12	238 269	3 429	4 762
Abruzzo	13	106 780	2 300	2 886
Molise	14	41 415	914	1 037
Campania	15	274 862	3 354	3 886
Puglia	16	350 604	11 980	8 989
Basilicata	17	83 355	2 762	3 126
Calabria	18	211 962	3 733	4 427
Sicilia	19	40 404	14 073	9 160
Sardegna	20	117 871	5 874	6 848
Trento	41	27 435	641	911
Bolzano	42	36 069	669	733
Total		**3 023 344**	**83 204**	**84 048**

Appendix 2

European constraints for accuracy expressed in terms of variance coefficient, observed accuracy in the 1993 survey and expected accuracy in the 1995 survey.

Variable	European constraints	Expected accuracy for the 1993 survey	Observed accuracy for the 1993 survey	Expected accuracy for the 1995 survey
Soft wheat	2%	1.1%	1.7%	1.1%
Durum wheat	2%	0.5%	1.4%	0.7%
Barley	2%	1.2%	1.5%	1.1%
Oats	2%	1.4%	2.0%	1.4%
Maize	2%	1.0%	1.1%	1.0%
Vineyard for DOC and DOCG vines	3%	2.1%	2.4%	2.7%
Vineyard for others vines	3%	1.0%	1.7%	1.4%
Vineyard for table grape	3%	2.7%	3.6%	4.0%
Olive threes	3%	0.8%	1.3%	0.9%
Grain leguminosae	3%	2.8%	4.5%	5.2%
Fodder leguminosae	5%	3.6%	17.6%	4.1%
Hoed plants	3%	1.5%	19.0%	1.5%
Industrial plants	3%	1.2%	2.4%	1.3%
Total fodder production	**2%**	**0.9%**	**1.2%**	**0.6%**
Vegetable	3%	2.4%	3.0%	1.8%
Non-utilised land	3%	1.3%	1.5%	1.5%
Head of cattle	5%	2.7%	2.8%	0.5%
Head of pigs	3%	2.3%	4.7%	0.6%
Head of sheep	5%	1.7%	3.0%	0.5%
Head of goats	3%	2.6%	4.4%	1.4%
SAU	3%	0.2%	0.8%	0.2%

Part D

Creation and Destruction of Jobs and Enterprises

Dilling-Hansen, Madsen and Smith

The econometric models of entry behaviour in the Danish manufacturing industry determine the entry rate in an industry as a function of economic factors, e.g. profit rate, growth, and barriers against entry, e.g. concentration, capital/sales ratio, minimum efficient scale, and finally, the exit behaviour is included in the models.

Viviano

Given these results it is necessary to underline how the first size class (and more generally the lower size classes) tends to lose weight in a more systematic way if compared to the others. Such phenomenon is explained by the fact that, not considering the new enterprises (that tendentially distribute in the smaller sizes) it is not possible to correctly measure the processes of entering flows. This situation leads to a lowering bias overstressing the tendency of enterprises to move to upper size classes (a more detailed analysis will be developed in the future).

Mustaniemi

There are three criteria for a real enterprise birth. First, a new enterprise must start its activities by creating -not by taking over- an establishment i.e. a new enterprise creates its factors of production. Second, a new enterprise is not allowed to share employees with dead or still active enterprise(s). This criterion was used, because a high proportion of shared employees usually indicates an administrative (not real) enterprise opening. Third, a new enterprise must be economically active.

Ilmakunnas and Topi

The traditional exit model in industrial Organization is based on the idea of voluntary exit. The macroeconomic theories of monetary transmission mechanism, on the other hand, are more concerned of forced exit in the form of bankruptcy. Both approaches treat entries as voluntary investments. This may explain why the financial factors worked well in the entry models, but did not seem to explain exits.

Vainiomäki and Laaksonen

... the high technology sector has higher job creation and destruction rates, and it has experienced a somewhat different cyclical pattern than other sectors. We also find that the high and low technology sectors are contributing differently to job reallocation: high technology is more important (compared to its employment share) in job creation, entry, and gross reallocation, while low technology is more important in job destruction, exit, and net job decrease.

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ENTRY INTO DANISH MANUFACTURING INDUSTRIES

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In recent years much attention has been paid to especially entry studies but also to exit studies within industrial organisation research. A high degree of firm mobility is important in order to move resources from low productive to high productive industries in the economy. Furthermore, potential entry of new sellers can restrain established sellers from exploiting their market power and from rising their profits. Also the threat of new firms entering the industry forces the established firms to minimise their costs in order to keep entrants out of the market. Finally, a high firm mobility is important as the diffusion of new technology is often correlated with a high entry rate.

This paper analyses the entry behaviour of Danish firms from 1991 to 1993 based on a newly constructed longitudinal sample of 10000 firms. High historical profit rates are found to induce entry whereas a high minimum efficient plant size reduce entry into an industry. Market growth and the capital requirement prove to have no effect on entry rates in the Danish manufacturing industries.

Key words: Entry, Exit, Firm Mobility, Barriers to Entry, Firm Data, Firm Behaviour, Manufacturing.

1. Introduction

High resource mobility is generally accepted as a prerequisite of ensuring efficient markets and economic growth. A high degree of firm mobility is important to move resources from industries with low productivity to industries with high productivity in the economy. Furthermore, the potential entry of new agents in an industry can restrain established firms from exploiting their market power and from increasing their profits. Also, the threat of new firms entering the industry forces the established firms to minimise their costs in order to keep entrants out of the market. Finally, a high firm mobility is important as the diffusion of new technology is often correlated with a high entry rate.

A number of international studies of market entry at industry level have been carried out during the last decade. However, only a few (partial) studies on Danish firm mobility exist and an important reason for that has been lack of data at firm level. In this paper, the entry behaviour of Danish firms in the period 1991–93 is analysed based on a new longitudinal sample of approximately 10,000 firms.

The data set includes account information on individual firms at a 5-digit industry level for a period of eight years (1988–95). However, for the use in the present analysis the data is aggregated to a 4-digit industry level, leaving 207 industries with relevant information, e.g. excluding industries with no activity.

The following section of the paper discusses models of entry behaviour. Importance is attached to factors such as the concentration of industries, industry sales growth, profit rates and scale effects. Section 3 presents the database mentioned above and the results from the estimation of the econometric models are presented in section 4. Section 5 concludes the paper.

2. Theoretical and Empirical Reflections on Barriers to Entry

J. S. Bain's first study from 1951 of industry profitability and market structures gave rise to completely new literature on market structure and performance, Bain (1951). The theoretical literature has made vast contributions, but no common theory has resulted from this work. The models are different, and to a large extent the conclusion depends on the assumptions concerning the competitors' expected reaction. Although several oligopoly models have been developed, the Cournot model is the model most widely used to describe the production and pricing behaviour in an oligopoly market. The model also gives a nice theory for the structureconductperformance framework, with a simple relation between market profitability, concentration and elasticity of demand.

In the empirical literature a large number of crosssection studies have examined this structureconductperformance theory by studying the correlations between market profitability, concentration and other characteristics of the market conditions. For a survey of this literature, see Schmalensee (1989). Most of the crosssection studies are based on the following model:

$$P_i^* = P(C_i, D_i, B_i) \tag{1}$$

where P_i^* is the normal profit or price-cost margin in industry i given the market structure. C_i is the market concentration, D_i is demand conditions, e.g. elasticity of demand. B_i is a barrier to entry such as economic of scale, advertising, product differentiation, research and development and capital requirement. The main result of this study is that a positive but weak correlation exists between concentration and profitability. Also, the different barriers to entry normally explain a large part of the variation in profitability between industries.

Because crosssection studies point out some industries in which the competition is weak and the profits are high, they give a rather static snapshot of the competition situation and do not provide any information as to whether this is only a transitory problem or it is a more permanent problem. To answer this question, an analysis of market dynamics is needed, and the analysis has followed two different directions. One type of study uses time series of market structure and profitability, while the other type of study looks at entry and exit in industries to reveal the dynamics of competition.

The main finding in the time series studies is a high degree of persistence both in market concentration and in profitability over time, see Gorecki (1991). An interesting question in this connection is which factor in the competitive process provides the relative stable performance frame-work. To answer this question, studies of the dynamic factors determining the direction of firms moving in or out of the industries are important, and here studies of entry and exit take over.

Most entry and exit studies are using a crosssection approach but pay attention to the number or the normal rate of entry and exit in the industries. In industries where the expected profit is equal to the limit or normal level given the market condition, there will be no net entry and the performance of the industry is in equilibrium. In industries in which the actual or expected profit is above the "limit" level there will be an incentive to entry. If more firms are moving into these highly profitable industries, the capacity expansion may be expected to reduce the profit in the future, as the market dynamics changed the competitive conditions.

Several entry studies have followed Orr's earlier work, according to which entry will take place if the expected post-entry profit is above the entryprecluding levels, which may be the normal profit earned elsewhere, Orr (1974). More formally, the resulting entry model can be expressed as:

$$E_i = E(P_i^e - P_i^*) \tag{2}$$

where E_i is the entry rate for industry i, P_i^e is the expected post-entry profit and P_i^* is the entryprecluding profit in industry i. The expected post-entry profit for an industry may be based on the actual or historical profit, P_i. Also, a rapid and unanticipated market growth, $P_i^e = P(P_i, G_i)$, may lead to a high profit which will persist for as long as it takes capacity to adjust to demand. The expected profit may be specified as . By substituting this expression and the entryprecluding profit in equation (1) into equation (2) the entry rate can be formulated as:

$$E_i = E(P_i, G_i, C_i, D_i, B_i) \tag{3}$$

The entry rate is expected to vary positively with the actual profit rate and market growth. Concentration and low elasticity of demand weaken the actual competition and raise the actual profit in an industry. Thus, for given barriers to entry more concentrated industries provide an incentive to entry. However, for given actual profits and concentration in an industry barriers to entry provide a disincentive to entry.

The main findings in empirical studies on entry are that entry rates are normally hard to explain by profitability and entry barriers. Moreover, the entry rate reacts very slowly to high profit and is highly positively correlated with exit rates. For a summing-up of the main findings see Geroski (1995), and for a survey of the empirical literature see Siegfried and Evans (1994).

In this study the empirical form of (3) is formulated as:

$$E_i = b_0 + b_1 P_i + b_2 G_i + b_3 CONC_i + b_4 MES_i + b_5 MKR_i + u_i\,. \tag{4}$$

where E_i is the entry rate for industry i, P_i is the average rate of return on equity capital, G_i is the market growth rate, and $CONC_i$ is a variable measuring the concentration in industry i. MES_i is a measure of the minimum efficient plant size relative to the market, MKR_i is a measure of minimum capital requirement for entry in industry i and u_i is a stochastic term picking up other unobserved effects on entry in the industries.

The model in equation (4) explains the incentive to entry into a given industry. However, even if the entry responds positively to the expected profit rate, it may not have any implication for the competitive environment in the industry if there also is a large exit. What matters for the competition is not the gross entry rate but the entry net of exit. To examine whether this is the case the entry rate net of exit has been computed and regression analyses using the net entry rate as left hand side variable have been made.

3. Data

The data used in this paper are based on entries of new firms within the manufacturing industries, and the data are constructed at a 4-digit industry Nace-level, i.e. the analysis includes industries within the groups ranging from Nace-code 1500 to 3800. The underlying data set is constructed on a firm/company basis, and the information concerning all industries is made up of aggregate numbers from the individual firms.

The data were collected by a private company (*Købmandsstandens Oplysningsbureau A/S*) and the basic source of information found in the data set is firm-specific information derived from the firms' legal obligation to submit reports to the authorities. All firms have been assigned an industry code corresponding to the Nace at a 4-digit industry level, but with the modification that new superior industry codes have been established in cases where the Nace-code does not offer a direct match to a given firm. Personally owned firms (non-companies) with less than 10 employees are not obliged to publish information on turnover, number of employees etc. Hence, all information in the database is based on non-private owned firms, i.e. funds, limited liability companies (Ltd's) and partnerships and private owned firms with more than 10 employees.

The number of firms and the turnover for all firms in Denmark are shown in table 1 at the 2-digit industry level according to data from the Economic Council. The sample size from *"Købmandsstandens Oplysningsbureau A/S"* is listed as a percentage of the number of firms and their turnover in the different industries. As expected only a small number of companies are presented in the sample (29,4%) due to the omission of small private owned firms. However, the firms in the sample represent on average 68.6% of the total turnover. The classification of firms on industries is different in the two samples which explains the fact that our sample share is above 100 per cent in some industries. In the total sample for Denmark the classification is self-reported to the Central Statistic of Denmark while *"Købmandsstandens Oplysningsbureau A/S"* has their own staff evaluating the firms' main product market according to the Nace industry classification.

The basis for the aggregated industry data is the information of firms from the data set mentioned above. Thus, the number of firms in the database with a full set of information are approximately 10,000. All information concerning the firms' published accounts is converted to calendar year accounts, and accounts with a period of less than 6 months are discarded before data have been aggregated to the industry level. The period covered by the analysis is 1991–1993, and at the 4-digit industry level the resulting aggregated database contains 207 observations from the manufacturing industries (group 1500 to 3800).

Table 1. **Number of firms and turnover in Denmark, 1993**

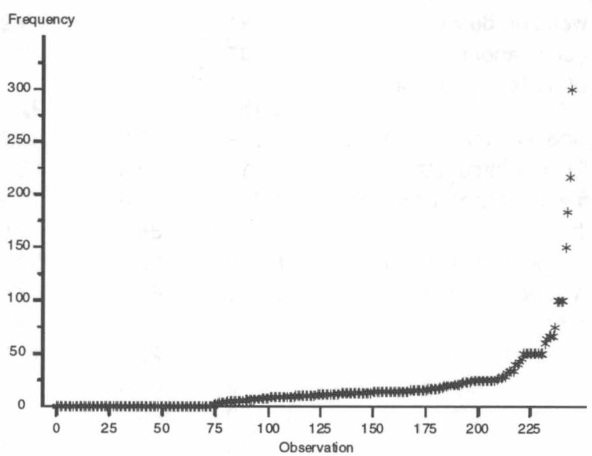
	Number of companies	Sample share per-cent*	Turnover million DKK	Sample share per cent*
15 Food, beverages and tobacco	3 019	24.3	134 564	61.6
17 Textiles	1 422	21.0	8 733	42.3
18 Wearing apparel and dressing of fur	2 170	16.8	6 256	55.9
19 Leather and leather products	279	14.7	1 984	60.0
20 Wood and wood products	1 481	35.1	9 909	116.3
21 Pulp, paper and paper products	307	53.1	9 380	61.2
22 Publishing of newspapers, printing etc.	6 157	27.5	27 147	63.5
24 Chemicals and man made fibres etc.	589	59.9	30 374	94.2
25 Rubber and plastic products	1 011	53.8	16 928	55.2
26 Other non metallic mineral products	1 709	24.8	13 937	67.8
27 Basic metals	243	88.5	7 520	73.1
28 Construct. materials of metal etc.	5 999	26.6	259 564	57.4
29 Machinery and equipment n.e.c.	3 150	44.9	47 992	53.3
30 Electrical and optical equipment	296	22.0	2 097	40.1
31 Electrical motors etc.	2 125	26.7	11 084	139.8
32 Radio and communicat. equipm. etc.	513	30.4	9 653	65.4
33 Medical and optical instrum. etc.	759	60.6	8 743	147.5
34 Motor vehicles	318	42.8	5 190	67.8
35 Transport equipment	868	28.1	12 214	98.0
36 Furniture; manufacturing n.e.c.	4 303	18.6	22 051	55.4
37 Recycling	18	11.1	142	88.7
15 – 37 Manufacturing	36 736	29.4	411 855	68.6
All industries	**439 731**	**14.4**	**1 559 959**	**62.9**

Note: * Sample from "Købmandsstandens Oplysningsbureau" in per cent of official data.
Source: Economic Council, 1995, and "Købmandsstandens Oplysningsbureau A/S"

To minimise random one-year effects, new entries are determined on the basis of the two-year period (1992–93). An entry is identified if an account for 1993 exists with relevant information but no accounts are reported in 1992 or the year before. To face the problem that some entries just reflect a change in organisation or ownership from private to corporate units, entries are dismissed if the official year of establishing the firm is 1991 or before. The entry rate has been defined as the number of entries in 1992 and 1993 divided by the number of existing firms in 1991.

The entry rate in the manufacturing industries is shown in ascending order in Figure 1. Almost half of the entry rate lies between 10 and 50 per cent, but a large number (approx. 30%) of industries have no entries at all in the period 1992–93. Finally, a few industries have a very high entry rate, and these industries are characterised by a few firms in the industry, e.g. the highest entry rate (300%) describes an industry (*Printing of newspapers*) with one firm in 1991 and 3 entries in the following two years.

Figure 1. **Entry rates in manufacturing industries, ascending order, 1991–93.**



The number of firms leaving the manufacturing industries is calculated in a similar way. An exit is identified if accounts are available in 1991 but no valid information is published in 1993. Similarly, the exit rate is calculated as the number of exits divided by the total number of firms in 1991 in an industry.

The number of firms with relevant public information on accounts in 1991 is 9,956 and the corresponding number for 1993 is 11016. The net entry of new firms (1,060) in the period is determined by 1304 new firms (entry) and 244 firms without an account for 1993 (exit). Exits from the industries are probably underestimated. First of all, a public account does not necessarily mean that the firm actually is active, and moreover the account from a firm that is no longer active will perhaps be published after the account period.

The following definitions of the explanatory variables are used in the next section. All data are based on firm-specific information from the year 1991.

$CONC_i$: Three different indices for concentration in the manufacturing industries have been calculated, Herfindahl-index, 4-firm concentration index, and Reciprocal of number of firms in an industry.

P_i : The average profit rate is calculated as the operation profit before tax (result of the year) divided by the own capital in the industry.

MES_i : Minimum efficient scale of a firm is calculated as the log of the industry average of the turnover per firm.

MKR_i : The minimum capital requirement in an industry is defined as the average capital/sales ratio and calculated as the operation assets divided by the turnover.

G_i : Market growth is calculated as the relative growth of the turnover in the industry from 1991 to 1993.

4. Empirical Results

The theoretical entry model is estimated on the data discussed above for the period 1991 to 1993. This period can be characterised as a period of low economic growth/stagnation in the Danish economy, i.e. the average growth rate in real GDP was as low as 0.8% to 1.5% p.a. As a consequence, the overall level of entries into industries could be affected negatively, compared with periods of normal business conditions where entrepreneurs/firms are more inclined to start up new activities.

Table 2 presents the results of OLS estimations of the entry rate model in equation (4). In general, the models explain between 11% and 13% of the total variation when disregarding the estimation equation using a very simple concentration measure[1]. R^2 in that interval is typical in cross-section material like this data set[2].

With focus on the concentration measures, alternative versions of the model are presented in table 2. The use of the Herfindahl index yields a positive and significant coefficient, indicating that entry is higher in indus-

Table 2. Entry rate equations, 1991–1993.

Intercept	15.68	11.86	15.43	15.48	16.40
	(6.49)	(7.27)	(6.62)	(6.57)	(7.16)
Concentration Measures, $CONC_i$:					
• Herfindahl index	0.073*				
	(0.031)				
• 4-firm concentration ratio		0.058			
		(0.050)			
• Reciprocal of firm numbers			–0.002		
			(0.045)		
Exit rate					0.655*
					(0.192)
Minimum efficient scale, MES_i	–1.271*	–	–0.921	–0.928	–1.128*
(Log of average sales)	(0.650)	1.056**	(0.657)	(0.642)	(0.579)
		(0.651)			
Capital/sales ratio, MKR_i	0.002	0.003	0.003	0.003	
	(0.004)	(0.004)	(0.004)	(0.004)	
Profit rate, P_i	0.110*	0.109*		0.106*	0.123*
	(0.031)	(0.031)	0.106*	(0.030)	(0.027)
			(0.031)		
Growth of sales, G_i	–0.004	–0.005	–0.005	–0.005	0.005
	(0.008)	(0.008)	(0.008)	(0.008)	(0.004)
R^2 (adj.)	0.13	0.11	0.05	0.11	0.15
Number of observations	207	207	207	207	207

Numbers in brackets are standard errors. * denotes that the estimated coefficient is significant at the 5 per cent level, and ** at the 10 per cent level.
The regression equation shown in the 5th column is estimated using a 2 SLS procedure where the Herfindahl index, minimum efficient scale, capital/sales ratio and growth of sales have been used as instruments.

1 Testing for the hypothesis that all dummy variables are equal to zero gives a F-statistic equal to 1.5 with 13,180 d.f. Thus, the F-test is in favour of the restricted model in table 2.

2 Furthermore, estimation of the model using the absolute number of entries as left hand side and on the other hand using number of firms as an extra explanatory variable results in R^2 values which are considerably larger than above, i.e. R^2 equal to 0.7–0.8. However, the estimated parameters are less significant compared with the above estimations.

tries dominated by few firms, which is rather surprising. The 4-firm concentration ratio gives the same result, even though the estimated coefficient is not significant. The very simple concentration measure, the reciprocal of the numbers of firms, gives a negative but insignificant coefficient. Thus, Table 2 suggests that the inflow of new firms is relatively larger in concentrated industries than in industries with less concentration.

This result is opposite to the general experience in the majority of empirical studies where highly concentrated industries usually experience less entry, see Siegfried and Evans (1994). Accordingly, the result suggests that some barriers to entry exist in highly concentrated industries in Denmark.

However, the tendency that concentrated industries experience a relatively higher entry of new firms should be seen in connection with the influence of the profit rate. In all the equations (except the model using the reciprocal firm number as concentration measure) the coefficient to the profit rate is positive and significant. Also, the size of the effect of the profit rate on entry is very stable, i.e. the estimated coefficient ranges from 0.106 to 0.123. This result is in line with other empirical results, see Siegfried and Evans (1994). In some studies the profit variable has an insignificant effect on entry rates and gives only little empirical explanation of entry, see Evans and Siegfried (1991) and Baldwin (1995).

In general, new firms are attracted by profit expectations to enter a new industry; higher profit leads to higher entry and vice versa. If this effect is combined with the positive effect from the concentration variable it suggests a situation of market disequilibrium in Denmark where some industries are characterised by a relatively small number of firms earning relatively high profits – higher than the limit set by entry barriers.[1] These market conditions attract new firms. Thus, the positive coefficient to the concentration measures is consistent with the positive coefficient to the profit variable.

Looking at other market conditions in the specific industries besides the concentration there are strong theoretical reasons to expect that higher growth of sales would result in higher entry, see above. But none of the equations presented in table 2 suggests that sales growth has any effect. The estimated coefficients are very small and insignificant in all the equations. Thus, the results indicate that new firms care about historical profit records but pay less attention to the conditions of market growth.

With focus on the effect of minimum efficient scale and capital/sales ratio, different models are used to control for barriers of entry caused by

1 The partial Pearson coefficient of correlation between the profit rate and the Herfindahl index is 32 per cent and significant at the 0.1 per cent level.

firm size and capital requirement. Whereas the capital/ sales variable is insignificant in all equations, the minimum efficient scale suggests that entry varies negatively with the firm size.[1] Thus, potential entrants are more attracted to enter industries with a relatively small firm size. This result is in accordance with the literature on limit price.

Finally, the model was estimated including the exit rate of the industries as an explanatory variable, see Table 2, column 5. Introducing the exit rates does not change the effects discussed above. However, the exit rate in itself has a positive and highly significant coefficient, indicating that industries with high exit rates experience a high level of entry. The explanation in this case is probably some kind of replacement effect, new firms squeezing out older and less efficient firms. This effect is probably more significant when estimating the model on longer periods. If new firms are successful and squeeze old firms out of the market, this is not likely to take place within one year for example. The capital/sales variable has been left out in this model of the estimation due to multicollinearity with the exit rate variable.

As an alternative to estimations on gross entry rates the net entry rate has been used. As the entry variable is censored, i.e. nonnegative, the OLS estimates are potentially biased, see below. Using net entry rates allows for negative values of the left hand side variable. If industries are in a position of market disequilibrium with relatively high profits, net entries are expected to be explained by the same variables as above. Further, if net entry is affected positively by higher profit market self-adjusting forces seem to work, and a profit over normal will be squeezed in the long run.

Table 3 shows that there is a positive, significant and clearly stable effect from the profit rate. The Herfindahl index has a significant positive sign confirming that there is a net entry into industries with few firms and high levels of profit. Finally, the minimum efficient scale is negative and significant (in column 3), suggesting (like above) that net entry is more frequent in industries where the production process is characterised by small production units compared to the size of market.

In general, using OLS regression analysis on gross entry as left-hand side variable may be inappropriate, partly because the linearity assumption hardly is fulfilled but more important because the gross entry variable is nonnega-

1 Experiments were performed leaving the capital/sales ratio or minimum efficient scale variables out of the regression equations, but the results were close to the above mentioned. The main reason for this is that the two variables are not strongly positively correlated as could be expected. On the contrary the Pearsons partial coefficient of correlation is negative.

Table 3. **Net entry rate[1] equations, 1991–1993.**

Intercept	17.36	17.66	20.35
	(10.10)	(9.99)	(7.59)
Herfindahl index		0.114*	0.102*
		(0.047)	(0.043)
Minimum efficient scale	–0.815	–1.346	–1.505*
	(0.980)	(1.000)	(0.737)
Capital/sales ratio	0.009	0.007	
	(0.006)	(0.006)	
Profit rate	0.219*	0.225*	0.240*
	(0.048)	(0.046)	(0.038)
Growth of sales	–0.015	–0.014	
	(0.013)	(0.013)	
R^2 (adj.)	0.18	0.20	0.19
Number of observations	207	207	207

Numbers in brackets are standard errors. * denotes that the estimate is significant at the 5 per cent level, ** at the 10 per cent level.
1) Entry rate minus exit rate.

tive, i.e. censored. Thus, using OLS may potentially lead to biased estimates. According to Amemiya (1984) one solution to the problem is to define a Standard Tobit model as follows:

$$\begin{aligned} y_i^* &= x_i'\beta + u_i, \qquad i = 1,2,\ldots,n, \\ y_i &= y_i^* \quad \text{if} \quad y_i^* > 0, \\ &= 0 \quad \text{if} \quad y_i^* \le 0, \end{aligned} \tag{5}$$

where y corresponds to the entry variable and u_i is assumed to be normal distributed by zero mean and standard error. The likelihood function becomes

$$L = \prod_0 \left[1 - \Phi\left(x_i' \beta/\sigma\right)\right] \prod_1 \sigma^{-1} \varphi\left[\left(y_i - x_i' \beta\right)/\sigma\right] \tag{6}$$

where Φ and φ are the cumulative distribution and density function of the standard normal variable. Finally, the model is estimated using maximum likelihood regression analysis.[1] The estimation results are shown in Table 4.

Table 4 shows that the level of significance is lower in the Tobit equations compared to the OLS estimates in Table 2. Thus, the effect of the

1 The computations have been done using the Standard Tobit Maximum Likelihood procedure in LIMDEP.

Table 4. **Tobit regression analysis of the entry rate.**

Intercept	28.39	17.29
	(13.69)	(12.91)
Exit rate		2.132*
		(0.378)
Herfindahl index	0.055	–0.007
	(0.059)	(0.063)
Minimum efficient scale	–2.305**	–1.485
(Log of average sales)	(1.302)	(1.287)
Capital/sales ratio	–0.0002	0.010
	(0.008)	(0.008)
Profit rate	0.267*	0.249*
	(0.063)	(0.058)
Growth of sales	–0.002	–0.020
	(0.017)	(0.016)
	26,09	24,13
	(1.537)	(1.414)
Log likelihood	781.5	766.5
Number of observations	207	207

Values in brackets are standard errors. * significant at the 5 per cent level. ** significant at the 10 per cent level.

concentration variable becomes insignificant which is more in line with other studies. However, the effect of the profit rate is highly significant and as expected larger than the corresponding effect in the OLS models, indicating that entrants react to profit expectations and that self-adjusting market forces are at work in the various industries.[1] Finally, the effect of minimum efficient scale becomes more uncertain and variable compared to the OLS estimates.

5. Conclusion

The database used in the analysis is a longitudinal database for the period 1988–93 of published accounts of Danish firms. The firm specific information is aggregated to a 4-digit Nace-level. The industry data for entry of new firms is analysed for the period 1991–93 and the entry of a firm is defined by a public account in 1993 combined with no information for the year 1991. The study of entries in this period shows that the number of new firms in the manufacturing industries is smaller than the number of new firms in the rest of the industry.

1 If the true model is non-linear, the OLS estimates will be biased towards zero.

The econometric models of entry behaviour in the Danish manufacturing industry determine the entry rate in an industry as a function of economic factors, e.g. profit rate, growth, and barriers against entry, e.g. concentration, capital/sales ratio, minimum efficient scale, and finally, the exit behaviour is included in the models.

There is a significant positive relation between the market entry and the profit rate in the market. The significant relationship between entry and profit rates is in line with other studies of entry behaviour. Further, as expected the size of the minimum efficient plant size affects entry negatively.

The market concentration variable has a significant positive effect on market entry, whereas capital requirement seems to have no significant effect. Thus, on the basis of data at a 4-digit Nace-level of market entry in manufacturing industries, it seems that market inequilibrium with high profit in some manufacturing industries is reduced by market entry of new firms in these industries.

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A STOCHASTIC ANALYSIS OF THE SIZE DISTRIBUTION OF THE ITALIAN MANUFACTURING FIRMS

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In this research the changing size of a group of enterprises within the manufacturing sectors (chemical, mechanical engineering and textile) is analysed, from 1986 to 1994, through the application of the probabilistic Markov process. This method is based, as tool of analysis, upon the calculation of matrices of transition probabilities among different size strata. It will be described the evolution of the structure by the size of the enterprises which have been active through the whole period by comparing the three distributions by size: the starting one (1986), the final one (1994) and that relating to the limit equilibrium distribution. The descriptive and predictive usefulness of this model is questioned. Some parameters indicating the level of mobility reached by each sector at a particular period, the differences of mobility among sectors and among size classes in each sector are presented.

Key words: Transition Probabilities, Size Distribution, Equilibrium Distribution, Mobility.

1. Introduction

The forces determining the distribution by size of a certain group of business enterprises are complex and of different nature. The interest in the study of relationships between market structures and firm behaviour led to development of models not only in order to individuate and describe these relations but also to use them for forecast.

Stochastic models concerning mobility by size have been developed and can be found in literature since the 1930s. Some of these models (i.e. the formulation advanced by Gibrat known under the name of 'law of proportional effects') did not lead to empirical results of particular relevance; others, more recently developed, (Jovanovic 1987; Nelson and Winter 1982;

etc..) have been addressed in the study of processes of size growth using very strong theoretical formulation and sometimes obtaining results of difficult interpretation.

In order to describe the movement among size classes, a model of particular interest is the Markov process based upon the construction and the use of stochastic matrices. The application of these kind of matrices was initially experienced in the 1950–60s (Anderson, Adelman, Preston & Bell) and more recently the same technique was also employed, in Italy, by some Labour economics analysts (Contini and Revelli 1986 & 1992; Pozzana 1995; Traù 1996).

In this research the changing size of a group of enterprises within industrial sectors is analysed, from 1986 to 1994, through the application of the probabilistic Markov process, with the purpose of obtaining:

1 the transition probabilities between the different size categories;

2 the size distribution of firms in a dynamic equilibrium (steady-state) corresponding to that structure which the industry would eventually reach if some past trends were to continue;

3 some measures of firm mobility both between size classes and concerning the global fluidity of the observed enterprise system.

2. Some Theoretical Considerations on the Model

The mobility of a group of firms among some size classes is analysed, as follows, according to a stochastic approach. Consideration of the evolution of an economic unit through classes as a stochastic process is based on the hypothesis that the transition from one class to another depends only on its size at the beginning of the period but not on its past history. The stochastic model here considered belongs to the class of the Markov chains having the propriety to be irreducible (with a non zero probability of movement among states) and ergodic (a finite recurrence mean time and aperiodic). This specific class of process (with a discrete state space and in discrete time) settles down in the long run to a condition of equilibrium not depending upon the initial conditions; from an economical point of view on the evolution of enterprises it means that the model properties can be summarised under the simplified assumptions that the forces operating during the period under observation will continue until a solution of equilibrium is reached. This solution is valid when the period examined is long enough to include at least one complete business cycle.

Let P denote the stochastic matrix of transition probabilities, and let p_{ij} $i,j=1,..k$ be the generic element indicating the probability for an enterprise being in state j starting from state i (under the condition that $\Sigma_j p_{ij} = 1$) it was shown, under certain conditions, the existence of a unique equilibrium solution $t=(t_1,...,t_k)$ where the transition probabilities among states, t_i , are independent of the initial configuration.[1]

3. The Application of the Model

The data used for the application of the method are related to the manufacturing sector and, more specifically, to the main three subsectors: chemical, mechanical engineering and textile. The time series of the number of enterprises and of the number of persons employed has been reconstructed on the basis of the information coming from the Sirio-NAI business register of Istat, recording the population of enterprises with more than nine persons employed.

The objective is to describe the evolution of the structure by the size of the enterprises which have been active through the whole period under observation (1986–1994) and to compare the three distributions by size: the starting one (1986), the final one (1994) and that relating to the limit equilibrium distribution. The analysis does not consider the impact of entries (births) and exit (cessations) of firms.

For this reason the present work has is meant as provisional and exploratory in order to investigate the descriptive and predictive usefulness of the model.

Because of the typology of the business register that does not provide exhaustive information about very small units, the class 1–9 persons employed, only concerned to allow the representation of enterprises shrinking into this class, should not be considered homogeneous to the others.

After having obtained the distributions of the firms into eight size classes (as proxy of the dimension the yearly average number of workers has been considered) for the years from 1986 to 1994, the different steps done for the application of the model can be simplified as follows:

a) Build-up of the transition matrices between states

For each couple of consecutive years we calculate the transition matrix of the enterprises between size classes $W=w_{i,j}(t)$, t =1,...,T where T is the n-1th year of observation.

1 see §3 Markov chains, D.R.Cox & H.D.Miller.

Summarising the corresponding cells of these matrices W over the years we obtain in this way the matrix of the absolute frequencies $W^*=w^*_{ij}$ showing the total of movements which have occurred, for each sector, during the whole period. Matrices of this kind allow identification of the direction of these movements.

b) Estimation of the transition probability (p_{ij})

The matrix of the transition probabilities $P= p_{ij}$ is estimated using a method that refers to the mover-stayer models; only enterprises changing state at least once during the reference period are considered, excluding therefore the units always remaining in the same class during the period. It has been shown (Goodman 1961) that estimates built in such a way are consistent.

The estimate of the generic element of the transition matrix is:

$$p_{ij} =[\Sigma\, w_{ii}\,(t) - Tc_i\,]/[\Sigma\, w_{i.}\,(t) - Tc_i\,] \quad \text{for } j=i$$

$$p_{ij} =[\Sigma\, w_{ij}\,(t)\,]/[\Sigma\, w_{i.}\,(t) - Tc_i\,] \quad \text{for } j\neq i$$

where w_{ii} is the number of firms remaining in the class i in two consecutive time points t–1 and t; w_{ij} is the number of units in the i-th class at time t and in the class j at following time; $w_{i.}$ is the total of units in the i-th class at the beginning of the period (row total); c_i is the number of units in the i-th class at the first year which remained in the same category through the whole period.

c) Determination of the equilibrium distribution (t)

Through multiplication of the estimated transition matrix P by the actual distribution of enterprises at the beginning of the period, the theoretical distribution of the following period $P^*S_0=S_1$ can be obtained. By iterating the process over the whole period it is possible to obtain $P^*P...^*P^*S_0=P^{T*}S_0=S_T$ representing the theoretical distribution of firms at the end of the period.

Iterating indefinitely the P matrix leads to the determination of a distribution among size classes, t, corresponding to a structure of a long-run dynamic equilibrium independent of the starting distribution. A simpler approach is to make use of the fact that for an invariant distribution it must be:

$$t^*P= t$$

where, as the elements of t are transition probabilities, we must also have:

$$\Sigma t_i=1 \quad i=1,..., k$$

The constrained solution of the equations system leads to the identification of the equilibrium distribution of enterprises by size.

d) Calculation of some indicators of size mobility

4. Main Findings

The transition probability matrices are shown in the Table 1; Chart 1 suggests that the relative frequency of the size movements to the lower classes is greater than to the upper ones. This is true for each sector and each class. The trend to move to lower size-classes is more evident in the textile sector, less evident instead in the chemical sector whose class 10-19 indicates, on the other side, a reversed behaviour.

In order to evaluate the accuracy of the model, the transition probability matrix, P, has been used to obtain the (theoretical) distributions of the units expected by year and size-class.

In Chart 2 the absolute frequency distribution observed during the period, by size-class and sub-sectors, are put in comparison to those theoretical. The comparison made shows that the model well approximates the evolution of the distributions.

Given that the economic general conditions continue to follow the observed evolution even in the following years[1], the relative frequency distribution of enterprises in the equilibrium situation are determined.

In Table 2 the equilibrium distributions are shown close to the actual ones for the first and the last years.

By conducting the analysis for each sector it is possible to compare the structure by size more recently observed with the predicted configuration corresponding to equilibrium, and therefore underline the changes expected between the size classes in the long run.

In the last columns the ratio is shown between the proportion of enterprises in the case of equilibrium and that observed in 1994. The numbers indicate that, if the allocation process over the size classes would continue to perform as it did in the past, then the enterprise distribution would tend to assume the following configurations:

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1 The manufacturing industry has been characterised, during the period, by two different cyclical phases; one consisting of expansion between 1986 and 1990, the other consisting of recession from 1991 to 1993–1994.

1 for the chemical sector a strong increase in the upper size classes, starting by that over 50, should be predicted;

2 for the mechanical engineering sector, the increase would concentrate in the classes between 50 and 1000 persons employed;

3 for the textile sector no remarkable differences would be stressed if we exclude a smooth growth in the 10–99 classes.

In general, for the whole manufacturing sector, excluding the first and the last size classes where the expected proportions of units should decrease, the central classes of the distribution tend, even if slightly, to increase their weight.

Given these results it is necessary to underline how the first size class (and more generally the lower size classes) tends to lose weight in a more systematic way if compared to the others. Such phenomenon is explained by the fact that, not considering the new enterprises (that tendentially distribute in the smaller sizes) it is not possible to correctly measure the processes of entering flows. This situation leads to a lowering bias overstressing the tendency of enterprises to move to upper size classes (a more detailed analysis will be developed in the future).

The comparison among distributions highlights some of the elements characterising the different mobility of firms by sector and over time (both the observed and the future). The calculation of some parameters of the process indicating the level of mobility reached by an industrial structure allows:

1 to understand how many mobility each sector has experienced (compared to that one in the equilibrium situation) at a particular period;

2 to discriminate the mobility among different sectors;

3 to measure the different mobility among size classes in each sector.

The index of permanence (L_i)[1] measuring the average number of years spent by a unit in each i-th class, can assume values greater than one. Values very close to 1 indicate that the probability of staying in the same class is very small showing a situation of very high mobility among classes. In Table 3 the ratio is also calculated between the index of permanence of the

1 $L_i = 1/(1 - p_{ii})$ for the period 1986–1994
$L'_i = 1/(1 - 1 - t_i)$ for the equilibrium distribution.

actual distribution and that corresponding to the equilibrium distribution. The result, common to all the sectors, is the greater tendency of larger enterprises to remain in the same class, while the average permanence period observed in correspondence of the lower size-classes approximates the theoretical one.

In the same table a synthetic indicator of mobility is also calculated referred to the structure at the end of the observed period; it is computed comparing a mobility index in the situation of perfect mobility and that of the actual situation[1]. This indicator, varying between 0 and 1, gives information on the distance of the observed size structure compared to that one would be observed in a situation of perfect mobility. The higher the value of the index, the better the actual distribution approximates the situation of perfect mobility.

The empirical results highlight quite rigid structures for all the analysed sectors, even if in particular the chemical sector is characterised by a lower mobility if compared to other sectors, while the textile sector by a higher and anyway stable mobility in the period.

5. Conclusions

The results obtained tend to stress the descriptive and predictive usefulness of this model; applications of statistical technique of this kind to the analysis of industrial changes of size are to be considered an exploratory instrument useful in order to find out some factors in a dynamic economy.

A limit that could raise in the predictive validity of such probabilistic instruments is that they lay on the hypothesis of invariance of economic conditions. Such hypothesis would be true in the presence of a productive structure subject only to cyclical variations, under the condition that the data on which estimates of the parameters are based on a long period of observation, such as to cover a whole economic cycle. As regards this point the experimentation has been conducted for a quite long time period.

1 The synthetic indicator of mobility at the period n is given by the ratio of the average number of years spent in a class in a perfectly mobile industry to the corresponding quantity for the sector in the 1994:

$$I_n = \Sigma\, [t_i \,/\, (1 - t_i)] \,/\, \Sigma\, [s_i^n \,/\, (1 - p_{ii})]$$

where:

t_i is the generic element of the transition matrix referring to a perfectly mobile industry (having the same equilibrium distribution found)

s_i^n is the proportion of firms of the generic class at time n (n=1994)

p_{ii} is the generic element of the transition matrix.

It has been demonstrated how the differences between the actual and the theoretical (calculated on the transition probability matrix) distributions are not significant in all the classes of the chemical and the textile sectors. On the other hand, in the mechanical sector, mainly in the intermediate size classes, the differences came out significantly. A likely explanation is that in the early nineties this industry was subject to intensive restructuring, caused by deep processes, and partly product innovations that have structurally modified its characteristics.

In conclusion the adopted model does not well adapt to the interpretation and prediction of those systems characterised, in the short time, by significant structural variations and therefore not easily to describe by the means of invariant theoretical models.

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Table 1. **Transition matrices by sector – period 1986–1994.**

Chemical sector

	1–9	10–19	20–49	50–99	100–199	200–499	500–999	>999
1–9	0.6384	0.3413	0.0187	0.0013	0.0003	0.0000	0.0000	0.0000
10–19	0.0820	0.8229	0.0938	0.0010	0.0002	0.0001	0.0000	0.0000
20–49	0.0054	0.1071	0.8226	0.0631	0.0016	0.0002	0.0000	0.0000
50–99	0.0035	0.0022	0.0977	0.8181	0.0764	0.0017	0.0000	0.0004
100–199	0.0009	0.0026	0.0051	0.1048	0.8049	0.0801	0.0009	0.0009
200–499	0.0000	0.0000	0.0017	0.0017	0.1124	0.8121	0.0654	0.0067
500–999	0.0000	0.0000	0.0000	0.0032	0.0032	0.0981	0.8386	0.0570
>999	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1486	0.8514

Mechanical engineering sector

	1–9	10–19	20–49	50–99	100–199	200–499	500–999	>999
1–9	0.6732	0.3122	0.0137	0.0009	0.0001	0.0000	0.0000	0.0000
10–19	0.1025	0.8114	0.0852	0.0008	0.0001	0.0000	0.0000	0.0000
20–49	0.0079	0.1290	0.8121	0.0499	0.0009	0.0001	0.0000	0.0000
50–99	0.0039	0.0034	0.1149	0.8060	0.0701	0.0015	0.0001	0.0000
100–199	0.0020	0.0014	0.0042	0.1231	0.8092	0.0587	0.0012	0.0002
200–499	0.0005	0.0000	0.0014	0.0052	0.1249	0.8299	0.0358	0.0024
500–999	0.0000	0.0000	0.0016	0.0016	0.0080	0.1413	0.7961	0.0514
>999	0.0000	0.0000	0.0000	0.0000	0.0043	0.0086	0.1760	0.8112

Textile sector

	1–9	10–19	20–49	50–99	100–199	200–499	500–999	>999
1–9	0.7262	0.2618	0.0116	0.0003	0.0001	0.0000	0.0000	0.0000
10–19	0.1160	0.7996	0.0839	0.0005	0.0001	0.0000	0.0000	0.0000
20–49	0.0132	0.1640	0.7869	0.0352	0.0006	0.0001	0.0000	0.0000
50–99	0.0067	0.0046	0.1483	0.7893	0.0499	0.0013	0.0000	0.0000
100–199	0.0048	0.0040	0.0087	0.1350	0.8031	0.0437	0.0008	0.0000
200–499	0.0000	0.0011	0.0034	0.0068	0.1466	0.8162	0.0237	0.0023
500–999	0.0000	0.0000	0.0000	0.0000	0.0000	0.1777	0.8122	0.0102
>999	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2059	0.7941

Manufacturing sector

	1–9	10–19	20–49	50–99	100–199	200–499	500–999	>999
1–9	0.6991	0.2875	0.0126	0.0008	0.0001	0.0000	0.0000	0.0000
10–19	0.1104	0.8071	0.0817	0.0007	0.0001	0.0000	0.0000	0.0000
20–49	0.0108	0.1408	0.8028	0.0445	0.0010	0.0001	0.0000	0.0000
50–99	0.0051	0.0044	0.1261	0.7972	0.0655	0.0016	0.0001	0.0001
100–199	0.0028	0.0026	0.0072	0.1239	0.8050	0.0575	0.0009	0.0002
200–499	0.0004	0.0004	0.0018	0.0049	0.1284	0.8208	0.0407	0.0026
500–999	0.0000	0.0000	0.0012	0.0031	0.0050	0.1314	0.8171	0.0422
>999	0.0000	0.0000	0.0000	0.0000	0.0019	0.0076	0.1733	0.8171

***Chart 1.* Relative frequencies of size-class shifts by sector.**

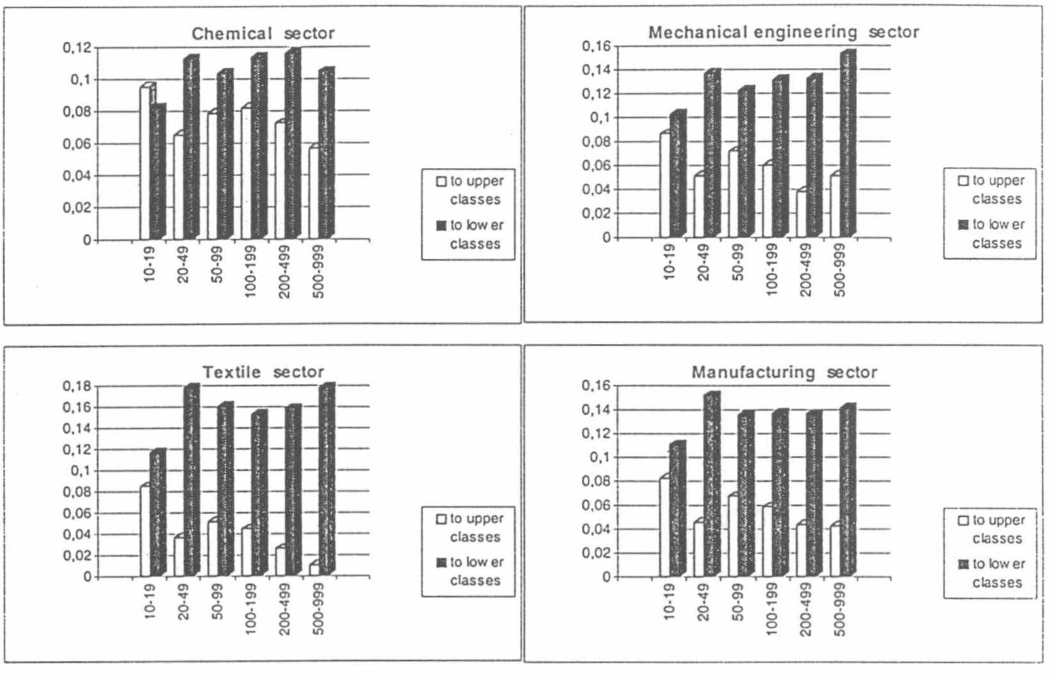

Table 2. Actual and equilibrium relative frequency distributions of firms by sector.

Chemical sector

Class	1986	1994	Equilibrium	Equi/1994
1–9	0.2279	0.1500	0.0700	0.4669
10–19	0.3762	0.3693	0.2853	0.7725
20–49	0.2337	0.2870	0.2430	0.8469
50–99	0.0740	0.0945	0.1474	1.5608
100–199	0.0442	0.0495	0.1033	2.0869
200–499	0.0285	0.0321	0.0734	2.2889
500–999	0.0084	0.0105	0.0530	5.0476
>999	0.0069	0.0073	0.0246	3.3703

Mechanical engineering sector

Class	1986	1994	Equilibrium	Equi/1994
1–9	0.2954	0.2294	0.1339	0.5834
10–19	0.4110	0.4066	0.4013	0.9869
20–49	0.1898	0.2438	0.2592	1.0631
50–99	0.0563	0.0676	0.1077	1.5933
100–199	0.0267	0.0306	0.0599	1.9593
200–499	0.0142	0.0155	0.0281	1.8125
500–999	0.0038	0.0037	0.0074	2.0146
>999	0.0029	0.0027	0.0024	0.8942

Textile sector

Class	1986	1994	Equilibrium	Equi/1994
1–9	0.2584	0.2692	0.2133	0.7923
10–19	0.4603	0.4250	0.4727	1.1122
20–49	0.1982	0.2237	0.2353	1.0518
50–99	0.0503	0.0511	0.0530	1.0374
100–199	0.0213	0.0201	0.0188	0.9349
200–499	0.0096	0.0093	0.0059	0.6333
500–999	0.0015	0.0013	0.0009	0.7420
>999	0.0005	0.0004	0.0001	0.3104

Manufacturing sector

Class	1986	1994	Equilibrium	Equi/1994
1–9	0.2866	0.2574	0.1701	0.6610
10–19	0.4228	0.4059	0.4348	1.0712
20–49	0.1960	0.2328	0.2450	1.0523
50–99	0.0529	0.0590	0.0819	1.3878
100–199	0.0241	0.0264	0.0416	1.5765
200–499	0.0124	0.0133	0.0188	1.4104
500–999	0.0031	0.0032	0.0061	1.8815
>999	0.0021	0.0020	0.0017	0.8770

Chart 2. **Observed and estimated frequency distributions by class and sector – period 1986–1994.**

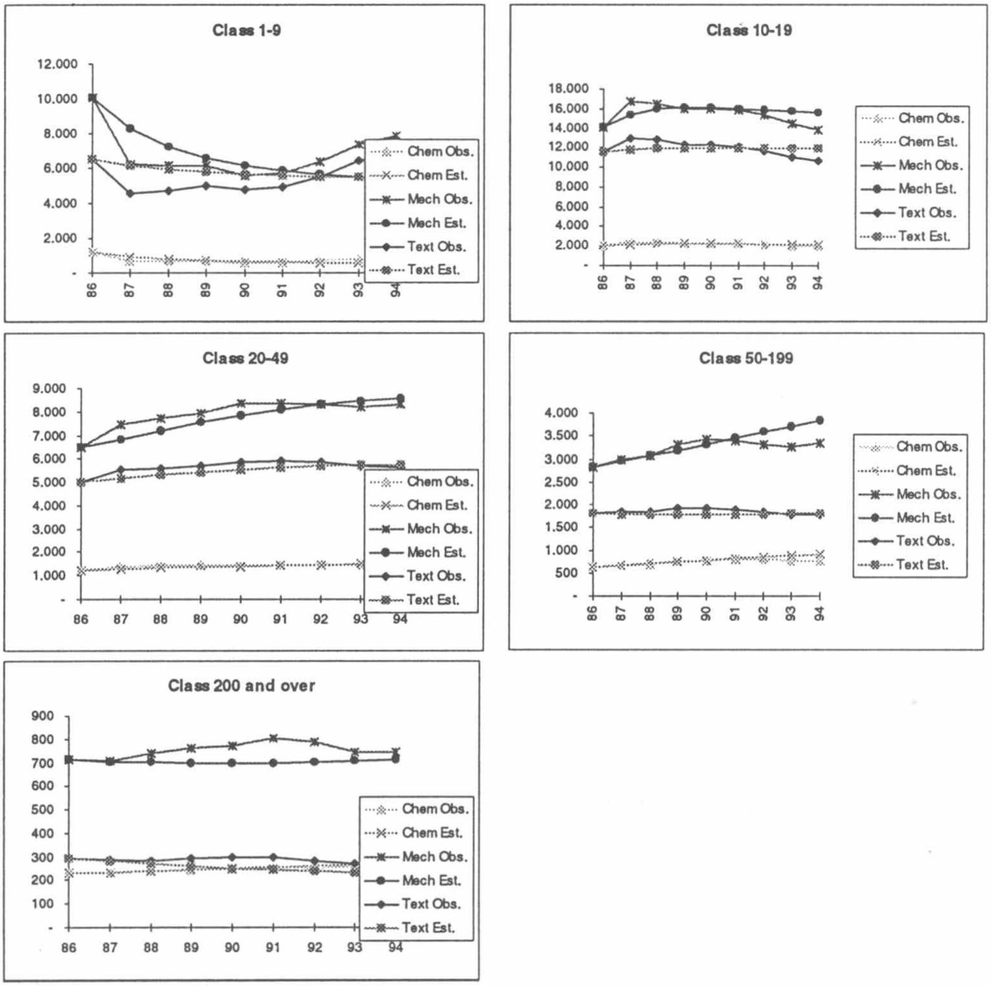

Table 3. Permanence and mobility indieces by sector.

Chemical sector

Class	L_i	L'_i	L_i / L'_i
1–9	2.766	1.075	2.572
10–19	5.647	1.399	4.036
20–49	5.636	1.321	4.266
50–99	5.499	1.173	4.688
100–199	5.127	1.115	4.597
200–499	5.321	1.079	4.931
500–999	6.196	1.056	5.868
>999	6.727	1.025	6.562
I 1994	0.240		

Mechanical engineering sector

Class	L_i	L'_i	L_i / L'_i
1–9	3.060	1.155	2.650
10–19	5.302	1.670	3.174
20–49	5.322	1.350	3.943
50–99	5.154	1.121	4.599
100–199	5.242	1.064	4.928
200–499	5.878	1.029	5.713
500–999	4.906	1.007	4.869
>999	5.295	1.002	5.283
I 1994	0.292		

Textile sector

Class	L_i	L'_i	L_i / L'_i
1–9	3.652	1.271	2.873
10–19	4.989	1.896	2.631
20–49	4.692	1.308	3.588
50–99	4.745	1.056	4.494
100–199	5.079	1.019	4.983
200–499	5.442	1.006	5.410
500–999	5.324	1.001	5.319
>999	4.857	1.000	4.857
I 1994	0.342		

Manufacturing sector

Class	L_i	L'_i	L_i / L'_i
1–9	3.323	1.205	2.758
10–19	5.183	1.769	2.930
20–49	5.071	1.325	3.828
50–99	4.931	1.089	4.527
100–199	5.129	1.043	4.916
200–499	5.580	1.019	5.475
500–999	5.468	1.006	5.435
>999	5.469	1.002	5.459
I 1994	0.312		

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ENTERPRISE DEMOGRAPHY AS A METHOD OF STUDYING REAL ENTERPRISE BIRTHS.
An Application to Enterprise Births in Manufacturing and Retail Trade in Finland in 1990

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Enterprise demography can be applied in many ways. The Business Register of Statistics Finland has also started a project, the main purpose of which is to study the demography of the enterprise population. The first step of this project was to study enterprise openings in retail trade and manufacturing. In Finland the enterprise openings covered by the Business Register are administrative. Administrative enterprise opening is not always a real enterprise birth, because an opening may be due to changes in the legal form or the ownership of an enterprise or changes in employership or VAT obligation. Enterprise opening may also be due to merger or demerger. The main object of this study was to find out the share of the real enterprise births of the administrative ones. For the analysis a longitudinal worker-establishment database (WEDB) covering the years 1988–1992 was created. The data included variables from the Business Register, the Regional Employment Statistics and the Statistics of Bankruptcies. Employee (i.e. social security number) was used as an observation unit. The social security number of the employee made it possible to track the personnel of a certain enterprise, since there is a link between the social security number and the establishment identifier number. Every establishment can also be linked to the certain enterprise with the enterprise identifier number.

There are three criteria for a real enterprise birth. First, a new enterprise must start its activities by creating -not by taking over- an establishment i.e. a new enterprise creates its factors of production. Second, a new enterprise is not allowed to share employees with dead or still active enterprise(s). This criterion was used, because a high proportion of shared employees usually

indicates an administrative (not real) enterprise opening. Third, a new enterprise must be economically active.

The analysis showed that only 54 percent of all enterprise openings in retail trade and 63 percent in manufacturing could be classified as real births. It was also found out that these enterprises employed only a few employees in the first three years. Two thirds of these enterprises had no other employees but the entrepreneur himself. Furthermore, these enterprises had a high level of death rate. Almost half of them died before the fourth year.

Key words: Administrative Enterprise Opening, Enterprise Demography, Real Enterprise Birth.

1. Introduction

The intensity of enterprise births and deaths is an important indicator of the economy. According to the Business Register of Statistics Finland the number of enterprise openings has been about 20,000 per year during the years 1988–1992. At the same period of time the number of enterprise closures has varied between 14,000 and 20,000 per year (Statistics Finland 1994). However, these numbers of enterprise openings and closures do not give a right picture of the development of enterprise population. The main problem is that both the enterprise openings and closures covered by the Business Register are not statistical but administrative i.e. an enterprise opening is identified by the birth of a new enterprise identifier number and correspondingly, an enterprise closure is identified by the death of an enterprise identifier number. This means that enterprise openings and closures may be due to changes in the legal form or the ownership of an enterprise (on the one hand there is a death of an enterprise identifier number, and on the other there is a birth of an enterprise identifier number) or the changes in employership or VAT obligation (i.e. the birth of an enterprise identifier number). Administrative enterprise openings and closures may also be due to mergers and demergers (these events may cause several births and deaths of enterprise identifier numbers).

None of the examples of administrative enterprise openings and closures mentioned above cannot be considered as *real enterprise births or deaths*. First, in the cases of births the factors of production of a new enterprise are not new. Correspondingly in the cases of deaths the factors of production do not disappear even if the enterprise identifier number ceases to exist in the Business Register. Second, the birth of a new enterprise identifier number may not have any impact on the labour market. Similarly, an enterprise identifier number may cease to exist without any losses in the number of jobs. Finally, the examples above of enterprise openings and closures describe demographic events concerning the *reallocation* of the factors of production. However, real enterprise births and deaths always concern the *existence* (birth, death) of factors of production.

The first step of the enterprise demographic study of Statistics Finland was to study enterprise openings. The main object was to separate the real enterprise births from the administrative enterprise openings. This separation is an absolute prerequisite in order to study the job creation of new-born enterprises compared to the impact of old ones on employment, for instance. The share of the real enterprise births tells also a lot about the volume and the quality of changes in economy. That is why a longitudinal worker-establishment database (WEDB) was gathered up. This panel data covered the years 1988–1992. In the beginning the database was used to classify the enterprise openings by the manner of birth. In order to do this the factors of production were studied. Three different classifications were created. In the first two methods the factors of production refer to the establishment(s) (i.e. local Kind-of-Activity Unit). In the third classification the factors of production include also the employees of an enterprise. The main criterion of the real enterprise birth is in all three classifications the beginning of the existence of the factors of production. The data were also used to study the legal form, turnover, number of employees and establishments of new-born enterprises. Also the death rates were studied.

2. The Longitudinal Worker-Establishment Database (WEDB)

As stated before, the first step of the enterprise demography study was to find out the share of the real enterprise births of the administrative ones. Enterprises are usually characterized by variables like a unique identifier number, location, economic activity unit, legal form and size of enterprise, which identify an enterprise at different points of time. However, there is also the personnel that characterizes a certain enterprise. The employees constitute the human capital and resources of an enterprise. Employees learn their specific tasks and routines while working. Teaching of these tasks and routines is an expensive and time-consuming investment for the enterprise and thus the employees become a valuable resource for the enterprise.

However, the same group of employees is not as valuable for another enterprise, since enterprises' activities and routines differ from each other.

This is a fundamental justification for tracking the shared employees over time between different enterprises. The high proportion of shared employees creates a link between enterprises. This means that two enterprises at different points of time may actually be the same enterprise with different enterprise identifier numbers. The shared employees may also indicate a merger (i.e. a new enterprise shares its employees with at least two no-longer-active enterprises) or a demerger (i.e. a new enterprise shares its employees with no-longer-active enterprise (break-up of an enterprise) or with still-active enterprise (split-off of an enterprise)) (see e.g. Eurostat 1996). A similar method has been used in Canada (see Baldwin et al. 1992) in order to track the employees of dead enterprises. See also Struijs and Willeboordse (1995).

Finding out enterprises with shared employees means that only the enterprises that have employees can be studied. However, over 50 percent of Finnish new-born enterprises have no paid employees. These new enterprises without employees were tracked and linked only by means of their establishments.

The first step in forming the longitudinal worker-establishment dataset was to collect all the employees belonging to the labour force and having a link to an enterprise or establishment at least in one year during 1988–1992. The employees and the respective identifier numbers (social security number, enterprise identifier number and establishment identifier number) were gathered from *the Regional Employment Statistics* of Statistics Finland, as well as variables characterizing this population. Variables like age, district of residence, principal activity, industrial status, level of education and wages were collected. The observation unit of the data was employee.

The variables of enterprises and establishments were collected from the Business Register. Both the enterprise identifier number and the establishment identifier number were used as links. The variables characterizing both enterprises and establishment included home municipality, turnover, the sum of wages, principal activity code, type of ownership, legal form and variables which describe the *state of an enterprise*; the date of setting up activity, the date of transfer or take-over of establishment(s), the date of cessation of activities, some variables identifying mergers and demergers of the units etc. The possible information about the bankruptcy of an enterprise was collected from the Statistics of Bankruptcies.

The data that was gathered up by linking the data of the Regional Employment Statistics, the Business Register and the Statistics of Bankruptcies included about 1,500,000 employees. The number of enterprises varied between 210,000 and 240,000 and the number of establishments varied between 260,000 and 300,000 per year. These numbers included also no-longer-active and dead enterprises and establishments, which was an absolute prerequisite in order to link enterprises and establishments over time.

3. The Methods of the Classification of Administrative Enterprise Openings

The longitudinal worker-establishment dataset enables us to study many different aspects of enterprise demography. In this study the dataset has been used to the classification of administrative enterprise openings and the experiences have turned out to be quite promising. The dataset enables us to study real enterprise births in two ways. First, we can use the information about the state of a new enterprise; has the enterprise started its activities by creating an establishment or by taking over an establishment; was it born by merger of other enterprises or by demerger (break-up or split-off) of an enterprise. Second, we can find out, whether a new enterprise shares employees with other enterprise(s) i.e. where do the employees of a new enterprise come from. If most of the employees come from a certain enterprise, the birth of the new enterprise cannot be considered as a real birth. Thus, three different methods were created to classify the administrative enterprise openings. The recommendations of Eurostat (1995) were followed as far as possible.

Method I

The first method utilizes only the information about the state of a new enterprise. Enterprise openings are classified into two groups: real enterprise births and administrative (not real) enterprise openings.

Table 1. **The criteria of the classification in method I.**

Real enterprise birth
The new enterprise starts its activities by creating, not by taking over, an establishment i.e. the new enterprise creates its factors of production.
Administrative enterprise opening
The new enterprise starts its activities by taking over an establishment or a whole enterprise.

Method II

The second method is based on the first method. Administrative (not real) enterprise openings are now classified into two groups: openings caused by the transfer of an enterprise and openings caused by merger or demerger.

Table 2. **The criteria of the classification of administrative enterprise openings in method II.**

Administrative enterprise opening: the birth caused by the transfer of an enterprise
The new enterprise continues the business of another enterprise. In this case there is always a counterpart (a dead enterprise) for a new enterprise in the Business Register. For example in the case of the incorporation of previously unincorporated enterprise a new enterprise identifier number is born and the old enterprise identifier number ceases to exist in the register.
Administrative enterprise opening: the birth caused by merger or demerger
The new enterprise starts its activities by taking over establishment(s) of other enterprise(s). In the case of merger the new enterprise continues the business of at least two enterprises. In the case of demerger the new enterprise continues the business of still-active enterprise (split-off) or the business of no-longer-active enterprise (break-up).

Method III

The third method utilizes the panel data information about the shared employees and the information about the state of a new enterprise at the same time. The enterprise openings can be divided into three groups.

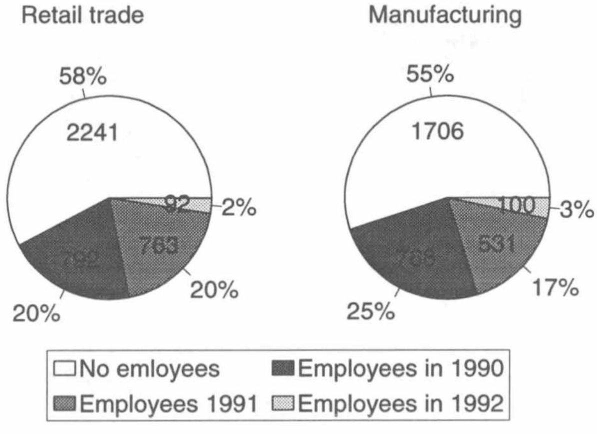
Table 3. **The criteria of the classification in method III.**

Real enterprise birth
Enterprise opening which cannot be considered as an opening caused by the transfer of an enterprise or an opening caused by merger or demerger.
Administrative opening caused by the transfer of an enterprise
There is a counterpart (a dead enterprise) for a new enterprise OR the new enterprise shares <u>over</u> 60 percent of its employees with an enterprise which also shares <u>over</u> 60 percent of its employees with this new enterprise.
Administrative opening caused by merger or demerger
A new enterprise starts its activities by taking over establishment(s) of other enterprise(s) OR the new enterprise shares <u>over</u> 60 percent of its employees with an enterprise which shares <u>under</u> 60 percent of its employees with this new enterprise ('demerger') OR the new enterprise shares <u>under</u> 60 percent of its employees with an enterprise which shares <u>over</u> 60 percent of its employees with this new enterprise ('merger').

4. New Enterprises in Retail Trade and Manufacturing in Finland in 1990

The classification of enterprise openings was first applied to the new enterprises in 1990. In 1990 the number of new enterprises was in retail trade 3,888 and in industry 3,105. During the years 1990–1992 the total number of employees in these new enterprises was 7,900 in retail trade and 49,000 in manufacturing. The new enterprises form a very heterogeneous group if their role as employer is studied; almost 60 percent of them did not employ any paid employees in the first three years. Only a little less than one fourth of them had employees in the first year. The share of those enterprises that employed their first employee in the second year was about 20 percent (Figure 1).

Figure 1. The role of new enterprises as employer.



According to the first method 72 percent of all administrative enterprise openings in retail trade and 85 percent in manufacturing turned out to be real enterprise births. The second method showed that half of the administrative (not real) births turned out to be births caused by the transfer of an enterprise. (Figure 2)

The third method showed that 68 percent of all administrative enterprise openings in retail trade could be classified as real births. The share of real births in manufacturing was 79 percent. However, in 20 percent of the cases of real births the new enterprise turned out to be economically inactive i.e. its turnover did not reach the boundary of 20,000 FIM (about 4,000 USD) in any of the first three years. Hereby the share of the real enterprise births of all administrative openings turned out to be 54 percent in retail trade and 63 percent in manufacturing. (Figures 3 and 4)

The new enterprises which started their activities by real birth turned out to be very small. In retail trade these enterprises employed one fourth of the employees of all new-born enterprises of retail trade sector (Figure 3). In manufacturing the corresponding share was only 6 percent (Figure 4). This means that most of the employees of the new enterprises are employed by the enterprises which are created to continue an existing business (Figures 3 and 4).

Figure 2. The classification of new enterprises by method II.

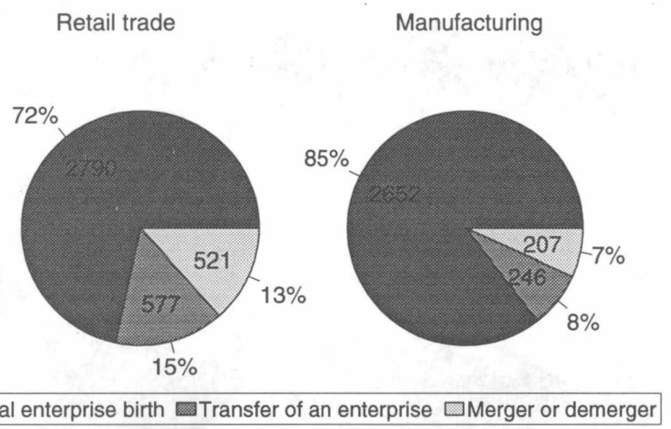


***Figure 3.* The new enterprises of retail trade and their employees classified by the method III.**

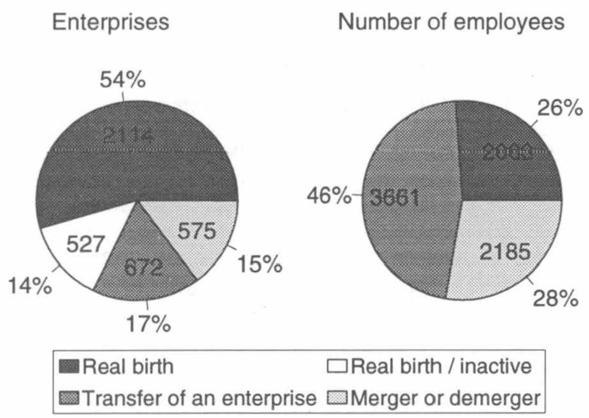
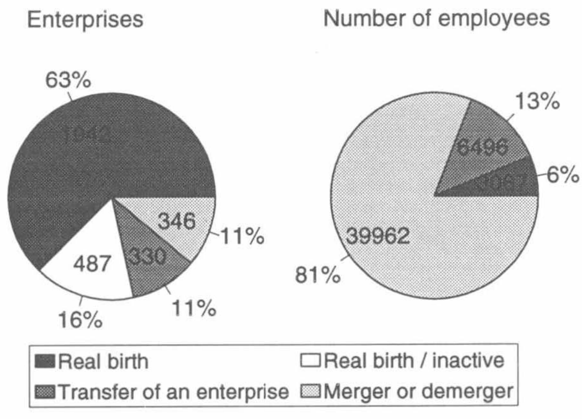
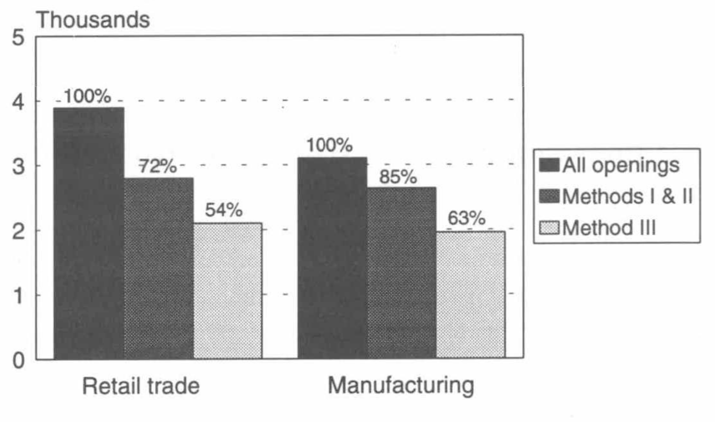


Figure 4. The new enterprises of manufacturing and their employees classified by the method III.



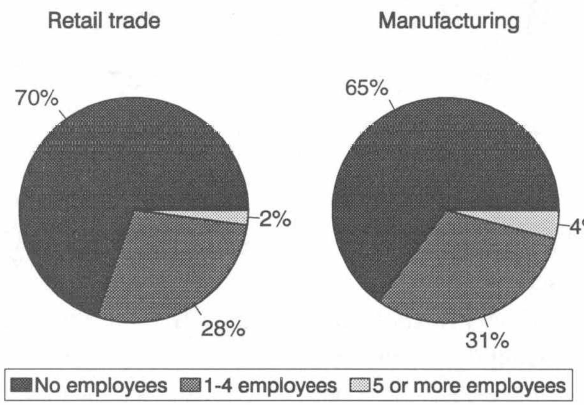
As we can see, the most efficient way to classify enterprise openings covered by the Business Register is the method III. The share of the administrative (not real) enterprise openings it reveals is the biggest and correspondingly the share of the real enterprise births is the smallest compared to the methods I and II. Figure 5.

Figure 5. Three different ways to define enterprise birth (Administrative enterprise opening, real enterprise birth by methods I and II and real enterprise birth by method III).



Over two thirds of the enterprises which started their activities by real birth had no paid employees in any of the first three years. However, these enterprises may provide the livelihood of the entrepreneur. About one third of these enterprises employs 1–4 employees in their first year as employer. Only two percent of these enterprises in retail trade and four percent in manufacturing employs more than four employees. (Figure 6).

Figure 6. **The new enterprises which have started their activities by real birth classified by the number of paid employees.**



About 40 percent of the enterprises which started their activities by real birth were personal owned enterprises and 99 percent of them had only one establishment. The survival rates of these enterprises were lower than general. In retail trade 54 percent and in manufacturing 43 percent of these enterprises died before the fourth year. However, these shares describe the number of administrative deaths.

5. International Comparisons and Conclusions

The results of this study are supported by the results of similar studies in some other countries. For example 39 percent of all new personal owned enterprises could be classified as really new businesses in Denmark in 1990 (Bøegh-Nielsen et al. 1995). In Netherlands only 35 percent of new enterprises could be classified as really new businesses in 1985 (Ritzen 1995).

The fact that really new enterprises are small and the survival rates of these enterprises are low holds true also in other countries. In Denmark about 90 percent of all the really new personal owned enterprises in service sector had no paid employees and 44 percent of these enterprises died before the fifth year. In retail trade the death rate was 50 percent (Bøegh-Nielsen et al. 1995). According to Ritzen & van der Ven (1990) 25 percent of really new enterprises died before the fifth year in Denmark.

The worker-establishment database (WEDB) of Statistics Finland enables us to study enterprise openings in many ways. The most efficient way is the method III, because the amount of administrative (not real) openings it reveals is the highest. However, the method III is also the most time-consuming way to study real enterprise births, because for the classification the information about the employees is needed. The utilisation of the information of the Business Register only (methods I and II) is very fast way to classify enterprise openings but in order to get a proper picture of the share of real births, information about the employees is needed.

Finally, this study shows that although the amount of new enterprises is high in Finland, only half of them can be considered as really new businesses. Furthermore, these really new enterprises are small if their size is measured by the number of employees. In addition the survival rates of these new enterprises are low. This means that in the short run new enterprises are not the solution for the unemployment problem. In the long run their impact on employment may be higher. But in order to study this the cohort of the new enterprises should be followed for a longer period. Three years time period, as in this study, is not enough to make final conclusions about the impact of really new enterprises on job creation.

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BIRTHS AND DEATHS OF FIRMS IN FINLAND

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The birth of new firms and discontinuation of old firms in the Finnish manufacturing is studied using a six-year three-digit industry level panel data set. Descriptive analysis of the data shows big differences in entry and exit across industries and over time. Entry and exit are highly positively correlated. Econometric analysis using Poisson models shows that both microeconomic and macroeconomic variables can be used for explaining the entry and exit of firms.

Key words: Entry, Exit, Count Data Models.

1. Introduction

There is a strong policy interest in the small business sector in all industrial countries. This sector may play an important role in employment, innovation, technological change, and competition. Since changes in the population of firms through births of new firms and deaths of existing firms mainly concern this sector, enterprise demography has gained increasing attention among researchers. This takes various forms from studies of entry and exit to analysis of job creation and destruction and research on the determinants of entrepreneurship.

The purpose of this paper is to study the determinants of the creation of new firms and disappearance of old firms in the Finnish manufacturing industries. The basic framework is adopted from the industrial Organization research and the research on the monetary transmission mechanism.

The structure of the paper is as follows. In Section 2 we briefly summarise the microeconomic and macroeconomic factors that can be expected to influence entry and exit. Section 3 presents a descriptive analysis of the data. Estimation results are presented in Section 4 and Section 5 concludes the paper.

2. Explanations of Entry and Exit

We sketch here the arguments behind the variables chosen to explain entry and exit of firms. A more detailed discussion is in Ilmakunnas and Topi (1996). Typically the industrial Organization literature explains entry by the profit opportunities seen by prospective entrants and the cost of entry (see e.g. Geroski 1991). Profit opportunities can be approximated by past profitability, although often it does not explain entry very well. The cost of entry is related to the scale needed for entry. This is approximated by median firm size in relation to the size of the industry. In addition to this natural entry barrier, existing firms may use strategically created entry barriers. The strategic element is approximated by the five firm concentration ratio. The growth of the industry, measured by change of sales normalised by median firm size, or the change of real sales, is likely to influence entry of firms, since growth creates room for new firms. The influence of scale economies, concentration, and growth on the exit of firms should be opposite to their influence on entry. This assumes that entry barriers are also exit barriers. In addition, the size of the industry, measured by the number of firms in the previous period should be positively related to entry and exit. Since entry and exit are interrelated, past entry should have a positive impact on exits, either through the displacement of old firms by new firms, or through the short life expectancy of new firms.

Macroeconomic influences have received less attention. The theory of the monetary transmission mechanism has been used for explaining investment and bankruptcies (see e.g. Kashyap and Stein 1993), and can by analogy be used for the analysis of births and deaths of firms. According to the traditional view (money channel), real interest rate has a direct negative effect on investment, and analogously on the birth of new firms. In the same way, high interest rates should have a positive impact on the exit of firms. The alternative view (credit channel) emphasises the special role of the banking sector in the economy and argues that the banks' credit supply has an influence on some borrowers' activities, independent of the market real interest rate. A rise in credit supply has a positive influence on entry. This influence may vary with the possible entrants' access to capital markets, which can be approximated by the median firm size in the industry. The effects of an increase in credit supply on exits should be negative since a decline in credit supply causes liquidity problems for the firms with poor credit ratings.

Exchange rates also have a significant role as a determinant of entry and exit especially in small open economies. They affect the prospects of exporting firms, but also influence the competitiveness of home firms subject to foreign competition. In addition, exchange rate changes also influence the home currency financing costs of the firms with foreign currency denominated debt.

The general economic climate has effects both on entry and exit. The "pull" hypothesis says that entrepreneurs are more inclined to enter a market when the growth rate of real GDP is high. The alternative approach, "push" hypothesis, is based on the microeconomic theory of the supply of entrepreneurship. A fall in economic activity may actually increase the number of new firms, since a higher unemployment rate reduces a potential entrant's opportunity cost of starting a new business (see Storey 1991). As to exits, the growth in real GDP reduces the number of exits, but unemployment's should have no direct influence on them.

3. Descriptive analysis

We examine births and deaths of firms in the Finnish manufacturing using data from the Register of Enterprises and Establishments of Statistics Finland. The data set covers the years 1988–1993 and 70 three-digit industries. The data on the number of firms and their sales and employment, and the data on the entering and exiting firms are published separately, and the published numbers are not totally compatible in the sense that the identity

number of firms at end of year t
= number of firms at end of year $t-1$
+ firms entering during year t
– firms exiting during year t

does not hold exactly. The inconsistency is partly caused by different classification criteria. The data on operating firms include firms that have operated at least half a year during the year, whereas the data on entries and exits may contain also firms that have been a shorter period in operation.

The numbers may also exaggerate the true number of births and deaths of firms, since some ownership changes or changes in legal status have been classified both as an entry and an exit, although the firm is actually continuing its operation. Also mergers and break-ups of firms may cause "artificial" births of firms. Changes in the nature of output may lead to a reclassification of a firm to a new industry. These data problems may vary between industries and over time, e.g. according to business cycles which may influence the frequency of ownership changes. Mustaniemi (1996) concludes that in 1990 real enterprise births accounted for 63 per cent of all recorded births in the Finnish manufacturing. Hietaniemi (1996) has calculated the share of unreal firm births in Finnish manufacturing and construction industries over time. There is an upward trend in this share in 1988–1993.

The simplest way to measure the birth of firms is to use gross entry, or the number of new firms starting during a year, and correspondingly gross exit, or the number of exiting firms during a year. The difference of these variables is net entry, which can be positive or negative. The data problems mentioned above are not likely to be as serious in the case of net entry. Since gross entry and exit may be greatly influenced by the number of firms in the industry, often entry is measured by entry rate, i.e. entry divided by the pre-entry number of firms, and exit by exit rate, or the number of discontinuing firms divided by the previous number of firms. Visual inspection of the data actually revealed a fairly straight line relationship between industry size and entry (Ilmakunnas 1996). Correspondingly, net entry rate is net entry divided by the number of firms. We present evidence on both measures, but concentrate in the econometric analysis on the number of entering and exiting firms.

The sum of entering and exiting firms is called turbulence, and this sum divided by the total number of firms is called turnover rate. These measures describe the total mobility of firms to an industry or out of it, but the statistical problems may exaggerate these figures even more than the entry and exit rates. A better measure of the extent of entry would be entry penetration, i.e. the market share of entering firms, but our data do not allow the calculation of this variable. There are no published data available on the sales or employment of the entering and exiting firms.

Table 1 shows entry and exit in two-digit industries over time. Table 2 shows the corresponding figures for entry and exit rates. Table 3 exhibits entry and exit rates over time. The means have been calculated from the two-digit level figures in Tables 1 and 2, and the standard deviations, maxima, and minima from the three-digit level figures in each two-digit industry. In Table 3, the means have been calculated for each year using the figures for total manufacturing, and the standard deviations, maxima and minima from all the three-digit figures in each year.[1]

1 Note that the entry and exit rates differ slightly from those reported in Ilmakunnas (1996), where the denominator in these measures was defined differently.

Births and deaths of firms vary considerably across industries (and also over time, as evidenced by Table 3). Actually the variation across industries is even greater than what appears in the Table, since the two-digit figures hide considerable differences between the three-digit industries. Some industries have experienced a downward trend in the number of new firms and an increase in exits throughout the data period, whereas some industries have had an increasing number of entries even during the general recession. The smallest numbers appear in the following industries: paper and pulp (15), oil products etc. (19), chemicals (18), rubber and plastics (21) and basic metals (23). These are industries where one could expect scale economies to be large, so that there are natural entry barriers. The biggest numbers for entry can be found in the following industries: clothing, shoes etc. (13), wood products (14), metal products (24), and machinery (25). In these fields, scale economies are most likely smaller and hence entry is easier. Of course, this examination at the aggregate level does not yet give a systematic picture of the influences of different factors. In Table 2 it can be seen that entry and exit rates have less variation across industries than entries and exits. It is noteworthy that the industries with the largest entry and exit rates do not coincide with the industries with largest numbers for entry and exit. The net entry rate varies from –.028 to .078. In six two-digit industries the net entry rate is negative, so that the number of firms has fallen over the data period.

Table 3 shows that the entry rate has fallen and the exit rate increased during the recession in the 1990's so that the net entry rate became negative in the total manufacturing in 1991–1992. The turnover rate has remained fairly stable. In 1991, when the aggregate entry rate was at its lowest level, and the aggregate exit rate at its highest level, the share of industries that had no entries fell, and the share of industries without exit increased, as can be seen from the development of the share of zero observations. This shows that there are large interindustry differences in changes in the population of firms over time.

Table 4 shows the correlations of entry and exit. The correlation in the same year is very large. This may be due to the statistical problems, but also due to the displacement effect. The correlation is even higher over time, which may be due to the short life-cycle of new-born firms. Ahola (1996) shows that of all firms started in Finnish manufacturing in the period 1987–1993, almost 6 per cent closed down within one year and 15 per cent stayed alive less than two years. This table also shows that both entry and exit are very autocorrelated. Table 5 shows the same figures for entry and exit rates. These correlations are considerably lower.

Since there are big interindustry differences in entry and exit, it is useful to purge the differences in levels across industries. The correlations calculated after industry means have been deducted, indicate whether periods that have many entries, also have many exits. These correlations are much lower and now entry is actually negatively correlated with same period exit.

Alternatively, we can purge the annual differences in levels. It is likely that macroeconomic factors influence births and deaths of firms in most industries more or less in the same way. When annual averages, calculated over all industries, are deducted from the figures, the correlations describe better the relationship of entry and exit which is related to industry specific influences. These correlations are fairly similar to the original correlations. This shows that the interindustry variation in the data is larger than the variation over time caused by the general business cycle.

The analysis has so far included all 70 three-digit industries in the data set. Due to some missing data and apparent changes in the classification of firms to industries (see e.g. the high exit rate in industry 19), eight industries were left out of further analysis, so that the final data set has 62 industries. The data period is 1988–1993 so that the data forms a balanced panel with 372 observations. Due to the use of some lagged variables, 310 observations were used in the estimations. In addition to the enterprise statistics, we used data on profitability from the Financial Statements Statistics and various macroeconomic data on general business conditions and financial market situation. The data sources and variables are explained in more detail in Appendix 1.

4. Estimation Results

Since the entry and exit figures are non-negative discrete variables with considerable share of zero observations, the use of the Poisson model for the econometric modelling of the determinants of entry and exit seems useful. We also used the negative binomial to account for overdispersion in the data and the fixed effects Poisson model to take into account the combined time series and cross section nature of the data (see Hausman, Hall and Griliches 1984). Table 6 gives the estimation results for the entry and exit models. More results are presented in Ilmakunnas and Topi (1996).

Past profitability did not obtain a significant coefficient, so that it was left out of the final entry models. The other microeconomic influences on entry are largely in accordance to our expectations. Entry has a clear positive connection with the industry size, measured by the lagged number of firms (lnfirms_1), and the elasticity of entry with respect to industry size seems to be quite close to unity. The proxy for scale economies (med/sales) has a negative influence and the measure of industry growth (drsales) a positive influence on entry. Finally, the effect of concentration (c5) on entry is negative.

The macroeconomic influences on entry are also quite expected. Entry seems to be negatively related to the real interest rate (rhelibor). The coefficient of the change in the real credit supply (drcredit) is positive. Our estimation results also support the hypothesis that the influence of credit constraints on entry varies with the average firm size. The coefficient of the interaction term drcredit*rmed is negative. In accordance with our hypothesis, entry is positively connected both to the real GDP growth (drgdp) and to the change in the unemployment rate (dunemploy). This result suggests that unemployment and GDP developments have different roles in the analysis of new firm formation.

In the exit model the coefficient of profitability is negative. The other microeconomic influences also behave in an expected way. The entry-exit interaction was taken into account by introducing lagged entry (entry_1) as a determinant of exit. Exit has a positive connection to industry size in the same manner as entry. Scale economies have again a negative influence. Industry growth (dsales/med) has a negative coefficient. The coefficient of the concentration rate has a negative sign in all estimations, but its significance is poor.

Exit is positively connected to the real interest rate, as expected, but the significance of the coefficient is low. The coefficient of the relative change in the real credit supply is not significant and positive, contrary to a priori expectation. The coefficient of the interaction variable drcredit*rmed has a negative sign in all estimations. Part of the impact of the financial variables on exit seems to come indirectly, since they have a positive impact on entry which in turn increases exit. Exit is negatively connected to the relative change in the real GDP, as expected.

In addition to the results shown, we also included real exchange rate (drexrate) in the models. Its coefficient was positive in the entry models, which implies that the influence of exchange rates on entry works through foreign trade prospects. In the exit models the coefficient of the exchange rate was positive, but not significant. This result suggests that the influence of a real devaluation on the amount of foreign debt and interest expenditure and its positive influence on export demand to a large extent outweigh each other.

In general, the results give support to the negative binomial model, since the parameter, which can be used for testing the Poisson model against the negative binomial model, is significantly different from zero.

In the entry models the fixed effects estimation lowers the explanatory power of the industry variables, which is understandable since they may have more variation between industries than across time. An exception is the concentration rate variable, which gains significance. The impact of the macroeconomic variables on entry is similar to that obtained in the other estimations. In the exit models the fixed effects results are mainly the same as in the estimations with pooling. Among the macroeconomic explanatory variables, GDP growth gains more significance. However, the influence of past entry on exits seems to vanish.

5. Conclusions

The descriptive analysis showed that there are large variations in the birth of new firms and the exit of old firms both over time and across industries. This was confirmed in the econometric estimations, where both industry level variables and macroeconomic variables explained entry and exit.

The traditional exit model in industrial Organization is based on the idea of voluntary exit. The macroeconomic theories of monetary transmission mechanism, on the other hand, are more concerned of forced exit in the form of bankruptcy. Both approaches treat entries as voluntary investments. This may explain why the financial factors worked well in the entry models, but did not seem to explain exits.

In future work, it may be useful to model bankruptcies rather than exits. In this way one could also avoid the problems with false exit observations. Further work is also needed in a more careful analysis of the interaction and autocorrelation of entry and exit.

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Data Appendix

The data are from three primary sources. Firm and industry level data are from the Register of Enterprises and Establishments of Statistics Finland (SFREE) except for profitability which is from the Financial Statements Statistics of Statistics Finland (SFFSS). Macro data have been obtained from the database of Bank of Finland (BOFDB). The definitions of the variables and the respective data sources are the following:

entry	the number of entries in the industry (SFREE)
exit	the number of exits in the industry (SFREE)
c5	concentration ratio, turnover of five largest firms in the industry / total turnover of the industry (includes plants of firms classified in other industries) (SFREE)
med/sales	median firm turnover in the industry / total turnover of the industry (SFREE)
drsales	relative change in total real turnover of the industry from previous period (SFREE)

dsales/med	change in total turnover of the industry from previous period / median firm turnover in the industry (SFREE)
drcredit	relative change in total real credit supplied by the banking sector from previous period (BOFDB)
drcredit*rmed	drcredit* median real firm turnover in the industry (BOFDB / SFREE)
rhelibor	average real three-month helibor interest rate (Helsinki interbank offered rate) (BOFDB)
lnfirm_1	natural logarithm of the number of firms in the previous period (SFREE)
dunemploy	change in the ratio of unemployed to total work force from previous period (BOFDB)
drgdp	relative change in real gross domestic product from previous period (BOFDB)
drexrate	relative change in official real exchange rate index from previous period (BOFDB)
profitability	return on investment, (profit/loss after financing costs + interest expense + other expenses on liabilities) / (liabilities subject to interest + shareholders equity + reserves + valuation items) (SFFSS)

The consumer price index is used for deflating the nominal values of certain variables (BOFDB).

Table 1. Entry and exit over time 1988–1993.

Industry	Entry				Exit				Net Entry
	Mean	St.Dev.	Max	Min	Mean	St.Dev.	Max	Min	Mean
11	234.5	38.7	144	0	192.2	32.5	120	0	42.3
12	196.2	49.2	194	19	21.0	49.5	162	20	–20.8
13	317.7	126.9	378	6	340.5	120.8	340	6	–22.8
14	355.0	55.5	179	17	350.5	54.3	191	1	4.5
15	29.3	4.1	16	1	18.8	4.3	17	0	10.5
16	299.7	36.2	167	49	270.3	43.3	188	29	29.3
17	183.5	16.5	199	164	195.0	33.2	253	164	–11.5
18	26.3	3.1	12	0	21.5	3.1	12	0	4.8
19	1.3	0.7	2	0	0.7	0.5	1	0	0.7
21	84.0	36.0	95	3	66.7	29.3	73	3	17.3
22	114.5	13.3	44	0	101.7	13.2	46	0	12.8
23	10.3	2.7	9	0	12.0	2.7	11	0	–1.7
24	523.2	47.4	273	107	458.0	52.9	247	48	65.2
25	356.7	59.9	228	51	274.0	45.2	181	38	82.7
26	173.7	23.0	68	5	126.5	19.4	71	2	47.2
27	117.0	23.8	90	0	106.7	22.8	78	0	10.3
29	175.7	32.5	225	136	166.2	45.0	257	138	9.5
All industries	**3198.5**	**64.3**	**378**	**0**	**2918.2**	**60.9**	**340**	**0**	**280.3**

Means have been calculated at the two-digit levels over time. Standard deviations, maxima and minima have been calculated from three-digit level figures over time in each two-digit industry.

Table 2. Entry rate and exit rate over time 1989 – 1993.

Industry	Entry rate					Exit rate					Net entry rate	Turn-over rate
	Mean	St. Dev.	Max	Min	Share of Zero Obs.	Mean	St. Dev.	Max	Min	Share of Zero Obs.	Mean	Mean
11	.148	.097	.429	.000	.178	.120	.063	.250	.000	.222	.027	.268
12	.131	.045	.241	.072	.000	.160	.031	.228	.110	.000	.028	.291
13	.150	.052	.219	.059	.000	.174	.044	.212	.062	.000	.024	.324
14	.124	.057	.242	.083	.000	.125	.042	.258	.101	.000	.002	.249
15	.149	.069	.298	.017	.000	.108	.052	.198	.016	.000	.042	.257
16	.136	.047	.276	.091	.000	.127	.028	.177	.087	.000	.009	.263
17	.114	.017	.140	.098	.000	.126	.020	.152	.102	.000	.012	.239
18	.128	.109	.455	.000	.244	.098	.155	1.000	.000	.289	.031	.226
19	.157	.353	1.000	.000	.600	.078	.256	1.000	.000	.733	.078	.235
21	.122	.054	.226	.042	.000	.102	.039	.206	.064	.000	.021	.224
22	.141	.308	1.500	.000	.133	.125	.075	.250	.000	.222	.016	.265
23	.099	.074	.250	.000	.133	.112	.080	.286	.000	.067	.013	.211
24	.127	.152	.653	.054	.000	.117	.026	.184	.083	.000	.010	.243
25	.138	.030	.190	.086	.000	.110	.024	.142	.075	.000	.028	.248
26	.123	.055	.264	.088	.000	.094	.033	.190	.056	.000	.029	.217
27	.144	.103	.500	.000	.100	.137	.073	.385	.000	.100	.007	.280
29	.155	.031	.186	.119	.000	.158	.038	.225	.137	.000	.003	.313
All industries	**.133**	**.155**	**1.500**	**.000**	**.111**	**.127**	**.092**	**1.000**	**.000**	**.137**	**.006**	**.260**

Means have been calculated at the two-digit levels over time.
Standard deviations, maxima and minima have been claculated from three-digit level figures over time in each two-digit industry.

Table 3. Entry and exit rates over industries.

Year	Entry rate					Exit rate					Net entry rate	Turnover rate
	Mean	St. Dev.	Max	Min	Share of Zero Obs.	Mean	St. Dev.	Max	Min	Share of Zero Obs.	Mean	Mean
1989	.166	.145	1.00	.000	.100	.118	.123	1.000	.000	.143	.048	.284
1990	.132	.081	.355	.000	.143	.118	.122	1.000	.000	.143	.014	.250
1991	.110	.247	1.500	.000	.100	.150	.073	.385	.000	.157	–.040	.260
1992	.125	.147	1.000	.000	.086	.132	.063	.286	.000	.143	–.007	.257
1993	.137	.096	.500	.000	.129	.115	.053	.250	.000	.100	.022	.252
1989–1993	**.133**	**.155**	**1.500**	**.000**	**.111**	**.127**	**.092**	**1.000**	**.000**	**.137**	**.006**	**.260**

Means are figures for total manufacturing.
Standard deviations, maxima and minima have been calculated from all three-digit level figures in each year.

Table 4. Correlation of entry and exit.

a) without fixed industry or year effects

	Entry(t)	Entry(t–1)	Entry(t–2)	Exit(t)	Exit(t+1)	Exit(t+2)
Entry(t)	1.000	.964	.939	.908	.925	.958
Exit(t)				1.000	.958	.922

b) with fixed industry effects

	Entry(t)	Entry(t–1)	Entry(t–2)	Exit(t)	Exit(t+1)	Exit(t+2)
Entry(t)	.000	.397	–.229	–.170	.063	.420
Exit(t)				1.000	.190	–.425

c) with fixed year effects

	Entry(t)	Entry(t–1)	Entry(t–2)	Exit(t)	Exit(t+1)	Exit(t+2)
Entry(t)	1.000	.967	.946	.921	.937	.961
Exit(t)				1.000	.966	.938

Table 5. Correlation of entry and exit rates.

a) without fixed industry or year effects

	Entry rate(t)	Entry rate(t–1)	Entry rate(t–2)	Exit rate(t)	Exit rate(t+1)	Exit rate(t+2)
Entry rate(t)	1.000	.155	–.048	.099	–.085	.172
Exit rate(t)				1.000	.018	.023

b) with fixed industry effects

	Entry rate(t)	Entry rate(t–1)	Entry rate(t–2)	Exit rate(t)	Exit rate(t+1)	Exit rate(t+2)
Entry rate(t)	1.000	–.212	–.514	.070	–.081	.240
Exit rate(t)				1.000	–.238	–.270

c) with fixed year effects

	Entry rate(t)	Entry rate(t–1)	Entry rate(t–2)	Exit rate(t)	Exit rate(t+1)	Exit rate(t+2)
Entry rate(t)	1.000	.164	–.047	.094	–.078	.171
Exit rate(t)				1.000	.019	.029

Table 6. **Estimation results of entry and exit models.**

Variable	Entry			Exit		
	Poisson	Negative binomial	Fixed effects Poisson	Poisson	Negative binomial	Fixed effects Poisson
constant	−1.003***	−1.637***		−1.062***	−1.477***	
	(−7.108)	(−5.067)		(−6.723)	(−6.440)	
c5	−0.394***	−0.171	−0.648***	−0.268***	−0.230*	−1.033***
	(−4.380)	(−0.908)	(−3.070)	(−2.822)	(−1.685)	(−3.573)
med/sales	−0.016***	−0.009***	−0.006	−0.017**	−0.010	−0.012
	(−3.692)	(−2.580)	(−0.773)	(−2.432)	(−1.465)	(−1.237)
drsales	0.103***	0.055	0.002			
	(3.849)	(1.057)	(0.048)			
dsales/med				−0.327***	−2.207*	−0.162**
				(−5.334)	(−1.866)	(−2.269)
profitability				−2.339***	−2.359***	−0.901
				(−6.755)	(−4.427)	(−1.502)
drcredit	0.638**	1.344	0.714***	0.061	0.225	0.258*
	(1.909)	(1.476)	(2.635)	(0.420)	(0.774)	(1.824)
drcredit*med	−0.203***	−0.140***	−0.198***	−0.084**	−0.054	−0.091
	(−5.353)	(−3.131)	(−3.252)	(−2.120)	(−0.673)	(−1.222)
rhelibor	−0.009	−0.005	−0.003	0.006	0.006	−0.000
	(−1.550)	(−0.310)	(−0.627)	(1.093)	(0.502)	(−0.011)
lnfirm_1	0.870***	0.941***	−0.220***	0.846***	0.917***	0.776***
	(55.105)	(28.021)	(−5.632)	(41.097)	(26.889)	(7.307)
entry_1				0.155***	0.112***	0.040
				(8.825)	(2.830)	(1.280)
dunemploy	3.117**	4.971	3.226***			
	(2.494)	(1.551)	(2.912)			
drgdp	3.362***	3.134***	2.782***	−0.786*	−1.166	−1.943***
	(8.724)	(2.687)	(7.244)	(−1.959)	(−1.542)	(−6.112)
		0.099***			0.031***	
		(9.233)			(5.984)	
Log-L	−1576.645	−1082.151	−766.724	−1043.071	−956.844	−687.296
	Restricted Log-L = 11500.99			Restricted Log-L = 11637.53		

Note: * denotes coefficient significant at 10 % level, ** at 5 % level, and *** at 1 % level; t-statistics in parenthesis.

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THE EFFECTS OF TECHNOLOGY ON JOB CREATION AND DESTRUCTION IN FINNISH MANUFACTURING, 1986–93

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We examine job creation, destruction and reallocation rates using data on Finnish manufacturing establishments for the period 1987–93. The technology levels of establishments are based on a classification of the technology levels of manufacturing industries. We focus on differences in these rates across the technology levels, and on the effects of the 90's recession on the rates. Our results indicate that the high technology sector has higher job creation and destruction rates, and it has responded to the recession somewhat differently than other sectors. We also find that the high and low technology sectors are contributing differently to job reallocation: high technology is more important (compared to its employment share) in job creation, entry, and gross reallocation, while low technology is more important in job destruction, exit, and net job decrease.

Key words: Job Creation and Destruction, Manufacturing Industries, Technology.

1. Introduction

Recently there has been renewed interest in the notion of technological unemployment. It argues that technical change leads to job loss (destruction) due to its pace, labour saving bias or obsolescence of old products and production techniques. On the other hand, it is also a common conjecture that the high-technology firms (establishments) act as creators of new jobs, and some studies have indeed found that innovations have a positive effect on employment, see e.g. van Reenen (1993).

In this paper we report some initial results on the effects of the level of technology on job creation and destruction in Finland using plant/establishment level data on employment in the Finnish manufacturing sector. The plant level data come from a panel data file of industrial establishments (DIE) for 1974–93 constructed at Statistics Finland. Due to data restrictions we examine here only the latest years 1987–93. Although short, this period may be of special interest because of the dramatic changes in the Finnish economy from the end of the 1980s ('boom') to the beginning of the 1990s ('recession').

We take a special interest in if any differences in the job creation and destruction rates can be detected according to the level of technology. We also examine if the technology groups have experienced different developments in job creation and destruction during the early 90's recession. The technology level of plants is determined according to their main industry. Although our technology indicator is not ideal, we use it to obtain a preliminary understanding of the possible effects of technology.

In Section 2 we briefly review some theoretical points and the measurement of job creation and destruction. Section 3 presents our empirical results, and Section 4 concludes. The appendix gives details on the data set and variables used.

2. Some Theoretical Considerations and Measurement of Job Creation and Destruction

Measures of job creation and destruction are based on employment changes of individual firms or plants, as will be discussed below. Any theoretical insight on the effects of technology on employment should therefore be relevant for the effects of technology on job creation and destruction.

Within the competitive labour market model the important factors affecting the employment effects of technology are the labour demand and supply elasticities, the complementarity/substitutability of different factors of production, and the bias of technological change. It should be emphasised that on purely theoretical grounds the effect of technological change on employment is ambiguous. For example at the level of an individual firm, assuming that the wage is given and employment is set according to the marginal revenue product of labour equal to wage condition, the employment effect of labour saving technical change (process innovation) is positive only if the wage elasticity of labour demand is greater than unity, see e.g. van Reenen (1993). At the industry or economy level labour supply may not be fully elastic, and supply elasticity also affects.

In non-competitive labour market models additional factors, like efficiency wage considerations or union bargaining power, could affect employment determination. For example van Reenen (1993) argues that the condition for technical change (innovations) to increase employment is relaxed in some union bargaining models, but is not affected by efficiency wage considerations or bargaining over effort. However, both increases and decreases of employment are still possible as a result of technical change. These models therefore do not provide unambiguos predictions concerning the extent of job creation and destruction in different sectors of the economy defined by technology.

Recent literature includes some models that analyse job creation and destruction more directly. For example, Baldwin, Dunne and Haltiwanger (1994) have presented such a model based on the job flows (or matching) model of the labour market. Consider the economy consisting of different sectors that differ in some fundamental factor which determines different job creation and destruction rates for the sectors in equilibrium. The steady state equilibrium is determined by the requirement that total unemployment and sectoral vacancy rates are constant. Since change in total unemployment is determined by the net job creation (creation - destruction) and labour force growth, a constant unemployment requires that in equilibrium total job creation equals job destruction plus labour force growth. However in such an 'intermediate' run steady state this equality need not be fulfilled in each sector separately. If in addition it is required that in a long run steady state sectoral employment shares are constant then net job creation must equal labour force growth rate in each sector. However, equal net job creation may be achieved with different levels of creation and destruction in different sectors, the level being determined by the fundamental factors affecting creation and destruction. The important prediction is that sectors with high job creation also have high destruction in such a long run steady state equilibrium. In a Figure with job creation and destruction as axes, all sectors would lie on the 45 degree line whose vertical position is determined by the labour force growth rate, c.f. Figure 3. In an intermediate run steady state individual sectors may deviate from this line, as long as the aggregate economy lies on the steady state line.

Our interest here lies in the possible effects of technology on job creation and destruction. So we apply the above ideas on sectors determined according to their level of technology, but should we expect more or less job reallocation in the higher technology sectors. Using also a matching-model Mortensen and Pissarides (1995) have argued that under certain conditions a higher technological (productivity) growth rate implies higher job creation and destruction. Making the reasonable assumption that our indicator for level of technology, which is based on R&D intensity, is positively correlated with productivity growth rate, we would expect as a working hypothesis that the higher technology sectors should be characterised by higher job creation and destruction in long run steady state.

To empirically study this hypothesis, we measure job creation, destruction and reallocation following the conventions of Davis and Haltiwanger (1990, 1992). At the level of an individual plant job creation or destruction flow is simply defined as the absolute value of change in its employment between two periods $JCF(e,t) = DL(e,t) = L(e,t)-L(e,t-1)$, when $DL(e,t)<0$, and $JDF(e,t) = -DL(e,t)$, when $DL(e,t)$ These flows may be expressed as rates when divided by a size measure of the unit, defined as the average employment of the two periods, $X(e,t) = [L(e,t)+L(e,t-1)]/2$. For any group of plants (a sector) the sectoral job creation and destruction rates are sector flows divided by sector size as follows

$$JCR(s,t) = \Sigma \{JCF(e,t)\}/X(s,t), \quad e \in E(s,t), DL(e,t)>0$$
$$JDR(s,t) = \Sigma \{JDF(e,t)\}/X(s,t), \quad e \in E(s,t), DL(e,t)<0$$

where $E(s,t)$ denotes the set of plants in sector s at t, including the plants entering or exiting at t, and $X(s,t) = \Sigma\{X(e,t)\}$ is the sector size. The gross job creation sums employment gains at expanding and entering (new) plants, and gross job destruction sums employment losses at shrinking and exiting (dying) plants within sector s. Creation and destruction rates may be defined separately for entering (ENTRY), expanding (INCR), shrinking (DECR), and exiting (EXIT) plants. Then JCR = ENTRY + INCR and JDR = EXIT + DECR.

To further describe the process of job reallocation in a sector the following measures are defined. The net measure ($NET(s,t) = JCR(s,t) - JDR(s,t)$) simply measures the net employment growth in the sector. The gross job reallocation rate ($SUM(s,t) = JCR(s,t) + JDR(s,t)$) measures what proportion of sector's jobs are lost or newly created so it describes the reallocation of jobs among plants. Finally, the excess job reallocation rate ($EJR(s,t) = SUM(s,t) - |NET(s,t)|$) describes the job turnover in excess of the minimum needed to accommodate the net change in jobs, i.e. how many more jobs are created or destructed than needed to achieve the net gain or loss in sector employment. In computing these measures the 'sector' may be total economy, some part of it like manufacturing, or groups of plants defined by some observable plant characteristics like industry, size, and technology as used here.

Approaching the question of driving forces of job creation and destruction it is informative to examine whether job reallocation occurs between or within sectors. Job reallocation (simultaneous job creation and destruction) is due to individual plants facing different conditions or shocks, or reacting to these differently, and therefore experiencing different employment development, some increasing some decreasing their employment. If these conditions or shocks are common to some group of plants, i.e. sector-specific, they would amount to similar (homogeneous) employment changes within a sector but different across sectors. Then gross job reallocation would be due to between-sector employment shifts. On the other hand, if conditions and shocks are plant-specific, there would be simultaneous job creation and destruction within each sector, and total job reallocation due to within-sector employment shifts across plants. In this case there would be heterogeneous employment development in different plants within a sector.

The importance of sectoral differences may be examined first of all by calculating job reallocation rates for each sector separately. If the rates differ, some important determinants of job creation and destruction differ across sectors. It may not be the observable characteristic itself that is important, but rather some 'underlying factor' that is correlated with it. Second, using the sectoral breakdowns, the total manufacturing gross job reallocation can be decomposed to (i) total net employment change, (ii) between-sector employment shifts and (iii) excess job reallocation within sectors as follows (e.g. Davis and Haltiwanger 1992)

$$\begin{aligned} \mathrm{SUMF}(t) = {} & |\mathrm{NETF}(t)| && \text{total net change} \\ & + \{\Sigma|\mathrm{NETF}(s,t)| - |\mathrm{NETF}(t)|\} && \text{between-sector} \\ & + \{\mathrm{SUMF}(s,t) - |\mathrm{NETF}(s,t)|\} && \text{within-sector} \end{aligned}$$

Konings (1993) has suggested the following index of within-sector reallocation to examine whether job reallocation reflects sectoral shifts or job reallocation within sectors

$$\mathrm{Index}(t) = 1 - \Sigma\ \{|\mathrm{NET}(s,t)|\} / \Sigma\ \{\mathrm{SUM}(s,t)\}$$

If job flows are entirely due to employment shifts across sectors, the index obtains a value of 0, while a value of 1 reflects job reallocation across plants within sectors.

We use these measures to quantify the importance of total employment change, between-sector reshuffling of employment and within-sector reallocation to gross job reallocation. Our sectoral breakdowns are based on plant size, industry, and technology.

In order to gain understanding of the job reallocation process, the correlations between various measures, e.g. r(JCR,JDR) and r(NET,SUM) are often examined. Across periods or sectors, when job creation is high one might tend to expect low job destruction, i.e. r(JCR,JDR)<0, especially if plant specific conditions and shocks matter little. A positive correlation on the other hand indicates that there is simultaneous job creation and destruction during the period or within the sector. This heterogeneity in plant employment responses indicates that plant specific conditions and shocks or reactions to these are important. For the second correlation, it may be shown that sign{r(NET, SUM)} = sign{var(JCR)–var(JDR)}. So, a positive (negative) r(NET,SUM) indicates that the variation in job creation is more (less) pronounced than variation in job destruction. For example, a negative r(NET,SUM) across time indicates that gross job reallocation is countercyclical, which arises from the fact that job destruction is cyclically more volatile.

3. Some Results on Technology and Job Reallocation

We focus here on our results on job reallocation by technology levels. We also present some results for the total manufacturing and with respect to plant size and industry. In 1985/86 the plant/enterprise coding system of the Census of Manufactures was changed, so we use here only data from the 1986 Census onwards. Since the calculation of creation and destruction rates requires two years of data, our observation run from 1987 trough 1993. Since our data covers only 7 years we do not report any correlations between different measures. To examine the pro/countercyclicality issues we instead examine how various measures of job reallocation have changed between the 'peak' (1987–90) and 'through' (1991–93) years.

Figure 1a. Job Creation, Destruction, Unemployment and GDP Growth Rate. Total Manufacturing, 1987–93

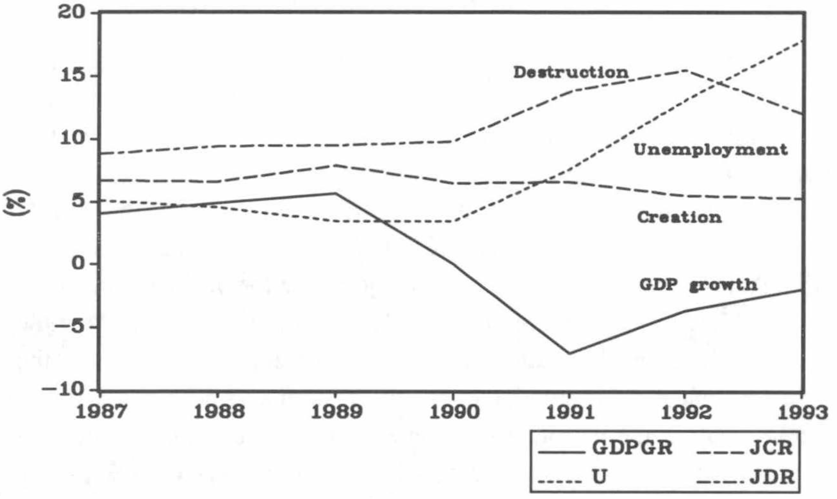


Figure 1b. Total Employment and Net Employment Change. Total Manufacturing, 1987–93

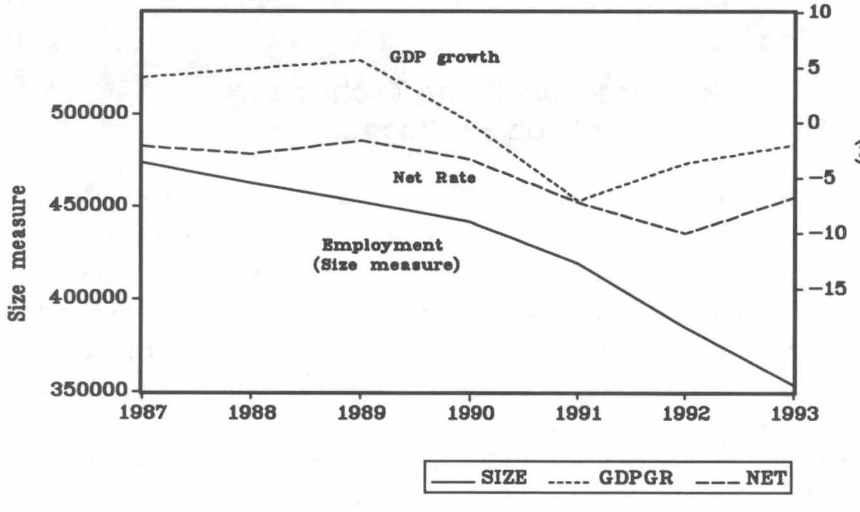


Table 1. Job Reallocation, Manufacturing Sector, 1987–93

a. Rates

YEAR	JCR		JDR		NET	SUM	EJR
1987	6.7	(41)	8.8	(34)	–2.0	15.5	13.4
1988	6.6	(27)	9.4	(42)	–2.8	16.0	13.2
1989	7.9	(44)	9.5	(39)	–1.5	17.4	15.9
1990	6.5	(44)	9.8	(28)	–3.3	16.4	13.0
1991	6.6	(67)	13.8	(31)	–7.3	20.4	13.1
1992	5.5	(46)	15.5	(37)	–10.0	21.0	10.9
1993	5.3	(28)	12.0	(36)	–6.7	17.3	10.6
Weighted averages							
1987–93	6.5	(42)	11.1	(35)	–4.6	17.6	13.0
1987–90	6.9	(39)	9.4	(36)	–2.4	16.3	13.9
1991–93	5.8	(48)	13.8	(35)	–8.0	19.6	11.6

Numbers in parentheses are entry and exit shares (%) from total creation and destruction respectively.

b. Flows

YEAR	JCF	ENTRY	JDF	EXIT	NETF	SUMF	SIZE
1987	31850	13095	41492	13946	– 9642	73342	473758
1988	30512	8146	43515	18103	–13003	74027	462436
1989	35951	15640	42784	16701	– 6833	78735	452518
1990	28798	12636	43508	12249	–14710	72306	441746
1991	27526	18327	57989	18095	–30463	85515	419160
1992	21008	9752	59592	21960	–38584	80600	384636
1993	18828	5260	42357	15308	–23529	61185	353580
Average	**27782**	**11837**	**47320**	**16623**	**–19538**	**75101**	

Figures are the actual numbers of jobs as indicated by the column headings.

Table 1 and Figure 1 present the annual development of job reallocation measures and total employment (using the size measure) for total manufacturing, as well as the unemployment and GDP growth rate. From these we observe that:

1 In each year the net employment change was negative (–4.6% on average), and rising dramatically in 1991 (from –2.4% for 1987–90 to –8% for 1991–93). Hence total employment of manufacturing sector declined during whole period, and more rapidly in 1991–93. The total decline in manufacturing employment, as reflected in the size measure, from 1987 to 1993 was 25%. The development of net employment change reflects the severe recession of the Finnish economy in the beginning of 90's, as indicated by the GDP growth rate being negative and unemployment rate soaring.

2 The net rate is 'procyclical' which arises from job destruction rising strongly but job creation being fairly constant. In terms of (weighted) averages for the periods 1987–90 and 1991–93 job destruction rate increased by over 4%-points and job creation rate declined by 1%-point. The gross job reallocation (SUM) respectively increased by over 3%-points (from 16.3 to 19.6). These patterns are consistent with the findings in other studies that the time variation in gross job reallocation is countercyclical, and job destruction is cyclically more volatile than job creation.

3 Table 1, panel b, shows the actual job flows, including also the components of entry and exit from job creation and destruction. The entry flow, and its share from total creation (in panel a), seems to be less stable than the exit flow and its share. Using the weighted averages for 1987–90 and 1991–93 the share of entry has increased, but it may be due to an exceptionally high value in one year 1991.

4 The job creation, destruction and excess job reallocation rates and flows indicate that even in a time of a bad recession, as experienced in 1991–93, there is a lot of job creation and excess reallocation. Much more jobs are created and destructed than needed to achieve the net decline in sectoral employment. For example in the worst year of 1992, when net decline in jobs was app. 38 000, another 42 000 jobs were created and destructed in excess to this.

Table 2. Job Reallocation Rates by Plant Characteristics.

a) Plant Size

Size	JCR	(%)	JDR	(%)	ENTRY	(%)	EXIT	(%)	NET	(%)	SUM	(%)	EJR	(%)	Share
– 9	16.3	(6)	20.5	(4)	12.5	(10)	13.3	(7)	–4.2	(3)	36.9	(4)	28.9	(5)	2.1
10 – 19	13.1	(11)	16.6	(8)	8.4	(16)	9.1	(13)	–3.5	(4)	29.8	(9)	25.0	(11)	5.5
20 – 49	9.8	(19)	15.0	(17)	5.0	(24)	7.6	(25)	–5.2	(13)	24.7	(18)	19.5	(20)	12.8
50 – 99	8.1	(16)	13.6	(16)	3.5	(17)	5.9	(20)	–5.5	(16)	21.6	(16)	16.1	(17)	13.1
100–249	5.9	(22)	11.4	(25)	2.2	(19)	3.6	(22)	–5.6	(30)	17.3	(24)	11.8	(22)	23.8
250–499	4.8	(13)	8.7	(14)	1.1	(7)	1.3	(6)	–3.9	(11)	13.4	(13)	9.4	(13)	17.6
500–999	4.6	(10)	6.9	(9)	1.6	(8)	0.7	(3)	–2.3	(2)	11.5	(9)	8.0	(9)	14.4
1000 –	2.3	(4)	7.5	(8)	0.0	(0)	1.7	(5)	–5.2	(22)	9.7	(6)	4.5	(4)	10.8

Size class is determined according to average size over years of observation.

b) Technology

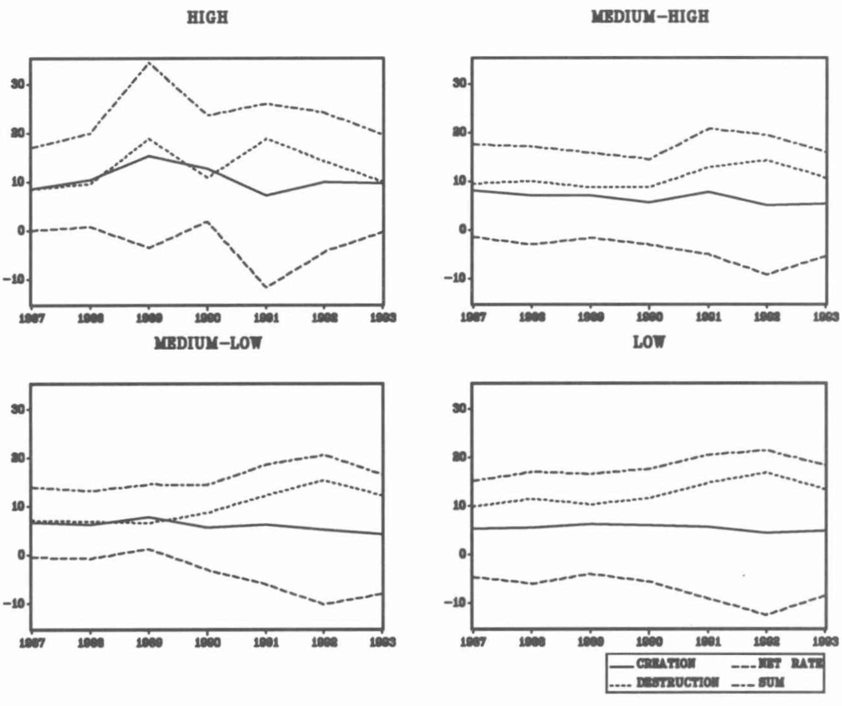
Group	JCR	(%)	JDR	(%)	ENTRY	(%)	EXIT	(%)	NET	(%)	SUM	(%)	EJR	(%)	Share
High	10.6	(16)	13.0	(11)	4.8	(16)	4.6	(11)	–2.3	(5)	23.6	(24)	20.4	(16)	9.7
Med-High	6.7	(22)	10.6	(21)	2.9	(23)	3.0	(17)	–3.9	(19)	17.3	(17)	13.4	(23)	21.7
Med-Low	6.1	(34)	9.7	(31)	2.6	(34)	3.2	(29)	–3.6	(17)	15.9	(16)	11.9	(33)	36.0
Low	5.6	(28)	12.4	(37)	2.3	(27)	5.1	(44)	–6.8	(60)	17.9	(18)	11.1	(28)	32.7

Technology is the current technology level each year.
Notes to both sections:
Weighted average of annual rates (1987–93), using annual size metrics as weights.
Figures in parentheses are shares of total flow in each column.
Last column (SHARE) is employment share based on the size metric.

Table 2 presents results using plant size and technology to define sectors. The numbers are weighted averages of annual rates using the annual size as weights. With respect to plant size we obtain the (usual) result that the job reallocation rates, with the exception of net rate, are declining with size. For the net rate there is no clear pattern according to size. The rates for smallest plants are multiples (3 to 10 times larger) of the rates for large plants. However this does not necessarily mean that small plants are creating and destructing the bulk of jobs. Since the share of small plants in total employment is small, even very high rates may amount to only modest job flows. The table therefore also includes for each rate the share of each size or technology group in the total flow of jobs. Comparing these shares with the employment share (last column) one may induce whether the group is 'over' or 'under' contributing to that particular flow. Judged on this basis the high rates in small firms (up to 99 workers) do amount to 'over' contribution for each flow (except for net rate again), but not as much as the rates tend to imply. In particular in job creation, entry and exit flows small plants are more important than their employment share would indicate. Correspondingly three largest groups (over 250 workers) are 'under' contributing to job flows (at least to some extent). The size class 100–249 which has the highest employment share, contributes to job flows approximately according to its employment share. The exception is the net flow, where this size class, and the largest plants over 1000 workers, are 'over' contributing.

With respect to technology levels the job creation, destruction, gross reallocation and excess reallocation rates are clearly higher in the high technology group, other groups being fairly similar. Only in job destruction the lowest technology group also has a high rate, which is mainly due to a high exit rate in this group. These patterns amount to the net rate (employment growth) being clearly most negative in the lowest technology group, and least negative in high technology group. Again, since the employment shares of technology groups are different, in particular the high group share is 10% compared to a third for both low and medium-low, the shares from job flows may deviate from the picture given by rates. In this respect high technology group is 'over' contributing in particular to job creation, entry, and gross and excess reallocation, and 'under' contributing to net job decrease. The low technology group is opposite to high – 'over' contributing to job destruction and exit, and in particular to net job decrease, where its share is 60% of total decrease in jobs.

Figure 2. Job Creation and Destruction Rates by Technology Level. Annual values 1987–93



The results discussed above are weighted averages of annual rates. The development of annual rates by technology level are described in Figure 2, which confirms that the 'cyclical' pattern of total manufacturing holds equally within technology levels. The high technology sector experiences more volatility, and in particular job destruction but also job creation was high in 1989. Also job destruction declined already in 1992, and has been in fact at the same level as in 1987–88. In other sectors job creation tends to be lower in 1993 than in 1987–88 (in low group only slightly), and job destruction higher (not in medium-high). Whether these differences are due to some exceptional individual plant developments in the smaller high technology sector, or due to some fundamental differences between sectors is unclear at this point.

Figure 3. **Job Creation and Destruction Rates by Technology. Weighted Average 1987-93**

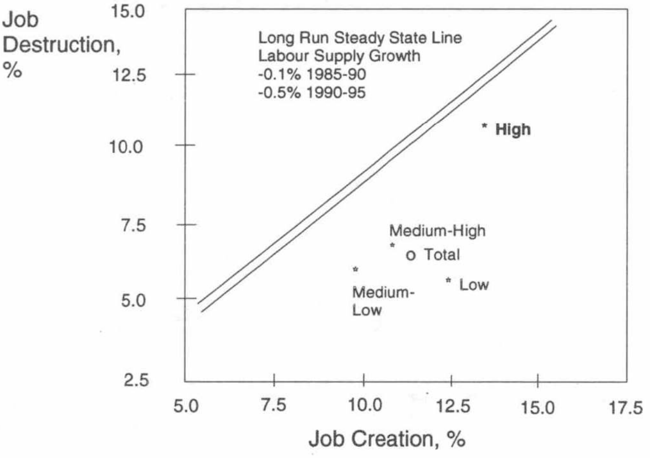
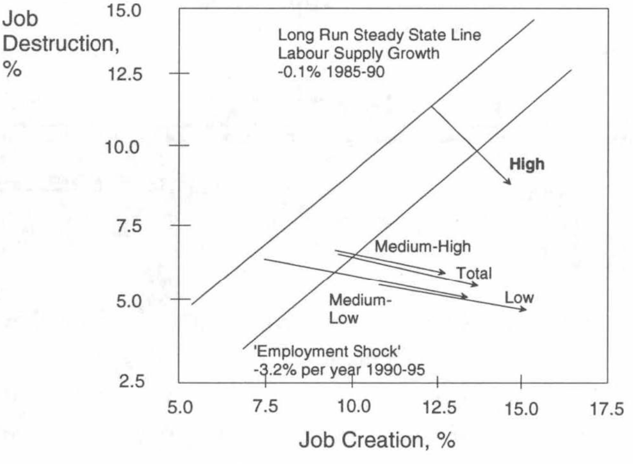


Figure 4. **Change in Job Creation and Destruction By Technology. 1987–90 to 1991–93**



Figures 3 and 4 cross-plot job creation and job destruction rates by technology level and for total manufacturing, using weighted averages for the whole period and the sub-periods 1987–90 and 1991–93. We interpret these figures using the insights provided by the models of Baldwin, Dunne and Haltiwanger (1994) and Mortensen and Pissarides (1995). As discussed in the previous section, we would expect that the higher technology levels are characterised by higher job creation and destruction in long run steady state, i.e. be furthest from the origin on the steady state line in Figure 3. This prediction is partially fulfilled, as job creation and destruction are indeed rising with level of technology, with the exception of the lowest group, where job destruction is 'too high'. Naturally the whole scatter plot is away from the steady state line, indicating that the economy as a whole during this period was at best in an intermediate run equilibrium, where the employment share of manufacturing was decreasing, since total manufacturing lies below the steady state line (i.e. job destruction exceeds job creation). Correspondingly some other sectors of the economy would have to lie somewhere above the steady state line.

However, it is obvious, that the data points do not depict even the intermediate run equilibrium, as we know that the unemployment rate was not constant for the whole period, rather it was rising rapidly after 1990. But unemployment was almost constant during 1987–90 (see Figure 1), during which period also labour force was virtually constant. We characterise this by the steady state line (effective for the earlier period) in Figure 4. During the period 1990–95 employment decreased on average by –3.2% per year, which we characterise in Figure 4 by the 'employment shock' line (effective for the latter period). If the employment shock would have been symmetric with respect to sectors (technology levels) all sectors would move south-east as the shock line compared to the steady state line. With respect to technology levels we observe that only the high group lied on the long run steady state in the 1987–90 period (medium-low group almost). With respect to the employment shock it seems that total manufacturing and all technology levels separately have been affected more by the shock (recession) than the economy on average. Furthermore, as the direction of the arrow of movement indicates, the shock has affected lowest technology sectors similarly, but in high technology group job creation decreased more than in other levels. However, the larger drop in job creation is due to high levels of creation in 1989–90 as annual values in Figure 2 show.

Finally, with respect to the issue of gross job reallocation arising from between sector employment reallocation, or within sector heterogeneous behaviour of different plants we present some results in Table 3. The main result is that the main source is within sector reallocation, i.e. simultaneous job creation and destruction within sectors, although its average share has dropped from 1987–90 to 1991–93. But equally the small between sector share has declined, with the share of total net employment change increasing dramatically. This of course reflects the large decline in total employment caused by the recession. The sectoral classification according to size and technology together results to a between sector share of almost 10% in the 'normal' times of 1987–90, and 'two-digit' industry a share of 9%. This is

Table 3. Decomposition of Gross Job Reallocation.

Sector/Plant Characteristic	Net Change (%)	Between Sector (%)	Within Sector (%)	Index of Within sector Reallocation
A. Size				
87–93	24.8	2.0	73.2	75.9
87–90	14.9	2.0	83.1	83.8
90–93	40.6	1.9	57.6	63.4
B. Technology				
87–93	24.8	1.3	73.8	77.0
87–90	14.9	2.2	82.9	85.7
90–93	40.6	0.0	59.4	63.3
C. Size and technology				
87–93	24.8	7.4	67.8	72.6
87–90	14.9	9.8	75.3	77.8
90–93	40.6	3.6	55.8	64.3
D. Industry				
87–93	24.8	5.9	69.2	66.1
87–90	14.9	8.8	76.4	69.9
0–93	40.6	1.4	58.0	60.0

Weighted averages of annual shares (%), using annual size as weights.
Index of within-sector reallocation is calculated as in Konings (1993). Value of 100 reflects reallocation is due entirely to within-sector shifts, and 0 due to between-sector or total net change.

considerably larger than the 1% share for two-digit industry obtained by Davis and Haltiwanger (1992) for US manufacturing.

6. Conclusions and Discussion

Our results indicate that the high technology sector has higher job creation and destruction rates, and it has experienced a somewhat different cyclical pattern than other sectors. We also find that the high and low technology sectors are contributing differently to job reallocation: high technology is more important (compared to its employment share) in job creation, entry, and gross reallocation, while low technology is more important in job destruction, exit, and net job decrease.

Overall, there seems therefore to be differences in the job creation and destruction patterns according to level of technology. The results seem consistent with a priori conjectures that more advanced technology sectors have a more positive employment development than the lowest technology sector, where bulk of the net job loss is concentrated. The share of low technology group in net job destruction (60%) may however be 'surprisingly' large.

Whether these findings stand a more thorough investigation using better technology indicators remains to be seen, but they seem interesting enough to reward further inspection. The fact that our technology indicator can only pick up technological differences across sectors may undermine its importance here. Most of the job reallocation occurs within sectors, but it is reasonable that some part of this within sector heterogeneity is due to technological differences across plants which our technology indicator cannot measure.

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Appendix: The data base and variables

The original source of the data file of industrial establishments (DIE) are the files of Annual Census of Manufacturing industries. The census has been mandatory to respond for establishments with 5 or more employees, but also other inclusion criteria based e.g. on sales revenue are used.

The DIE pooles the annual files of 1974–93 together using same variable labels and same classifications as far as possible. This pooled time-series of cross-section files includes the census year and the permanent identity codes for establishments, which are used to follow employment over time and identify plant entry and exit. There are some deficiencies in these codes for our purposes as the coding system was changed in 1985/86. Another change occurred in 1991, when the establishment coverage of the Census was cross-checked with the Register of Firms and Establishment, resulting in some increase in the Census coverage. However, the changes in the coding system in 85/86 does not affect our results, as we use information only for the period 1986–93.

The job flows and rates are calculated as explained in the text using employment for two consecutive years. The entry and exit information based on the existence of employment data for a certain administrative code in consecutive years introduces some measurement error to our results. We have no information of the reasons for the changes in the identity of an establishment or its entry and exit. It sometimes happens that although an establishment (code) exits, most of its employees will continue their job in the same location but in a different establishment. It also is possible that the same establishment exits in t+1 but enters again in t+2, because of data collection problems. In our data entry and exit include all these type of changes in the identifier of an establishment or its employment.

Variables used

- Establishment code:
  Permanent Census of Manufactures codes.
- Employment:
  Number of full time (equivalent) employees, annual average.
- Size class:
  Based on average employment for the 1986–1993 period to avoid the

regression-to-mean bias. Size classes are 5–9, 10–19, 20–49, 50–99, 100–249, 250–499, 500–999, 1000+

- Industry:
  Based on the Statistics Finland SIC classification of 1979, aggregated to the 22 groups used in the OECD technology classification (Englander and Gurney 1994).

- Technology group:
  Industries further aggregated to the four technology groups (HIGH, MEDIUM-HIGH, MEDIUM-LOW, LOW) based on Finnish R&D intensity from the late 1980s, see Virtaharju and Åkerblom 1993, 67.

Part E

R&D, Performance and Productivity

Powell

For projects which have received at least one year of funding, participants are reporting significant acceleration of R&D, stimulation of beneficial collaborations, and a change in the nature of R&D performed as a result of ATP (Advanced Technology Program) funding.

Jarmin

I estimate the model with data from 8 manufacturing extension centers in 2 states. The control group includes all plants from each state in the LRD. Preliminary results indicate that MEP (Manufacturing Extension Partnership) participation is systematically related to productivity growth but not to sales growth.

Politi and Taccini

The analysis of the data has showed that the enterprises that made technological innovation have better results than the total and that these results are different by economic sector. The information contents of the results could be higher if the period of the availability of the data should be longer.

Husso

The role of R&D was clearly highlighted in high-tech branches, whereas in other branches estimates of R&D capital elasticity were often at a much lower level. The productivity effects of R&D increased during the period of recession, i.e., in the early 1990's.

Niininen

To sum up, neither form of subsidies did conclusively improve productivity or profitability. It seems that technology subsidies induce new R&D projects but do not have a positive effect on productivity or profitability. At the same time, however, R&D investment has a positive effect on productivity. This might imply that the firms use subsidies to finance the riskiest R&D projects or basic research projects which take a long time to yield any results.

Maliranta
The results point out that different sort of structural factors together have had a positive and increasing effect on aggregate behaviour of labour productivity in Finnish manufacturing during the period from 1975 to 1994. Thus one cannot infer reliably labour productivity growth rate nor medium term changes in the growth rates at the plant level with aggregate data sets.

Paranque
Three stages in the assessment have then to be identified, *"namely, the recognition of levels that are too often confused in economic assessments: the "physical" level, the "market" level, and the "financial" level."*.

Coelli, Perelman and Romano
Both sets of results suggest that Asian and Oceanic airlines are technically more efficient than European and North American airlines but that the differences are essentially due to more favourable environmental conditions.

Motova and Sokolov
This analysis gives a possibility to highlight the main reasons of changes and principal trends in the transformation of the institutional infrastructure of science. It complements the results obtained with the help of scenario forecasts and gives, not very detailed, but real picture of forthcoming changes in the national S&T system.

The Evolution of Firms and Industries
Research Reports 223, 1997, pp 254–271
Statistics Finland

THE ATP'S BUSINESS REPORTING SYSTEM: A TOOL FOR ECONOMIC EVALUATION

Jeanne W. Powell,
Advanced Technology Program,
U.S.A.

Program evaluation has been an important part of the Advanced Technology Program (ATP) – a government-industry partnership – from its inception. The ATP's Economic Assessment Office (EAO) has implemented approaches for tracking short-term indicators of program results, while also developing new state-of-the-art evaluation tools for measuring long-term economic impact. An electronic survey for tracking evolution of projects towards achieving their business and economic goals is a core part of ATP's program evaluation framework. This comprehensive Business Reporting System consists of several parts. At the beginning of the project, project participants report on their planned application areas for the technology and strategies for commercialisation. Annually they report on progress towards implementing their commercialisation strategies and on short-term economic impacts of the projects, including early sales revenues, shortened R&D cycles, collaboration effects, intellectual property creation, and early job creation. Additional sections of the Business Reporting System now under development will focus on the post-ATP funding period, capturing technology commercialisation and diffusion. Over the following six-year period, participants will report three times, increasing the emphasis on economic impacts of the ATP-funded technology to the nation.

The Business Reporting System consists of a series of largely closed-ended questions and responses in electronic, database form. This database system is part of an integrated set of databases that supports comprehensive analyses covering all participants in ATP-funded research projects across nearly any desired subgroup. For short-term analyses, this integrated system provides a flexible analysis tool for generating reports of business progress of projects and early economic impacts. It also helps the ATP identify promising candidates for in-depth case studies of early ATP economic impact. In the longer term, the Business Reporting System will support efforts by inde-

pendent research economists to measure broad economic benefits of this Federal program to the nation.

For the reporting period ending December 31, 1995, there were nearly 400 organisations in the Business Reporting System. Although most of the participants/projects reporting to date are still in the early R&D phases, adequate data exists to 1) illustrate some of the types of analyses possible, 2) provide a snapshot of commercial opportunities that may be expected to result from the awards portfolio and an approximate time line, 3) give evidence that companies are taking necessary steps for successful future commercialisation, 4) provide early indication that the non-proprietary information developed with ATP funding is contributing to a shared knowledge base, and 5) indicate patent filings attributable to the research projects. For projects which have received at least one year of funding, participants are reporting significant acceleration of R&D, stimulation of beneficial collaboration, and deepening of their R&D effort as a result of ATP funding.

The Advanced Technology Program, administered by the National Institute of Standards and Technology of the U.S. Department of Commerce, assists U.S. businesses on a cost-share basis to develop high risk, enabling technologies for the purpose of stimulating U.S. economic growth and competitiveness of U.S. businesses. Authorised by the U.S. Congress in 1988, the ATP started operation with a small appropriation of $10M under the Bush Administration in 1990 and grew rapidly to a budget of $341M in 1995 under the Clinton Administration. To date the ATP has received 2,210 proposals in 22 merit-based competitions, and has announced 280 awards (178 for single-company projects and 102 for joint venture projects) for nearly $2 billion of research, with $970 million provided by the ATP. Although the ATP funds only research, funding decisions take into account business and economic merit of proposals as well as scientific and technical merit.

Key words: Acceleration of R&D, Business Progress, Collaboration, Database, Economic Evaluation, Electronic Survey, Enabling Technologies, Information Dissemination.

1. Introduction

The Advanced Technology Program (ATP), administered by the National Institute of Standards and Technology, assists U.S. businesses, on a cost-share basis, in developing high risk and enabling technologies for the purpose of stimulating U.S. economic growth. The ATP is similar in some ways to European programs that support industrial R&D; for example, the LINK Program in the U.K. and Business-Oriented Technology Program (PBTS) in the Netherlands.

The ATP funds research projects proposed by U.S. companies through a highly competitive selection process. Funded projects are expected to advance the state-of-the-art in overcoming challenging technical barriers to solving problems or exploiting opportunities with substantial economic significance. One condition of ATP's funding is that U.S. industry both lead the research and show a promising path to timely commercialisation of resulting technologies. A further condition is that the ultimate expected outcome generate spillover benefits beyond those accruing directly to funding recipients.

Program evaluation has been an important part of the ATP from its inception. The ATP's Economic Assessment Office (EAO) has implemented multiple approaches for tracking the short-term indicators of program results, while also developing new state-of-the-art evaluation tools for measuring long-term economic impact. (Other evaluation approaches employed by the ATP include peer review, case study, third-party survey, and econometrics and other statistical analyses.) An electronic survey for tracking evolution of projects towards achieving their business and economic goals is a core part of ATP's program evaluation framework. This comprehensive Business Reporting System (BRS) consists of several parts. At the beginning of the project, project participants report on their planned application areas for the technology and strategies for commercialisation. They report annually on progress towards implementing their commercialisation strategies and on short-term economic impacts of the projects, including early sales revenues, shortened R&D cycles, collaboration effects, intellectual property creation, and early job creation. Additional sections of the BRS now under development will focus on the post-ATP funding period, capturing technology commercialisation and diffusion. Over the six-year period following project completion, participants will report three times, with increasing emphasis on economic impacts of the ATP-funded technology to the nation.

The BRS consists of a series of largely closed-ended questions and responses in electronic, database form. This database system is part of an integrated set of databases that supports comprehensive statistical analyses covering all participants in ATP-funded research projects. For short-term analyses, this integrated system provides a flexible analysis tool for generating reports of business progress and early results.

Data are collected at the project participant level (from each company, university, and not-for-profit organisation participating in the project as a single-company award recipient or as a joint venture partner). This ensures maximum confidentiality and detail concerning the contributions of different types of organisations to the R&D effort and the multiple commercialisation paths of ATP-funded technologies. When fully implemented, the BRS database will also enable researchers to look inside the "black box" of the firm at previously unstudied characteristics of firm behaviour and their relationship to output and employment at the industry and national levels.

In combination, these features of the BRS enable it to meet its three objectives:

A Monitor *business progress* against plans for achieving
- Commercialisation
- Broad-based economic benefits

B Measure *short-term (R&D phase) impacts*

C Build a database to support *long-term (post ATP-project phase) evaluation* of economic impact

The BRS has been implemented for all projects funded in FY93 and later, from their inception. As of December 31, 1995, there were nearly 400 organisations, including all but the first 60 projects funded and a few not yet actually started, of the 280 projects funded to date, in the data system. Following is a brief picture of some of the early results to date in meeting the first two objectives.

2. Business Progress – Some Early Results

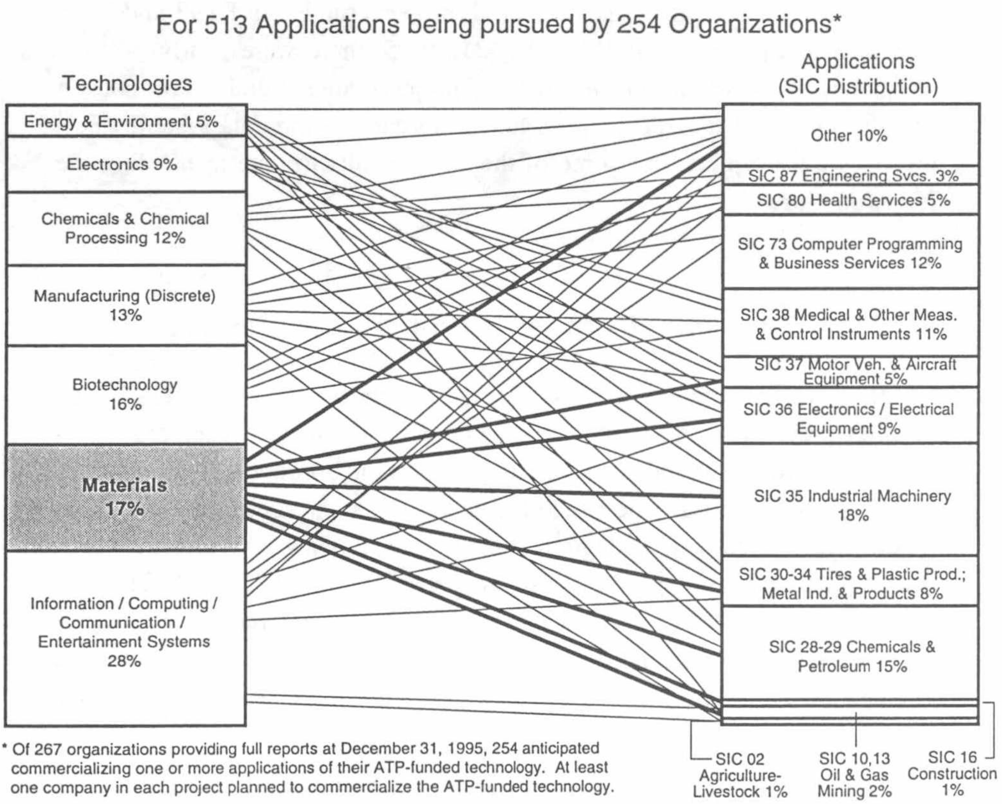
The BRS tracks business progress for each application of the ATP-funded technology that each participating company plans to pursue – whether it plans to manufacture a product in-house, adopt a new or improved manufacturing process, perform a service, license its technology, or some combination of these, possibly in alliance with strategic partners. The following early business progress results are based on the set of reports filed December 31, 1995. The data set was restricted to reports judged relatively complete (covering 70% of organisations in BRS at that date) and to companies expressing an intent to commercialise the technologies in these applications eventually (at least one company in each project).

Technologies with Diverse Applications

Consistent with the ATP mission of funding enabling technologies with potential for significant broad-based benefits, most ATP-funded technologies have multiple commercial applications. For example, projects in the materials technology area may have applications in the industrial equipment, motor vehicle, construction, petroleum drilling, and electronics industries, or some combination of these.

The ATP uses its own 5-digit technology code system in parallel with Standard Industrial Classification (SIC) Codes to establish technology-application/user industry linkages. Each company self-selects a 5-digit technology code and 4-digit SIC code to describe each application of that technology. Figure 1 summarises the two coding distributions and provides a picture of the linkages between ATP-funded technologies and their application areas. Companies working in the materials technology area, for example, have designated eight different SIC industry categories (2-digit level) as applications targets.

***Figure 1.* Development of technologies with diverse applications.**



* Of 267 organizations providing full reports at December 31, 1995, 254 anticipated commercializing one or more applications of their ATP-funded technology. At least one company in each project planned to commercialize the ATP-funded technology.

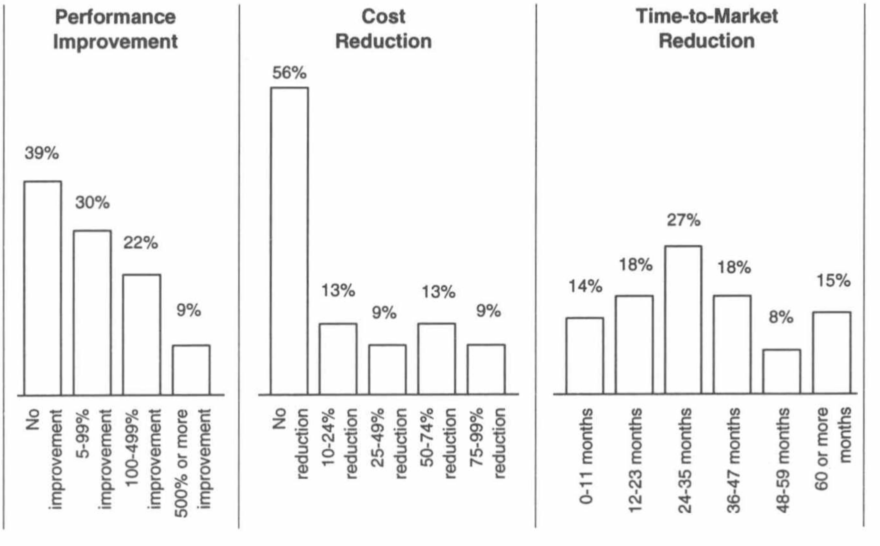
Business Goals

At the beginning of a project, companies identify key attributes of the technology from a business perspective and establish corresponding baseline values and end-of-project goals. This information establishes a benchmarking capability and means of measuring the technical accomplishments of ATP projects in the context of their broader business objectives. In general, most cited attributes involve performance or quality improvements, cost reduction, or some combination of these. In addition, acceleration of the R&D phase, resulting in time-to-market reduction, has consistently been cited as an important goal in the BRS and other ATP surveys. The ATP's mission specifically includes accelerating technology development and commercialisation.

ATP-funded companies have cited performance improvement as a goal more frequently than cost, see Figure 2. Performance-improvement goals ranging from 5% to more than 500% increases over current performance capabilities were reported for 60% of the applications. Cost reduction was cited as a major goal for 40% of the applications. Time-to-market reduction of a year or more was an additional goal for 86% of the applications.

Figure 2. Quantitive business goals.

For 513 Application being pursued by 254 Companies

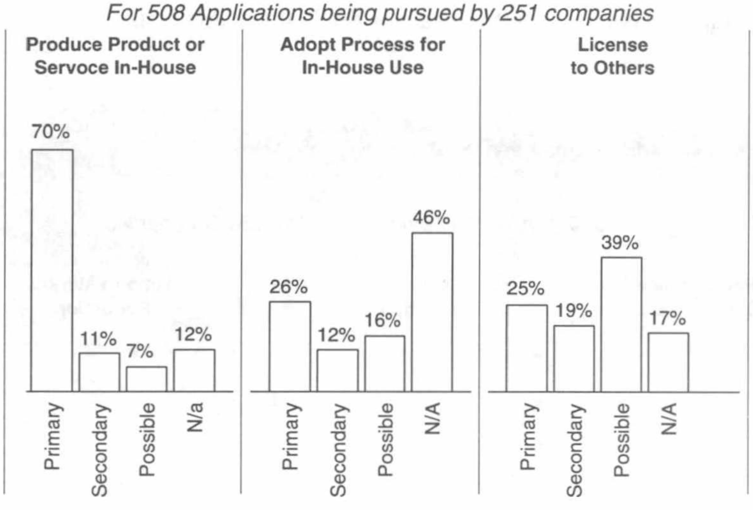


Commercialisation Strategies

Most ATP-funded companies plan to produce a product or service themselves, based on the technology platform they develop in the project, in their own existing or planned production facilities, see Figure 3. In-house production is the focus for 70% of applications. For 26% of applications, companies plan to implement a new process in-house as their primary strategy; for 44% of applications, companies indicate that licensing of the technology to other companies is a primary or secondary commercialisation strategy.

Companies report different strategies for different applications; for example, in-house production in areas where they have current manufacturing capability or market awareness, licensing in others. Some companies appear to be planning multiple strategies to achieve maximum market penetration for a given application.

***Figure 3.* Strategies for commercializing ATP-funded technologies.**



Note:
Some companies reported more than one strategy as "Primary"

When Are Revenues Expected?

Given the advanced nature of the research being performed in ATP projects, there are often significant R&D hurdles remaining when ATP funding ends. Confirming the long-term nature of ATP-funded R&D projects, and the need for patience before expecting to see wide-spread economic impacts from the program, companies report that 90% of their applications will not reach the marketplace at all until after ATP funding ends, see Figure 4. More than 30% are not expected to result in revenues until at least four years after ATP funding ends. The ATP does not fund product development, but there are sometimes product spin-offs during the course of research.

3. Short-Term (R&D Phase) Impacts – Some Early Results

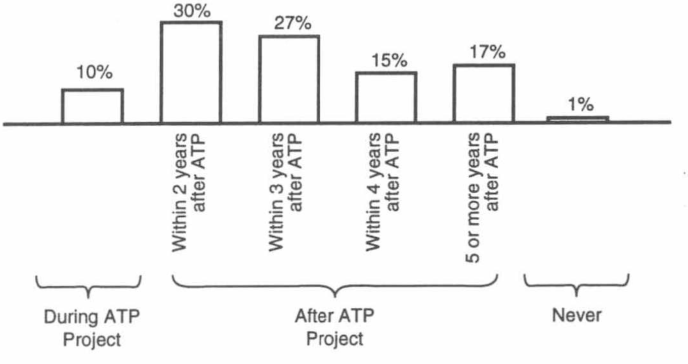
As of September 1995, the first projects to enter the BRS had completed a full year and submitted their first annual (anniversary) report. The following analyses are based on the first anniversary reports received from 41 organisations (19 in single-company projects; 22 in joint venture projects) funded in FY93. These reports cover 89% of active participants in FY93 projects at their first anniversary dates.

Early Commercialisation Impacts:

Some companies have taken advantage of early spin-off product opportunities or implemented processes that stem from partial achievement of the goals of the ATP project. Table 1 summarises the early commercialisation and employment impacts reported by the FY93 projects.

Figure 4. **When can we expect to see revenues from ATP-funded tehcnologies?**

For 513 Applications being pursued by 254 companies



A total of 162 new jobs have been created across the 18 projects and 25 companies reporting employment effects. Although most of these new jobs directly supported the R&D effort, the following comments seem to indicate that the ATP award has enabled a smoother hiring process and a more co-ordinated, longer-term planningapproach to hiring and resource management than likely would have occurred without it.

Anecdotal Comments:

"The ATP funding allowed us to pull together a cross-department team.... This is usually not done and had the effect of broadening interests and expertise."

"The mix of employees has changed. We have hired people with manufacturing experience. We also have added a die-cutter, a manufacturing process manager, and some production people. This is creating a new sub-culture, because up till now, we only had a scientific culture."

***Table 1.* Early commercialization impacts.**

For 41 companies in 24 FY 93 projects after first year of ATP funding

	Number of Projects	Number of Companies	Number of Applications
Able to Produce New or Better Products	13	16	36
Implementation of Process Improvements	9	10	20
Earned Revenue ($6.8 M)	6	6	13
Jobs Created	18	25	N/A

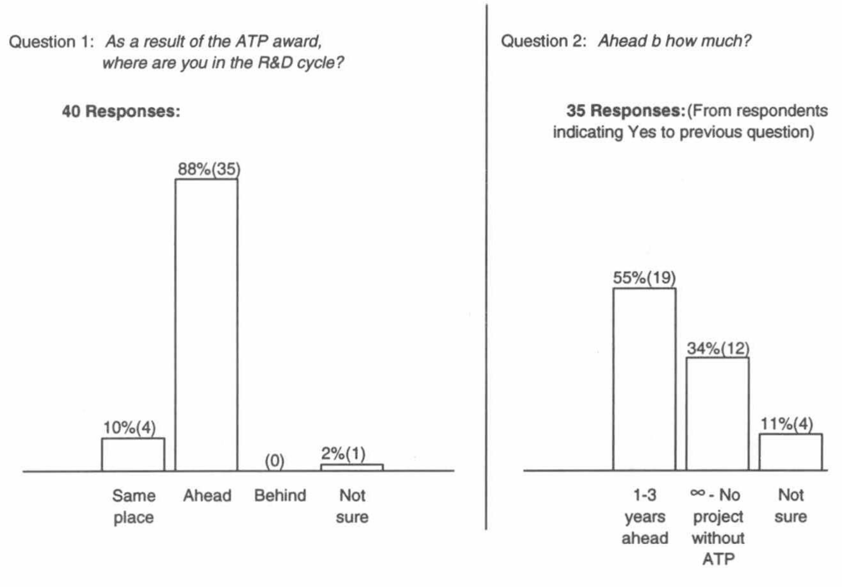
"The ATP award has made it easier to attract highly skilled scientists..."

Stimulation of High-Risk R&D

ATP seeks to fund projects that would not be funded by the private sector alone in a timely way due to the relatively high risk and high ratio of social benefits to private benefits. Thus, in its evaluation process, ATP seeks to determine if government funding is displacing private capital. If it appears likely that the project would be funded privately, it becomes important to assess whether the timing, scale, or scope of the research will be different because of ATP funding, with resulting net benefits to the U.S. public. The BRS anniversary report section contains a number of questions that address the effects of ATP finding on the timing, level of private funding, and type of R&D performed.

The FY93 first-year anniversary reports indicate that many of the projects would not have occurred without ATP funding or that the R&D is significantly further along as a result of it. see Figure 5. This result is consistent with recent third-party surveys. Eighty-eight percent of the FY93 awardees indicated they were ahead in the R&D cycle after one year of funding as a result of the ATP award; 34% of these indicated there would be no project without ATP.

Figure 5. **Acceleration of R&D.**

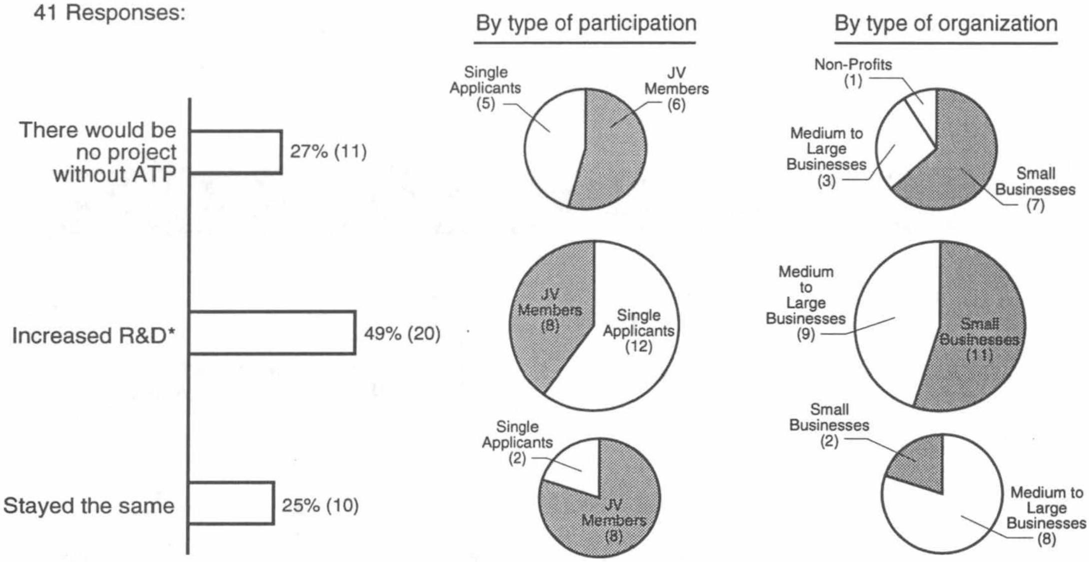


More than 75% of companies report that they have put in more funding (amounting to $22 million to date) as a result of the ATP award than they would have without it (See Figure 6), indicating that ATP awards have stimulated additional industry spending, not displaced it. Single-company projects and small businesses (in single-company projects and joint ventures) indicate greater leveraging effects from the ATP award on the level of industry R&D investment than do joint venture participants and medium-to-large businesses. Note that the effects on level of industry R&D investment (Figure 6) are reported separately from the effects on acceleration (Figure 5) and the effects on project size (Figure 7), but the series of effects need to be viewed as a whole for proper perspective.

Figure 6. Stimulation of industry R&D investment.

Question: *How has the R&D investment by your company changed as a result of the ATP award?*

41 Responses:



* These 20 companies reported increased level of R&D of over $22 million.

Seventy-six percent indicated that the ATP award had changed the nature or effects of the R&D performed by the company in the ATP-funded area, see Figure 7.

Figure 7. Change in the nature of industry R&D.

Question: *Has ATP funding changed any of the following aspects of the project?*

R&D scope?

Willingness to accept tehcnical risk?

Difficulty of technical goals?

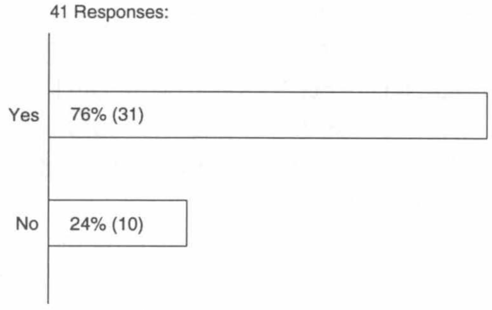
Interest in long-term research?

Interest in collaborations?

Project speed?

Preservation of U.S. ownership of the company?

Preservation of U.S. ownership of the technology?

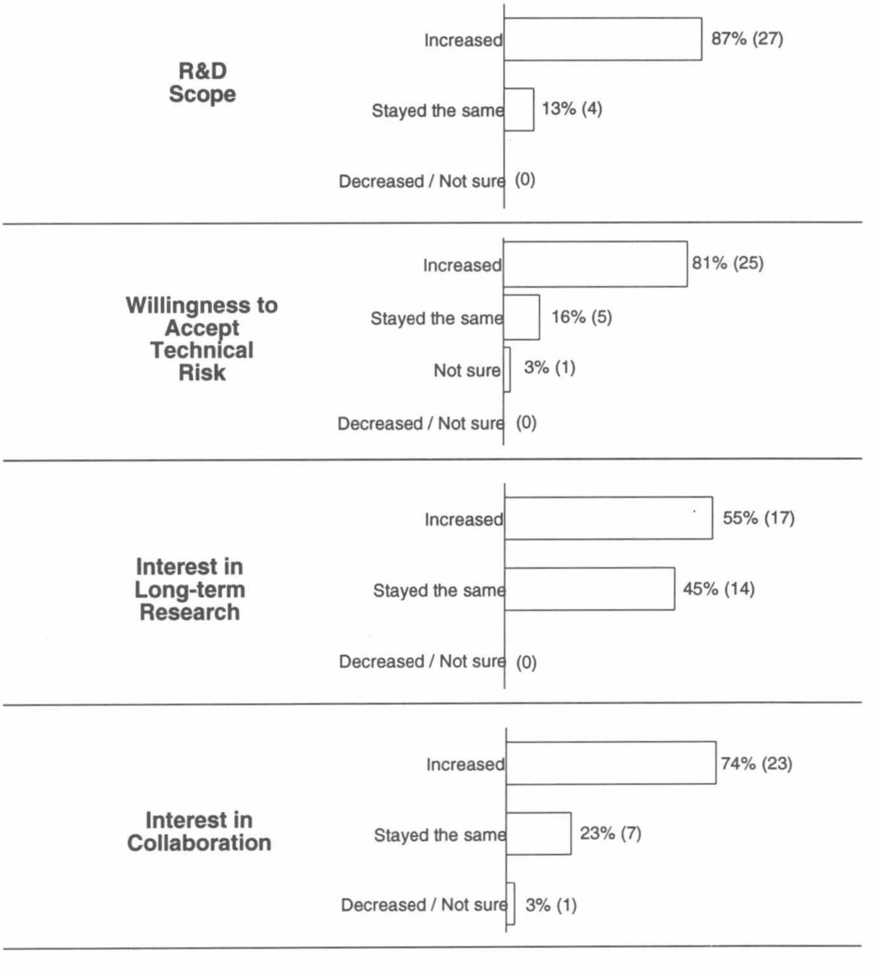


The respondents indicating a change in the R&D performed further identified the most significant areas of change, see Figure 8. Nearly 90% of these respondents reported that the ATP award enabled them to broaden the scope of their R&D; over 80% indicated that ATP has stimulated research with higher technical risk than the companies would have pursued alone. In essence, the ATP shares the technical risk along with the costs of the R&D projects, enabling companies to undertake more ambitious R&D projects, with more challenging goals, than they would take on alone. Nearly three-fourths of these same respondents indicated an increased interest in collaborations with other companies for performing R&D as a result of their ATP award.

***Figure 8.* Change in the nature of industry R&D.**

Question: *In what way?*

31 Responses: (Respondents indicating Yes to prior question)

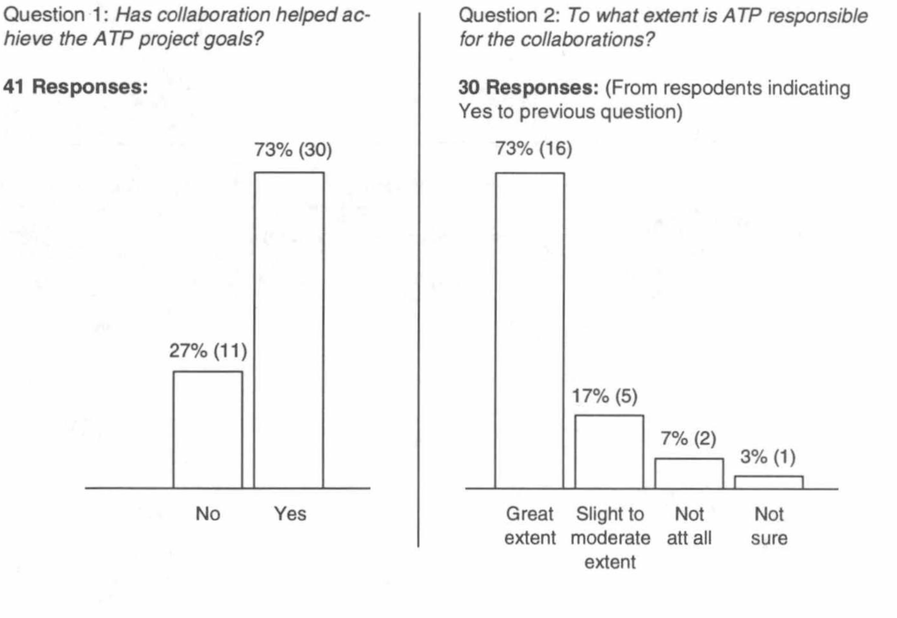


Collaboration Impacts

To date, the ATP has funded over 100 industry consortia involving formal joint venture agreements. In addition, a large number of the single-company projects involve subcontracts and strategic alliances with other firms. The BRS contains a number of questions that help assess the benefits and costs of these relationships, and the potential for a structural change in the way industry R&D is conducted in the U.S.

To start with, participants are asked whether the project has benefited from collaboration with other organisations. Nearly three-fourths of the companies gave a positive response (including many in single-company projects with informal collaborations); three-fourths of those giving a positive response further indicated that ATP was responsible for the collaboration "to a great extent," see Figure 9.

Figure 9. Stimulation of collaborations.



Anecdotal Comments (from Single-Company projects):

"... by working with collaborators rather than developing some of the capabilities in-house, we have maintained the flexibility to switch approaches (by switching collaborators) if a different approach proved to be better suited

... Avoided the time and cost to develop human capital in areas where others have a strong expertise."

"ATP has stimulated ongoing collaboration with companies and individual subcontractors that will continue long after ATP funding has ended."

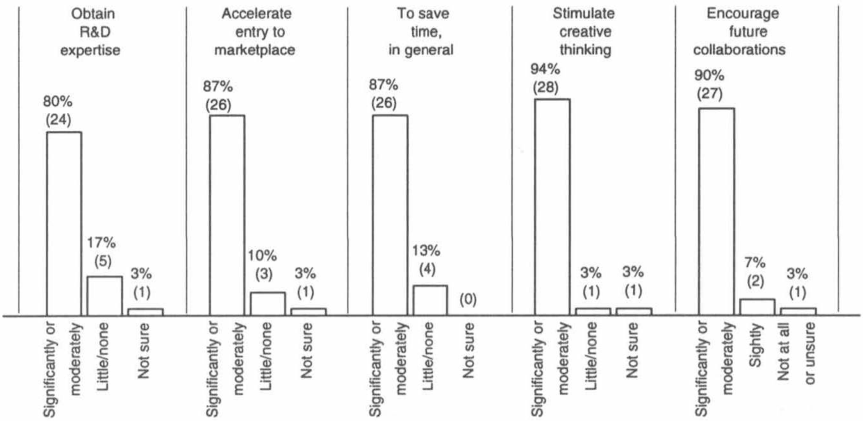
"Collaboration was primarily with a subcontractor doing usability studies for us. They gave us a unique perspective on the end-users' concern and how we should address these in our system design."

"Collaboration with research groups which has resulted from our ATP involvement has significantly expanded the list of possible applications for the ... technology and has accelerated the development of products for these applications."

Figure 10. Effects most enabled by ATP collaborations

Question: *To what extent has collaboration with other organizations to conduct your ATP project enabled your company to:*

30 Responses: (Respondents indicating Yes to prior question – Has collaboration helped achieve the ATP project goals?)



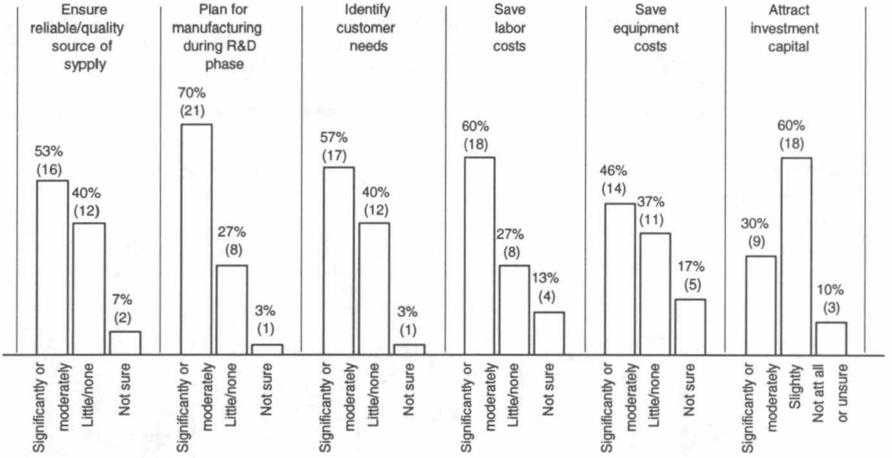
Project participants that have previously indicated a positive experience with collaboration (30 companies) are then asked to evaluate a number of specific potential effects of their collaborations. Results have been grouped into two categories: effects significantly or moderately enabled by collaboration in the ATP project for 80% or more of the participants in Figure 10 and effects less enabled by collaboration in Figure 11.

The companies most often reported that their ATP collaboration enabled the stimulation of creative thinking (94% indicated a "significant or moderate" effect), and many of them reported planning for future collaborations as enabled by their ATP collaboration (90% indicated a "significant or moderate" effect). The other effects cited most frequently as enabled by their ATP collaboration were a) obtaining R&D expertise not available within the company and b) acceleration of commercialisation/entry into the marketplace.

***Figure 11.* Other effects enabled by ATP collaborations.**

Question: *To what extent has collaboration with other organizations to conduct your ATP project enabled your company to:*

30 Responses: (Respondents indicating Yes to prior question – Has collaboration helped achieve the ATP project goals?)



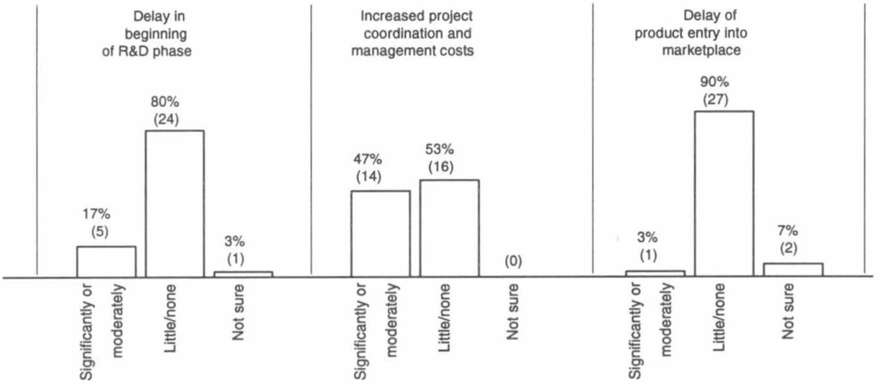
In addition, more than half the companies that indicated a positive experience with collaboration said it helped them to ensure a reliable/quality source of supply, plan for manufacturing concurrently with performance of the R&D, identify customer needs, and save labour costs.

To some extent, "transaction costs" and delays have occurred in the course of negotiating joint venture intellectual property agreements and ATP Terms and Conditions for starting projects. But for the same 30 companies, the negative effects of collaboration appear to be relatively minor in terms of delays, see Figure 12. Nearly half, however, note that project co-ordination and management costs were "significant or moderate."

Figure 12. Costs of collaboration.

Question: *To what extent has collaboration with other organizations to conduct your ATP project contributed to:*

30 Responses: (Respondents indicating Yes to prior question – Has collaboration helped achieve the ATP project goals?)



Information Dissemination

Sharing of knowledge is important to achieving widespread diffusion of the ATP-funded technologies and maximum knowledge spillover benefits. The BRS contains questions concerning strategies for dissemination of non-proprietary information and for protection of intellectual property, and for progress in implementation. Activity reported to date indicates that many of the ATP awardees appear to be quite active in communicating the results of their work to the scientific community. The number of formal journal articles and papers/presentations at conferences is growing rapidly, see Table 2.

Table 2. Creation and protection of intellectual property and dissemination of non-proprietary information

According to 320 organizations filing reports December 31,1995

Journal Articles	Conference Presentations	Patent Applications	Patents Received
81	202	52	2

4. Conclusions

Although most of the participants/projects reporting to date are still in the early R&D phases, adequate data exist to 1) illustrate some of the types of analyses possible, 2) provide a snapshot of the diverse applications and commercial opportunities that may be expected to result from the current ATP awards portfolio and an approximate time line, 3) give evidence that companies are taking necessary steps for successful future commercialisation, 4) provide early indication that the information developed with ATP funding – both the published non-proprietary information and the proprietary information revealed through patent disclosure – is contributing to a shared knowledge base, and 5) indicate patent filings attributable to the research projects. For projects which have received at least one year of funding, participants are reporting significant acceleration of R&D, stimulation of beneficial collaborations, and a change in the nature of R&D performed as a result of ATP funding.

5. Future Work

In addition to collection of additional data over time from ATP's portfolio of projects, considerable work is needed in a number of areas:

- *Improved data quality* – To achieve maximum data quality, more effort is needed to work with the companies to ensure they understand the meaning and intent of the survey questions and provide reasonably thorough reports.
- *Review for potential bias* – We have worked with consultants to design questions and response choices that minimise the chance of biased responses; however, more needs to be done to reduce the chances of bias in the data. In general, the BRS results for FY93- and-later ATP projects are consistent with surveys conducted by third-party contractors covering projects and participants funded prior to FY93.
- *Expanded coverage, analysis, and variety of reports* – The existing BRS can support much more in-depth analysis (for example, by organisation types, joint venture types, industry sectors, technology types, and geographical location) than can be covered here; furthermore, the results presented here reflect data for only a small fraction of existing survey questions. Future reports can address different issues and cross-sections of responses. Additionally, the BRS data can be linked to other SIC-based industry data sources.

- *Additional question development* – The major impacts of the ATP will likely occur some years after the period of funding covered by the ATP award. Additional question development is planned which will focus on the post-project commercialisation phase and address inter-industry and intra-industry diffusion and benefits to future producers and users of these technologies, as well as longer-term economic impacts on the companies funded.

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Statistics Finland

MEASURING THE IMPACT OF THE MANUFACTURING EXTENSION PARTNERSHIP

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In this paper, I measure the impact of the Manufacturing Extension Partnership (MEP) on productivity and sales growth at manufacturing plants. To do this, I match MEP client data to the Census Bureau's Longitudinal Research Database (LRD). The LRD contains data for all manufacturing establishments in the U.S. and provides a number of measures of plant performance and characteristics that are measured consistently across plants and time. This facilitates valid comparisons between both client and non-client plants and among clients served by different MEP centers.

The MEP is administered by the National Institute of Standards and Technology (NIST) as part of their effort to improve the competitiveness of U.S. manufacturing. The program provides business and technical assistance to small and medium sized manufacturers much as agricultural extension does for farmers.

The goal of the paper is to see if measures of plant performance (e.g., productivity and sales growth) are systematically related to participation in the MEP, while controlling for other factors that are known or thought to influence performance. Selection bias is often a problem in evaluation studies so I specify an econometric model that controls for selection.

I estimate the model with data from 8 manufacturing extension centers in 2 states. The control group includes all plants from each state in the LRD. Preliminary results indicate that MEP participation is systematically related to productivity growth but not to sales growth.

Key words: Manufacturing Extension, LRD, Program Evaluation, Productivity.

Any findings, opinions or conclusions expressed here are those of the author and do not necessarily reflect the views of the Census Bureau.

1. Introduction

This paper uses plant level census data to evaluate the effectiveness of the Manufacturing Extension Partnership (MEP). To do this, data from 8 MEP centers in 2 states are matched to the Longitudinal Research Database (LRD). The LRD is useful for evaluating the MEP for two reasons. First, it provides a control group against which to compare the performance of MEP clients. Second, the LRD contains a number of variables useful for evaluation that are measured consistently across clients and non-clients, across different MEP centers and over time.

The MEP is administered by the National Institute of Standards and Technology (NIST) as part of their effort to improve the competitiveness of U.S. manufacturing industries. The MEP operates several manufacturing extension centers around the country that provide technical and business assistance to small and medium sized manufacturers, much as county extension agents do for farmers. This assistance often consists of providing "off the shelf" solutions to technical problems. However, MEP centers can also channel more recent innovations generated in government and university laboratories to smaller U.S. manufacturing concerns that may not have access to such information. The idea is that MEP services will help these firms become more productive and compete more effectively in the international marketplace.

In order to maximise the effectiveness of the program, it is crucial that MEP stakeholders (e.g., MEP clients, MEP centers, NIST, state and local governments and Congress) have detailed information about its current performance and that a reliable evaluation framework be in place to analyse its future performance. Ideally, one would want to evaluate programs such as the MEP by collecting experimental data[1]. Namely, firms would be randomly assigned to treatment and control groups. Evaluation would then consist of a simple comparison of the performance of treatment and control firms. Unfortunately, this has not been done, nor is it likely to be done, for the MEP.

Therefore, MEP evaluation must be carried out with non-experimental data. As a result, the NIST/MEP evaluation staff asked the Center for Economic Studies (CES) of the U.S. Census Bureau about exploiting the LRD for evaluation purposes. This paper provides some of the early results from this effort.

Note that, in this paper, I am only trying to measure the direct gross benefits of MEP services to client plants. I do not attempt to measure indirect benefits

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1 See Heckman, Hotz and Dobs (1987), LaLonde (1986), LaLonde and Maynard (1987) and Moffitt (1991) for discussions of program evaluation methodology.

that may accrue to client suppliers or spillover from clients to non-client plants. Further, I have no information on the costs of the MEP. Therefore, I can not make any statements about the net social returns to the MEP.

In addition to the obvious task of measuring the impact of MEP services on client performance, this paper seeks to determine whether the LRD is an effective tool for program evaluation. An important part of this is to see if credible evaluation studies can be done while maintaining confidentiality standards[1].

The rest of the paper is organised as follows. First, in Section 2, I briefly review previous attempts to evaluate agricultural extension programs. Many of the problems encountered in these studies also need to be addressed in an evaluation of the MEP. In Section 3, I discuss the evaluation data set constructed by linking MEP client records to plant level census data. In Section 4, I outline the empirical models used to estimate the impact of MEP services on client performance. Estimation results are discussed in Section 5. Conclusions are given in Section 6.

2. Background

Only limited work has been done to rigorously measure the impact of manufacturing extension programs[2]. It is, therefore, instructive to first review the methods used in studies to assess the effectiveness of agricultural extension programs. Although significant differences exist between agricultural and manufacturing extension[3], both programs have generically similar objectives (i.e., improve farm/manufacturing performance through outreach and education), and share many of the same evaluation issues[4].

In evaluating either agricultural or manufacturing extension, the goal is to assess whether extension services have any impact on client performance. The agricultural economics and economic development literature contain many studies which seek to measure the impact of agricultural extension. Birkhaeuser, Evenson and Feder (1991) review this literature.

1 The Census Bureau collects data from business establishments under Title 13 that stipulates that individual respondent's data cannot be disclosed.

2 This is changing, however, see Martin (1994) and Oldsman (1996) for examples.

3 See Feller (1993) and Shapira (1990) for discussions about the differences between agricultural and manufacturing extension. See True (1969) for a history of agricultural extension in the U.S.

4 Much of the discussion in this section is based on Jarmin (1995).

In their review, Birkhaeuser, Evenson and Feder (hereafter, BEF) find that researchers typically employ regression analysis to examine the relationship between farm performance and the receipt of extension services. Most such studies find that extension has significant and positive impacts on knowledge diffusion, technology adoption, productivity and profits. BEF note that, although most authors stop short of claiming that agricultural extension has positive net social benefits, several suggest that the rates of return to agricultural extension can be very large.

However, BEF point out that the existing studies of agricultural extension are subject to a number of qualifications concerning data and methodology. First, most studies lacked a proper control group of similar farmers that did not receive extension services against which to compare the performance of those that did. Use of a control group is important because it permits an estimate of what might have occurred in the absence of a program.

The members of a good control group should be as similar to those receiving services as possible. In the agricultural extension context, an evaluator might first consider how closely selected characteristics of farms operated by those not receiving services corresponded to those of farms operated by service recipients. The most important characteristics would be those which most directly influence farm performance, such as crop types, soil quality, farm size and location.

Second, evaluation studies often fail to take into account the type of services received (e.g., training in silage storage techniques or in the choice of seed varieties) and the intensity with which these services are provided (e.g., number of field agent days of service or cost). This makes it impossible to know the extent to which individual extension services vary in their effect.

Third, these studies also fail to account for the influence of other non-extension programs and secondary information flows. If clients and non-clients differ systematically in their access to non-extension services (these could be offered, for example, by seed companies and other farm vendors), then estimates of the impact of extension may be biased. Also, these studies do not allow for the benefits of extension services to "spillover" from clients to non-clients. For example, it is likely that the knowledge of a new cultivation method flows easily from a client farmer to his non-client neighbours.

Finally and perhaps most importantly, many studies may have biased estimates of the impact of extension services due to selection bias. This can occur if farmers with some characteristic (e.g., ability) that is not observable by the evaluator, self select themselves into the group of farmers receiving extension. It could very well be the case that farmers with more ability are the ones most likely to seek out additional information through extension. Biased estimation may also occur if extension agents select high ability farmers to receive the bulk of their services. In either case, an evaluator might mistakenly credit extension with the superior performance of the high ability farmers. This is because the evaluator can't control for the unobserved characteristics that determine whether farmers receive extension services. To get unbiased estimates of the impact of extension services, the evaluator must account for the selection bias. To do so requires the evaluator model the process by which individual farmers become extension clients. Given this information, a two step estimation procedure can be constructed to correct for the selection bias[1].

In summary, in most studies of agricultural extension there is evidence that these programs provide substantial benefits. However, these studies suffer from four major methodological problems: 1) lack of a control group 2), failure to control for the influence of non-extension services and secondary information flows 3) failure to incorporate information about the characteristics of the services provided and 4) selection bias.

The data and methodology I employ below to evaluate manufacturing extension allow me to address all but one of these concerns. First, the LRD provides an excellent control group. Namely, I use all plants in the two states in which the 8 MEP centers are located. Second, a subset of the MEP centers studied here included some information on the type and intensity of the services provided to each client. Although I do not pursue this approach in the present paper, this type of information allows evaluators to see if the effect of MEP services varies by the resources devoted to them or by the type of service provided. Finally, I attempt to control for selection bias by estimating a Heckman style two stage model. Unfortunately, I do not have any data on other non-MEP services that clients and/or non-clients may have received during the period in which MEP services were provided.

3. Data

This study uses data from two primary sources: 1) plant level Census data contained in the LRD and 2) a small number of data items from MEP client records. For this study, NIST/MEP made data from 8 centers in 2 states available

1 LaLonde (1986) shows that the use of longitudinal data and/or a two step estimation procedure can reduce the potential for misspecification. These methods do not, however, alleviate the potential for misspecification. He also shows that econometric models which pass standard specification tests often fail to replicate experimental results.

to CES. These data are from older centers and cover services that were delivered between 1987 and 1992.

To carry out the analysis, records from these two sources must first be linked together. For the results of the analysis to be used in program evaluation, the Office of Management and Budget requires that at least 70% of the MEP records be matched to LRD.

To link the data from the two sources, I employ information contained in the Standard Statistical Establishment List (SSEL)[1]. The SSEL contains name, address and other fields that can be used to match establishments to MEP client records, whereas the LRD does not. The LRD and SSEL share establishment identifiers so that once client records are matched to the SSEL they can easily be linked to the LRD.

Linking the client and SSEL records is done by creating matching variables from one or more of fields that are common between them. For example, a useful matching variable consists of the concatenation of elements of the establishment's name and its zip code. The matching variable is then used to flag potential matches between the two data sets. These matches are then verified by hand.

In order to obtain a match rate in excess of 70%, I repeated this procedure four times. A different matching variable was employed in each round. The result of the matching process was that 8,516 of 11,343 client records from the 8 MEP centers were successfully linked to the SSEL and thus to the LRD. This yields a 75.1% match rate. However, this match rate is misleading since each MEP record refers to a project and individual clients often have multiple projects. There are 3,972 clients in the MEP data, 2,807 of which were successfully matched to the SSEL[2]. Thus, the true match rate is 70.7%, just over the 70% level desired by OMB.

All of the client records used in this study included a measure of employment. The matched clients account for 78% of the total employment contained in the client records. The matched establishments also account for 20.7% of total LRD employment in the two states where the client plants reside.

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1 See Doms and Peck (1994) for a more detailed description of the SSEL.

2 Note that the definition of a "client" does not necessarily correspond to an establishment. For instance, it was often the case that more than one "client" was found to match to a single establishment. These were often just different parts of the same plant. Also, there were cases where a client record matched to more than one plant. If the plants were all in the same zip code, I allowed the match.

4. Methodology

The goal of evaluation is to determine whether the performance of client plants is systematically related to the receipt of MEP services. Based on the evaluation literature reviewed earlier, an evaluation of the MEP should incorporate an appropriate control group and address the issue of selection bias.

The first step is to identify measures of plant performance that are of interest to MEP stakeholders, that can be measured reliably, and will provide credible results. For this paper I examine the impact of MEP services on sales and labour productivity growth. Both of these variables, as well as all the control variables used, are taken from the LRD so that they are measured consistently across both clients and non-clients and over time.

For this study, I employ two econometric specifications to estimate the relationship between these variables and MEP participation. The first is a simple OLS regression with a MEP dummy. This model is written as
Model 1 (OLS):

$$y_{it} = X_{it}\beta + \alpha MEP_{it} + u_{it} \ , \tag{1}$$

where X_{it} is a vector of characteristics for each plant i and $MEP_{it} = 1$ if plant i is a client in period t and 0 otherwise. The parameter α measures the mean difference in y between clients and non clients controlling for the characteristics in X.

This model is appealing because it is easy to estimate and interpret. The vector X contains control variables that are known or thought to influence the dependent variables. If these variables control for all other factors that influence y, then the parameter α measures the impact of MEP participation.

However, there are several reasons to believe that this might not be the case. First, the vector of control variables is unlikely to include all of the other factors that influence the dependent variable. In this particular study, one important "missing variable" is a measure on non-MEP services that either clients and/or non-clients may have received.

Second, plants were not randomly assigned to be in either the client or non-client groups. As a result, estimates of the β and α parameters in (1) are likely to suffer from selection bias. This is a well known problem in the applied econometrics literature, in general, and the program evaluation literature, in particular[1].

1 See Maddala (1983) for a large number of cites in the general applied econometrics literature. Stromsdorfer (1987) and Moffitt (1991) provide reviews of the evaluation literature.

If one has panel data, selection bias can be controlled for by estimating a fixed effects model. This, however, assumes that the omitted variable that is correlated with program participation is fixed over time. A more general way to control for selection bias, in an evaluation framework, is given by Maddala (1983) who suggests the following model.

Model 2 (Two Stage Model):

$$y_{ci} = X_{ci}\beta_c + u_{ci} \tag{2}$$

$$y_{nci} = X_{nci}\beta_{nc} + u_{nci} \tag{3}$$

$$MEP_i^* = Z_i\gamma + \varepsilon_i \tag{4}$$

$$MEP_i = \text{iff } MEP_i^* > 0 \text{ and } MEP_i = \text{iff } MEP_i^* \leq 0 \quad .$$

Subscript c denotes client observations and nc denotes non-client observations. We observe a client observation for plant i if $MEP_i = 1$ and a non-client observation if $MEP_i = 0$. The variable MEP_i^* measures the propensity of plant i to become a client. However, we only observe the binary variable, MEP, which tells us whether a given plant is client or not. The variables (Z) used in the probit regression include all those in X. In order to identify the model, I also include a dummy, in Z, for whether the plant is in a SMSA that contains a MEP center. It seems likely that being near a center would affect the likelihood of becoming a client, but not necessarily measures of plant performance such as sales and productivity growth.

This model is more general than (1) in two important ways. First, it allows the coefficients in to differ for clients and non-clients. Second, it accounts for the covariance between the errors in the two performance equations (u_c and u_{nc} in (2) and (3), respectively) and the errors in the client selection equation (ε in (4)). OLS estimates of (1) are biased when these covariance terms are non zero.

The first step in estimating this model is to estimate (4) using probit maximum likelihood. From this, I obtain estimates of the inverse Mill's ratio for each plant[1]. The Mill's ratio is then used as an additional instrument to correct for selection bias in second stage OLS regressions of (3) on clients

1 The inverse Mill's ratio is given by for client plants and by $-\phi(Z_i\gamma) / \Phi(Z_i\gamma)$ for client plants and by $\phi(Z_i\gamma) / (1 - \Phi(Z_i\gamma))$ for non-clients where ϕ and Φ are the normal density and cumulative distribution functions, respectively.

observations and (4) on non-client observations or of an augmented version of (1) on the pooled sample. The coefficients on these instruments estimate $\mathrm{cov}(u_c\varepsilon)$ and $\mathrm{cov}(u_{nc}\varepsilon)$ for the client and non-client regressions, respectively. If they are non-zero, then selection bias exists.

I use the model given in equations (2) through (4) to estimate the impact of the MEP on client performance in two ways. First, I include the Mill's ratio in second stage OLS regressions on the pooled client and non client sample. Like the single stage OLS model in equation (1), these regressions employ a MEP dummy variable to measure program impact by comparing client and non client performance.

For evaluation, however, I want to measure the difference between how clients perform after MEP intervention and how they would have performed had they not received any services. That is, I would like to measure $E(y_{ci}| MEP_i=1) - E(y_{nci}| MEP_i=1)$. Unfortunately, I can not observe the $E(y_{nci}| MEP_i=1)$ term. However, the model given in equations (2) through (4) does allow one to estimate this expression with non experimental data. Thus, the second way I measure program impact using the 2 stage model is to compute the following expression

$$E(y_{ci} \mid MEP_i = 1) - E(y_{nci} \mid MEP_i = 1) = (\overline{X}_c\hat{\beta}_c - \hat{\sigma}_{c\varepsilon}(\varphi(\overline{Z}\hat{\gamma})/\Phi(\overline{Z}\hat{\gamma}))) - (\overline{X}_c\beta_{nc} - \hat{\sigma}_{nc\varepsilon}(\varphi(\overline{Z}\hat{\gamma})/\Phi(\overline{Z}\hat{\gamma}))) \tag{5}$$

where ϕ and Φ are the normal density and cumulative distribution functions, respectively, and $\hat{\beta}_{nc}$ and $\hat{\sigma}_{nce}$ are estimates from the second stage non-client regression. This expression computes the predicted difference in performance between how client plants perform having received services and how they would have performed in the absence of manufacturing extension. To compute (5), separate second stage regressions must be run on the client and non client subsamples.

5. Results

For the analysis below, I restrict attention to plants that were in the LRD for the three most recent Censuses of Manufactures (i.e., 1982, 1987 and 1992). This is required in order to estimate the impact of MEP services on sales and productivity growth between 1987 and 1992, while controlling for growth in these variables over the previous 5 year period. I look at 5 year changes, since many of the client plants are small and, therefore, are not likely to be included in the LRD during non-census years.

Because of this restriction, the number of client plants included in the analysis drops from 2482 to 1559 and the number of non-client plants drops from 34,889 to 15,982. Table 1 provides some summary statistics for this reduced sample. These show that client plants are, on average, larger than non-client plants. They also show that MEP clients enjoyed more sales and labour productivity growth over the 1987 to 1992 period (the period in which client received services) than did non-clients. However, clients also grew faster during the previous 5 year period from 1982 to 1987.

A. The Impact of MEP Participation on Sales Growth

To determine whether or not MEP participation is systematically associated with improved sales performance, I first estimate several alternative specifications of the simple OLS model given by (1), where yit is the natural log of sales (in 1987 dollars). These regressions simply compare the performance of client and non-client plants. To mitigate the effects of selection bias, I estimate the model in growth rates (this is one method of estimating a "fixed effects" model). That is, I transform the model so that the dependent variable becomes the log difference of sales between 1987, before any plants received MEP services, and 1992, after clients had been served. This transformation sweeps out the effects of any omitted variables that remain fixed over time but still influence performance[1]. An important example of such a variable is managerial ability.

Estimates from this model are given in Table 2. The basic specification, in column 1, shows that MEP clients enjoyed 11.3% more sales growth than non-clients between 1987 and 1992, after controlling for sales growth in the previous five year period and the growth in the capital labour ratio and in the share of production workers at the plant. Column 2 substitutes the growth in sales between 1977 and 1982 for that between 1982 and 1987, since the latter is likely to be endogenous[2]. While the coefficient on previous sales growth changes considerably, the impact on the MEP coefficient is only marginal.

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1 This transformation removes all variables that remain fixed over time, such as dummy variables. The MEP dummy does not drop out, however, since its value changes (for clients) between 1987 and 1992.

2 Namely, the 1982–1987 sales growth term, $\log(\text{sales}_{87}) - \log(\text{sales}_{82})$ shares a term with the dependent variable, $\log(\text{sales}_{92}) - \log(\text{sales}_{87})$. Thus, the negative coefficient on the sales growth rate term in the first and third columns in not surprising. The specification in the second fourth columns, while it reduces the number of observations available, avoids the endogeniety problem encountered in the first and third columns.

The regressions in columns 3 and 4 are the same as in the first two columns except that they refer only to plants with 500 or fewer workers. This is the target population for MEP services. The results indicate that the difference between client and non-client performance is slightly larger for the small and medium sized plants for which the program is intended to serve.

Even though the growth rate specification may mitigate the effects of selection bias, the most rigorous way to control for the bias, in the current setting, is to estimate the Heckman style two stage model described above. The first step is to obtain estimates of the inverse Mill's ratio from probit model that explains the propensity of plants to become clients.

Table 3 contains the first stage probit estimates for the four basic specifications of the model. The probit model should include all the variables to be used in the second stage OLS regressions. I also include a number of dummy variables that are differenced out of the growth rate model, such as whether plants are located in an URBAN or rural area, are single unit enterprises or are owned by MULTI plant firms and 2-digit SIC and size class dummies. As mentioned above, I also include a dummy that measures whether plants are located within an SMSA that contains a MEP center to ensure the model is identified.

The results indicate that plants that grew faster prior to 1987 and single unit plants were more likely to become clients. Plants located near a MEP center are also more likely become clients. Thus, it appears that CENTER is a good instrument for program participation.

In Table 4, I re-estimate the regressions from Table 2 but include the inverse Mill's ratio obtained from the probit model to correct for selection bias. The results show that, in each case, the estimated Mill's ratio coefficient is significantly different from zero which indicates that selection bias is a problem in the OLS estimates[1]. Indeed, the bias corrected estimates suggest that the MEP had no significant impact on sales growth.

The MEP coefficients in Tables 2 and 4 estimate the difference between the mean sales growth rates for clients and non-clients controlling for several factors. Recall, however, that for evaluation we want to know how much better clients perform after receiving services than they would have had they not received any services. That is, we want to estimate the complete unrestricted model given in equations (2) – (4) and evaluate equation (5).

1 While OLS yields consistent parameter estimates in the second stage regression, it gives inconsistent estimates of the covariance matrix. To correct for this I use the covariance estimator in Lee (1982).

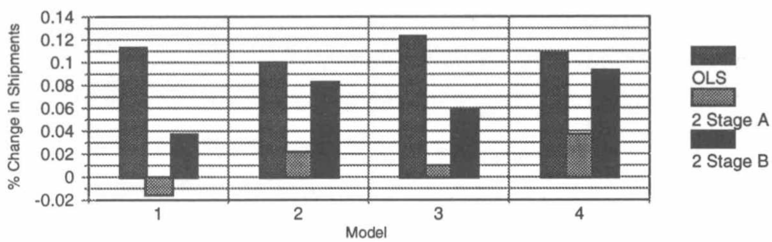
Tables 5 and 6 provide the second stage OLS estimates for clients and non-clients, respectively. The coefficient on the Mill's ratio term is significantly different from 0, at the 5% level, in all of the client only regressions and in 1 of the non-client regressions (where it was significant at the 10% level).

To get a measure of the difference between the sales growth that clients actually experienced and what they would have experienced had they not received any services, I use the non-client estimates, in Table 6, to compute the expression in equation (5) for each client plant. Recall that this expression measures the predicted gross change in sales growth for client plants conditional on them having client characteristics.

The estimated program impacts from the fully unrestricted two stage model are given in Table 7. Like in Table 4, these results show that controlling for selection bias reduces the estimates of the program impact on sales growth compared to the simple OLS estimates. Further, none of the estimates in Table 7 are statistically significant at the 5% level and only one case is significant at the 10% level.

The main result to take from Tables 4 and 7 is that simple OLS estimates of the impact of MEP services on sales growth are biased upwards due to selection bias. All of the estimates of program impact on sales growth are summarised in Figure 1. The OLS estimates range between 10.0 and 12.3%

***Figure 1.* Sales Growth Estimates, 1987–1992**

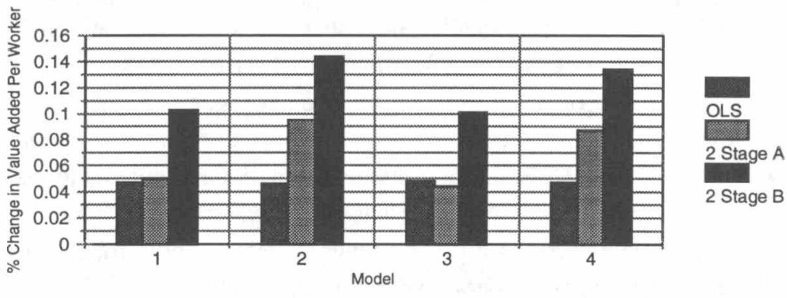


Notation: OLS: Average difference in % change in productivity between clients and non clients controlling for the characteristics in the regression.

2 Stage A: Average difference in % change in productivity between clients and non clients controlling for the characteristics in the regression plus the bias correction term.

2 Stage B: Predicted difference between client performance after MEP intervention and how they would have performed had they not been clients.

Figure 2. **Productivity Growth estimates, 1987–1992.**



Notation: OLS: Average difference in % change in productivity between clients and non clients controlling for the characteristics in the regression.

2 Stage A: Average difference in % change in productivity between clients and non clients controlling for the characteristics in the regression plus the bias correction term.

2 Stage B: Predicted difference between client performance after MEP intervention and how they would have performed had they not been clients.

and the two stage estimates range between –1.5 and 9.3%. Also, the two stage estimates are statistically insignificant except in one case. Thus, the case for a significant impact of MEP services on sales growth is weak.

B. The Impact of MEP Participation on Productivity Growth

To estimate the impact of MEP services on client productivity I specify the following standard value added production function

$$Y_{it} = A\, e^{\alpha\, MEP_{it}} L_{it}^{\beta}\, K_{it}^{\eta}\, e^{\varepsilon_{it}} \tag{6}$$

where Y_{it} is value added, L_{it} is employment and K_{it} is the book value of the capital stock of plant i in period t. This equation can be rewritten as

$$(y_{it} - l_{it}) = a + \alpha\, MEP_{it} + \eta(k_{it} - l_{it}) + (\mu - 1)l_{it} + \varepsilon_{it}\,, \tag{7}$$

where small letters denote logs, the parameter μ measures deviations from constant returns to scale and the dependent variable is the log of labour productivity. Again to mitigate the impact of omitted variables, such as managerial ability, I transform (7) into a growth rate specification by taking differences and I add a measure of previous productivity growth.

Table 8 lists the simple single stage OLS estimates. The format of this table is the same as that used in the sales growth regressions above. The estimated MEP coefficients suggest that MEP clients enjoyed around 4.7% more growth in value added per worker between 1987 and 1992 than did non clients.

The probit equations for the productivity models are the same as those used above, except that the change in employment is added. The results are nearly identical, so I do not list then in a separate table. Second stage estimates for the productivity growth regressions are provided in Tables 9 through 12. The regressions in Table 9 are the same as in Table 8 but control for selection bias. The results show that including the Mill's ratio increases the magnitude of the MEP coefficient in all but one case. Thus, unlike the sales growth estimates, OLS estimates of the impact of MEP services on productivity growth are biased downward. Note, however, that MEP coefficients in Table 9 are significant in only two cases (columns 2 and 4) and the Mill's ratio coefficients are never significant.

Tables 10 and 11 contain the second stage estimates for the unrestricted model. Taking both the client and non client regressions together, the results indicate that selection bias is a significant problem in 3 of the 4 specifications of the completely unrestricted model. The estimated gross impact of the MEP on client productivity are given in Table 12. These are all statistically significant and much larger than the OLS estimates in Table 8.

All of the estimates of the impact of MEP participation on productivity growth are summarised in Figure 2. The main finding is that these estimates are consistently positive, ranging between 4.4% and 14.4%. While selection bias is a problem in estimates of the impact of the MEP on productivity growth, the bias appears to be downward. Given this and the fact that significant positive estimates of program impact were computed for 10 of the 12 cases, it appears that the MEP participation is related to improved productivity growth for this sample of client plants[1].

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1 The two cases where the result was not statistically significant, in columns 1 and 3 of Table 9, is where the 1982–1987 growth rate in sales is used as a control variable. As discussed above, this variable likely leads to endogeniety bias. Thus, the results in columns 2 and 4 in all of the regression tables including Table 9 are probably more reliable.

6. Conclusions

The goal of this paper was to see if measures of plant performance (e.g., productivity and sales growth) are systematically related to participation in the MEP, while controlling for other factors that are known or thought to influence performance. To do this, I matched MEP client data to the Census Bureau's Longitudinal Research Database (LRD). The LRD offers two useful things for evaluation studies such as this one. First, because it includes plant level data for all manufacturing plants in the U.S., it is the best available database for constructing control groups. Second, it contains a number of both performance and control variables that are measured consistently across client and non-client plants and over time.

Because selection bias is often a problem in evaluation studies using non-experimental data, I specified an econometric model that controls for selection. I estimated the model with data from 8 manufacturing extension centers in 2 states. The control group includes all plants, in the LRD from each state.

The results indicate that MEP participation is systematically related to productivity growth but not to sales growth. These findings are consistent with those from other studies, such as Oldsman (1996). These results alone are not enough to evaluate the usefulness of the MEP. The analysis in this paper looks only at the direct impacts of MEP services on only two measures of client performance. Data on secondary program benefits and program costs are needed to ascertain whether the MEP provides positive net social benefits.

Finally, I believe that the paper demonstrates that the LRD can be utilised in evaluation studies. It is possible to match a sufficient number program records to the LRD in order to perform a credible analysis. Further, this can be done in a manner that does not violate Census Bureau data disclosure rules.

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Table 1. **Summary Statistics.**

Variable	Client Mean	Non-Client Mean
N	1559	15,982
Age, 1992	15.97	16.04
Employment, 1992	170.21	71.70
Employment Growth Rate, 1987–1992	0.013	–0.088
Sales, 1992	30,797,199	13,418,587
Sales Growth Rate, 1987–1992	0.052	–0.085
Sales Growth Rate, 1982–1987	0.427	0.338
Annual wage, 1992	28,072	25,013
Production Worker Share, 1992	0.699	0.724
Value Added Per Worker, 1987	53,042	50,853
Value Added Per Worker, 1992	56,709	52,797
Labour Productivity Growth Rate, 1987–1992	0.215	0.203
Labour Productivity Growth Rate, 1982–1987	0.052	0.010
# of MEP Projects	3.82	NA
Total Project Costs	**63,787**	**NA**

Notes:
Employment is the total number of employees from the LRD. Sales is the total value of shipments from the LRD. Wages is payroll ÷ employment from the LRD. Production worker share is the # of production workers ÷ employment from the LRD. Labour productivity is measured as value added per worker from the LRD. The # of MEP projects is the number of distinct project records per client from the MEP client data. Total project costs in the total client investment as a result of its engagements with the MEP. Real values for shipments obtained using the NBER's 4-digit deflators.

Table 2. **OLS Estimates: Sales Growth (absolute t statistics in parentheses).**

Variable	All Plants		L<500	
	1	2	3	4
Constant	–0.021*	–0.066*	–0.020*	–0.066*
	(3.962)	(12.265)	(3.679)	(11.867)
MEP	0.113*	0.100*	0.123*	0.108*
	(7.112)	(5.993)	(7.462)	(6.217)
Growth Rate in K/L	0.034*	0.035*	0.037*	0.037*
	(6.461)	(5.887)	(6.824)	(6.306)
Growth Rate in PW share	–0.090*	–0.031***	–0.097*	–0.039**
	(5.394)	(1.686)	(5.719)	(2.075)
Sales Growth Rate, 1982–1987	–0.053*		–0.052*	
	(7.977)		(7.823)	
Sales Growth Rate, 1977–1982		0.044*		0.044*
		(5.748)		(5.634)
N	15143	11556	14737	11162
R^2	0.012	0.009	0.013	0.034

Notes:
The dependent variable is the Sales Growth Rate for 1987 to 1992. K/L is the capital labour ratio. Capital is the book value of machinery and structures assets from the LRD deflated by 2-digit BEA capital stock deflators.
* denotes significant at the 1% level.
** denotes significant at the 5% level.
***denotes significant at the 10% level.

Table 3. **Probit Estimates: Sales Growth Model (Absolute t statistics in parentheses).**

Variable	All Plants		L<500	
	1	2	3	4
CONSTANT	–1.103***	–1.573***	–0.941**	–1.413***
	(1.772)	(1.770)	(2.095)	(1.779)
Sales Growth Rate, 1982–1987	0.076*		0.076*	
	(3.128)		(3.077)	
Sales Growth Rate, 1977–1982		0.053***		0.054**
		(0.026)		(1.907)
Growth Rate in K/L	–0.136	–0.132	–0.137	–0.143
	(0.954)	(0.553)	(0.957)	(0.598)
Growth Rate in PW share	–0.132	0.872	–0.192	0.791
	(0.319)	(1.277)	(0.455)	(1.119)
URBAN	–0.615	0.064	–0.662***	0.055
	(1.563)	(0.087)	(1.673)	(0.073)
MULTI	–0.701**	–0.897**	–0.762**	–1.005**
	(2.322)	(2.132)	(2.457)	(2.320)
AGE	–0.234	–0.025	–0.239	–0.020
	(1.524)	(0.087)	(1.547)	(0.069)
CENTER	1.246*	1.014**	1.241*	0.987***
	(3.832)	(1.952)	(3.793)	(1.884)
2-Digit SIC Dummies	yes	yes	yes	yes
Size Dummies	yes	yes	yes	yes
Interaction Terms	yes	yes	yes	yes
N	15057	11509	14652	11116
logL	–3780	–3088	–3578	–2888

Notes:
The dependent variable is MEP. K/L is the capital labour ratio. Capital is the book value of machinery and structures assets from the LRD deflated by 2-digit BEA capital stock deflators. URBAN=1 if inside an SMSA. MULTI=1 if owned by a multi plant firm. CENTER=1 if located inside an SMSA that contains a MEP center.

Table 4. **Second Stage OLS Estimates: Sales Growth Clients and Non-Clients (Asymptotic absolute t statistics in parentheses).**

Variable	**All Plants**		**L<500**	
	1	**2**	**3**	**4**
Constant	–0.011***	–0.058*	–0.012***	–0.059*
	(1.663)	(8.4217)	(1.752)	(8.355)
MEP	–0.015	0.022	0.010	0.037
	(0.399)	(0.538)	(0.245)	(0.877)
Mills Ratio	–0.082*	–0.051**	–0.072*	–0.047***
	(0.023)	(2.069)	(2.978)	(0.025)
Growth in K/L	0.034*	0.033*	0.036*	0.036*
	(5.799)	(5.037)	(6.446)	(5.414)
Growth in PW share	–0.088*	–0.032	–0.095*	–0.040***
	(4.520)	(1.509)	(4.860)	(1.889)
Sales Growth, 1982–1987	–0.048*		–0.048*	
	(5.896)		(5.820)	
Sales Growth, 1977–1982		0.033*		0.044*
		(5.025)		(4.896)
N	15057	11509	14652	11116
R^2	0.012	0.010	0.013	0.033

Notes:
The dependent variable is the Sales Growth Rate for 1987 to 1992. K/L is the capital labour ratio. Capital is the book value of machinery and structures assets from the LRD deflated by 2-digit BEA capital stock deflators.

Table 5. Second Stage Estimates: Sales Growth MEP Clients Only (Asymptotic absolute t statistics in parentheses).

Variable	**All Plants**		**L**	
	1	**2**	**3**	**4**
Constant	–0.117*	–0.112**	–0.093	–0.093
	(2.147)	(1.982)	(1.635)	(1.555)
Growth in K/L	–0.009	0.012	–0.005	0.019
	(0.396)	(0.521)	(0.222)	(0.779)
Growth in PW share	–0.172**	–0.121	–0.167**	–0.110
	(2.039)	(1.428)	(1.974)	(1.346)
Sales Growth, 1982–1987	0.004		0.003	
	(0.130)		(0.111)	
Sales Growth, 1977–1982		0.050**		0.047***
		(2.010)		(1.812)
Mills	–0.129*	–0.104**	–0.118*	–0.095**
	(3.367)	(2.529)	(2.983)	(2.221)
N	1442	1209	1344	1112
R^2	0.017	0.016	0.037	0.014

Notes:
The dependent variable is the Sales Growth Rate for 1987 to 1992. K/L is the capital labour ratio. Capital is the book value of machinery and structures assets from the LRD deflated by 2-digit BEA capital stock deflators.

Table 6. **Second Stage Estimates: Sales Growth Non-Client Plants (Asymptotic absolute t statistics in parentheses).**

Variable	**All Plants**		**L<500**	
	1	**2**	**3**	**4**
Constant	–0.013***	–0.065*	–0.014***	–0.064*
	(1.905)	(8.463)	(1.916)	(7.078)
Growth in K/L	0.038*	0.035*	0.040*	0.038*
	(6.228)	(5.097)	(6.471)	(4.751)
Growth in PW share	–0.080*	–0.025	–0.089*	–0.035
	(4.081)	(1.150)	(4.474)	(1.410)
Sales Growth, 1982–1987	–0.054*		–0.054*	
	(6.324)		(6.226)	
Sales Growth, 1977–1982		0.042*		0.043*
		(4.539)		(4.010)
Mills	–0.050***	–0.012	–0.043	–0.011
	(1.715)	(0.389)	(1.406)	(0.233)
N	13615	10300	13308	10004
R^2	0.010	0.029	0.010	0.020

Notes:
The dependent variable is the Sales Growth Rate for 1987 to 1992. K/L is the capital labour ratio. Capital is the book value of machinery and structures assets from the LRD deflated by 2-digit BEA capital stock deflators.

Table 7. **Second Stage Estimates of Gross Impact of the MEP on Client Sales Growth (Absolute asymptotic t statistics in parentheses).**

Model	$E(y_{ci} \mid MEP_i = 1) - E(y_{nci} \mid MEP_i = 1)$	
1	0.037	(0.755)
2	0.083	(1.636)
3	0.058	(1.127)
4	0.093***	(1.746)

Notes:
$E(y_c \mid MEP_i = 1) - E(y_{nc} \mid MEP_i = 1) = \bar{X}_c^* \beta_c - \bar{X}_c^* \beta_{nc} = \lambda$, where $\bar{X}_c^*$ is a vector containing the means of the variables used in the regressions in Tables 5 and 6 computed for client plants only. $Var(\lambda) = \bar{X}_c^* \, var(\hat{\beta}_c - \hat{\beta}_{nc}) \, \bar{X}_c^{*\prime} = \bar{X}_c^* \, (var(\hat{\beta}_c) + var(\hat{\beta}_{nc})) \, \bar{X}_c^{*\prime}$, where $var(\hat{\beta}_c)$ and $var(\hat{\beta}_{nc})$ are the asymptotic covariance matrices from the second stage client and non client regressions, respectively.

Table 8. **OLS Estimates: Productivity Growth (Asymptotic absolute t statistics in parentheses).**

Variable	**All Plants**		**L<500**	
	1	**2**	**3**	**4**
Constant	0.065*	–0.008	0.064*	–0.009
	(13.850)	(1.460)	(13.533)	(1.644)
MEP	0.047*	0.046*	0.048*	0.047*
	(3.255)	(2.771)	(3.204)	(2.706)
Growth Rate in K/L	0.130*	0.136*	0.131*	0.137*
	(26.940)	(23.290)	(26.942)	(23.289)
Growth Rate in L	–0.165*	–0.195*	–0.165*	–0.195*
	(21.819)	(20.516)	(21.626)	(20.344)
Labour Productivity Growth Rate, 1982–1987	–0.265*		–0.264*	
	(39.955)		(39.472)	
Labour Productivity Growth Rate, 1977–1982		–0.024*		–0.025*
		(3.099)		(3.266)
N	15248	11609	14848	11220
R^2	0.195	0.096	0.197	0.099

Notes:
The dependent variable is the growth rate in labour productivity for 1987 to 1992. K/L is the capital labour ratio. Capital is the book value of machinery and structures assets from the LRD deflated by 2-digit BEA capital stock deflators.

Table 9. **Second Stage Estimates: Productivity Growth Clients and Non Clients (Asymptotic absolute t statistics in parentheses).**

Variable	All Plants		L<500	
	1	2	3	4
Constant	0.065*	–0.012***	0.065*	–0.012***
	(10.837)	(1.777)	(10.710)	(1.762)
Mills Ratio	0.002	0.032	–0.003	0.027
	(0.080)	(1.303)	(0.123)	(1.068)
MEP	0.050	0.095**	0.044	0.087**
	(1.411)	(2.310)	(1.200)	(2.071)
Growth Rate in K/L	0.127*	0.131*	0.128*	0.132*
	(20.338)	(16.987)	(20.383)	(17.070)
Growth Rate in L	–0.170*	–0. 202*	–0.170*	–0.202*
	(17.970)	(16.672)	(17.818)	(16.534)
Labour Productivity Growth Rate, 1982–1987	–0.265*		–0.264*	
	(26.471)		(26.103)	
Labour Productivity Growth Rate, 1977–1982		–0.025*		–0.027*
		(3.121)		(3.251)
N	14940	11412	14544	11027
R^2	0.193	0.095	0.195	0.097

Notes:
The dependent variable is the growth rate in labour productivity for 1987 to 1992. K/L is the capital labour ratio. Capital is the book value of machinery and structures assets from the LRD deflated by 2-digit BEA capital stock deflators.

Table 10. **Second Stage Estimates: Productivity Growth Clients Only (Asymptotic absolute t statistics in parentheses).**

Variable	**All Plants**		**L<500**	
	1	**2**	**3**	**4**
Constant	0.051	0.016	0.034	0.008
	(1.005)	(0.290)	(0.629)	(0.133)
Mills Ratio	–0.051	–0.017	–0.061***	–0.021
	(1.449)	(0.446)	(1.666)	(0.526)
Growth Rate in K/L	0.108*	0.115*	0.102*	0.108*
	(4.874)	(4.571)	(4.518)	(4.177)
Growth Rate in L	–0.114*	–0. 149*	–0.109*	–0.151*
	(3.046)	(3.244)	(2.877)	(3.132)
Labour Productivity Growth Rate, 1982–1987	–0.317*		–0.316*	
	(9.080)		(8.780)	
Labour Productivity Growth Rate, 1977–1982		–0.001		–0.009
		(0.046)		(0.349)
N	1418	1191	1326	1100
R^2	0.180	0.056	0.179	0.053

Notes:
The dependent variable is the growth rate in labour productivity for 1987 to 1992. K/L is the capital labour ratio. Capital is the book value of machinery and structures assets from the LRD deflated by 2-digit BEA capital stock deflators.

Table 11. Second Stage Estimates: Productivity Non Clients Only (Asymptotic absolute t statistics in parentheses).

Variable	All Plants		L<500	
	1	2	3	4
Constant	0.059*	–0.018**	0.059*	–0.017**
	(8.911)	(2.326)	(8.840)	(2.236)
Mills Ratio	0.035	0.064**	0.033	0.056***
	(1.299)	(1.964)	(1.209)	(1.730)
Growth Rate in K/L	0.128*	0.132*	0.130*	0.134*
	(19.693)	(16.257)	(19.828)	(16.451)
Growth Rate in L	–0.175*	–0. 208*	–0.175*	–0.207*
	(17.915)	(16.473)	(17.791)	(16.347)
Labour Productivity Growth Rate, 1982–1987	–0.260*		–0.259*	
	(24.962)		(24.692)	
Labour Productivity Growth Rate, 1977–1982		–0.028*		–0.028*
		(3.242)		(3.288)
N	13522	10221	13218	9927
R^2	0.195	0.100	0.197	0.102

Notes:
The dependent variable is the growth rate in labour productivity for 1987 to 1992. K/L is the capital labour ratio. Capital is the book value of machinery and structures assets from the LRD deflated by 2-digit BEA capital stock deflators.

Table 12. Second Stage Estimates of the Gross Impact of the MEP on Client Productivity Growth (Absolute asymptotic statistics in parentheses).

Model	$E(y_{ci} \mid MEP_i = 1) - E(y_{nci} \mid MEP_i = 1)$	
1	0.103**	(2.290)
2	0.144*	(2.722)
3	0.101**	(2.200)
4	0.134**	(2.488)

Notes:
$E(y_{ci} \mid MEP_i = 1) - E(y_{nci} \mid MEP_i = 1) = \bar{X}_c^* \beta_c - \bar{X}_c^* \beta_{nc} = \lambda$, where $\bar{X}_c^*$ is a vector containing the means of the variables used in the regressions in Tables 10 and 11 computed for client plants only. $Var(\lambda) = \bar{X}_c^* \, var(\hat{\beta}_c - \hat{\beta}_{nc}) \, \bar{X}_c^{*'} = \bar{X}_c^* \, (var(\hat{\beta}_c) + var(\hat{\beta}_{nc})) \, \bar{X}_c^{*'}$, where $var(\hat{\beta}_c)$ and $var(\hat{\beta}_{nc})$ are the asymptotic covariance matrices from the second stage client and non client regressions, respectively.

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CONCENTRATION, PRODUCTIVITY AND TECHNOLOGICAL INNOVATION OF THE MANUFACTURING ENTERPRISES IN ITALY

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The paper concerns the relations between concentration, productivity, technological innovation and their influence on the stability of the industrial system. The study of the three mentioned variables for the Italian industrial system, gives information on the level of domination, efficiency and competitiveness of the enterprises. The results of the analysis are derived by the use of a panel of enterprises, for the years between 1985 and 1992, that made innovations, in term of products or production processes, in the years 1990–1992 (ad-hoc survey). Other data are obtained from the annual structural survey carried out on the enterprises with at least 20 employees and operating in the manufacture sectors.

The enterprises that innovated are investigated by a longitudinal analysis for studying the relations between index of concentration, index of productivity and costs for innovation.

Key words: Longitudinal Analysis, Panel, Technological Innovation, Productivity, Concentration.

1. Introduction

The main purpose of this research is to carry out an analysis of the Italian industrial system, from 1985 to 1992, studying the links between concentration, productivity and technological innovation and their influence on the stability of the industrial system.

1 The paragraphs 1, 2, 3 and 4 are written by Mauro Politi, paragraphs 5, 6 and 7 are written by Piero Taccini

Much interest has been devoted, in the last period, by several researcher into the dynamic aspects of economic data and into the analysis of micro data on the industrial enterprises. The results of the annual structural survey on industry give the possibility, if observed for some years, to evaluate, in the long period, the changes of the economical structure of the industrial enterprises. In this study it has been used a longitudinal analysis based on a retrospective panel of enterprises, it has been possible so to evaluate, in a period of eight years, the evolution of the links between technological innovation, productivity and concentration in the industrial sector.

The production of enterprise panel data by the National Statistical Institutes helps the researchers to investigate several interesting topics in national industrial economics and improves the possibility of international comparisons of the industrial statistics.

2. Technological innovation

The Italian National Statistical Institute (ISTAT) carried, in 1993, a survey on the enterprises of the industrial sector for studying the technological innovation in the years 1990–1992.

The definition of technological innovation conforms to the "Manual" of OECD, that considers innovation when a product new or very improved is introduced into the market or when a process new or very improved is used for producing goods for sale (OECD, 1992).

The results of this survey (ISTAT, 1995) give much interesting information, especially compared with the results obtained by the other Countries of European Union that carried out the survey CIS (Community Innovation Survey).

In the present study it is analysed the behaviour of the innovating enterprises in the period previous their expense for innovation: a) comparing them with the total universe of the enterprises with at least 20 employees and operating in the same industrial sectors (ISTAT, 1996), b) evaluating them as the only universe for analysing possible changes in the various economical sectors.

Another stage of the study consists of merging the results of the Structural Survey on value added and those of the Survey on Technological Innovation, for the years 1985–1992. This has been made possible using the new register of enterprises and the identification code of the enterprises that allowed the construction of a panel of enterprises.

The principal variables considered are:

1 economical activity classes according to the Italian classification of 1981 (ISTAT, 1981) similar to Nace 1970,
2 turnover,
3 number of employees,
4 value added,
5 value of production (expressed as turnover, changes in stocks of finished products and semi-finished products, capitalised production),
6 cost for the innovation (expressed as expenses for innovations and expenses for investments in plants and machinery connected with the introduction of new processes and/or products).

The last variable has been considered only for 1992, year in which the results of the survey concerning the innovating enterprises (7200 on a total of 32000 units of the universe) were available.

3. Productivity

The productivity measures the efficiency of the production process: it states the relation between the output and the input necessary to create it. An improvement of the relation between production and consume of the inputs means an improvement of the efficiency and an optimisation of the factors used.

Two possible definitions of the productivity of the enterprises are (Fourastié 1960) :

- Value added divided by the number of employees and this allows to evaluate better the contribution of the different internal factors of the enterprise (work, capital, plants etc.) for the improvement of the production capacity. The productivity of the class of economical activity i is:

$$PROD1_i = (value\ added)_i \,/\, (number\ of\ employees)_i$$

- Gross production divided the by number of employees; the production has to be evaluated at market prices and allows to compare the productivity of different sectors of activity because it is expressed in terms of value and not of quantities. The productivity of the class of economical activity i is:

$$PROD2_i = (value\ of\ production)_i \,/\, (number\ of\ employees)_i$$

For the innovating enterprises and for the total of the universe has been calculated the productivity in the two described ways, and this calculation has been made for the years between 1985 and 1992.

The ratios of productivity, so calculated, can be standardised for better comparing the values between the different classes of economical activity. They can be expressed in index form making 100 the value added (or the gross production) per employee of the total industry and calculating the ratio between the productivity of the different classes and that one of the total. The standardised index of productivity of the class i is:

$$STD(PROD)_i = [PROD_i \;/\; Mean\ (PROD)] * 100$$

The standardisation helps to evaluate the changes of the productivity of the enterprises during the period 1985–1992.

4. Concentration

Another important aspect of the study is the analysis of the concentration.

The concept of concentration is related to the way in which the total amount of a variable is distributed between the units of the population. A variable is more concentrated when larger is the part of its total amount that is detected by few units that have the most (Marshall and Olkin 1979).

The concentration, in the context of the analysis of industry, can be defined as the level of domination of few large enterprises in an economical activity; it is also a concise indicator of the structure of the market and therefore of the influence of one or more enterprises on it (Hay and Morris 1979).

The concentration has been calculated on the distribution of the total turnover of the first 5% (fifth percentile) of the enterprises sorted by the descending value of the turnover inside the group of the same economical activity (ISTAT 1996). In other words it has been investigated the importance, in term of turnover, of the few largest enterprises. It has been chosen the turnover but it could be used also the value added or the employment, because these two variables are strongly correlated with the first one. The concentration index of the class i is:

$$C_i = [\Sigma_j\, T(p5)_i / \Sigma_h\, T_i] * 100$$

where T = turnover, $p5$ = fifth percentile, $j = 1...n$ enterprises of the fifth percentile, $h=1...m$ total enterprises of class i.

The index has been calculated considering first only the innovating enterprises and after all the enterprises of the structural survey carried out on the units with at least 20 employees.

5. The Panel

The Panel surveys are surveys in which the units are measured in two or more times. They provide information on individuals studying their behaviour for long periods. These longitudinal analysis can be used also for evaluating significant changes of the economical structure in different periods; they allow to reduce the costs of the surveys, the variance for differences of cross-sectional estimates and the errors of the respondents (Lavallèe 1994).

The use of a panel supposes the study of a panel design. For the present work it has been built a retrospective panel (Garofalo and Taccini 1995) using the set of enterprises that declared to make innovation of process and/or product for the year 1992.

This panel is not balanced because not considering the events related with the mergers and demergers of the enterprises that happened during the period 1985–1992.

The panel has been used, starting from the indicators calculated in 1992, for a longitudinal analysis on the behaviour of the innovating enterprises in the previous eight years.

Another calculation has been made considering also the influence (in term of turnover and employees) of the innovating enterprises belonging to the group of the fifth percentile (largest enterprises) on the total of every economical activity. The aim of this operation has been to investigate which and how many were the innovating enterprises and how much was their weight on the first 5% of the total.

In term of turnover this ratio for the class i is:

$$H_i = [TIN(p5)_i \; / \; TT(p5)_i] * 100$$

where $TIN(p5)$ = turnover of the innovating enterprises included in the fifth percentile of turnover, $TT(p5)$ = turnover of the total enterprises of the fifth percentile.

Considering that the index of concentration is determined by the turnover of the first 5% (fifth percentile) of the total of enterprises, for all the innovating enterprises belonging to this subset is also possible to calculate the weight in term of employment. In this case the ratio for the class i is:

$$W_i = [EIN(p5)_i \; / \; ET(p5)_i] * 100$$

where $EIN(p5)$ = employees of the innovating enterprises included in the fifth percentile of turnover, $ET(p5)$ = employees of the total enterprises of the fifth percentile.

6. Analysis of the Results

The longitudinal analysis before described begins with the data of the year 1992.

In table 1 there are, for every class of economical activity:

1 indexes of productivity calculated by value added per employee and value of production per employee;
2 indexes of concentration expressed in term of percentage of turnover of enterprises belonging to the fifth percentile on the total of the class;
3 incidence (%) of the cost of innovation on the total of turnover.

The indexes of the first two points have been calculated for the subset of innovating enterprises and for the total of the universe (all the enterprises with at least 20 employees) .

The data of table 1 show that, in 75% and 87,5% of the classes (it depends which of the two indexes is considered), the productivity results higher for the innovating enterprises than for the total. The classes that show more productivity are the industry of petroleum products and all the mechanical and engineering industries.

As regard the concentration index it can be observed that, in 58% of the classes, the set of innovating enterprises is more concentrated than the total (always in term of turnover). The distribution of the concentration between the classes shows that the most concentrated sectors are those of the mechanical and engineering industries.

The table shows also that, in the sectors with higher cost for the innovation, not always the productivity is the highest (but higher than the average); the incidence of innovation costs on the turnover for these sectors is: 12.4% for motor vehicles, 10.7% for the other means of transport, 8.7% for extraction of minerals, 8.4% for precision instruments and 8.2 % for metal processing industry. The concentration index results very high for these sectors with the exception of the extraction of minerals where there are many small and medium-sized enterprises.

In the tables 2 and 3 is possible to observe the data of the productivity standardised in the way described in paragraph 3; the calculation has been made for the total of the enterprises and for the subset of the innovating. The analysis has been performed for eight years starting from 1985: the tables show only the results of the first and the last year because in the intermediate years the results are similar.

In 1985 the sectors with higher standardised productivity (expressed by value added and value of production per employee) than the average are: petroleum products, electricity and gas, office machines and computers. The sectors with lower productivity are: footwear industries (where there are many small and medium enterprises) and water supply (because the most enterprises are public and the prices are imposed by Government Agencies).

The table of 1992 does not show significant differences. In table 4 is possible to observe (for some main sectors) the results of the longitudinal analysis for the considered variables. Whereas in table 2 and 3 the productivity is presented referring to a static situation, in this new table it is presented as dynamic changes.

In particular the productivity indexes of the food industries and electrical engineering products increase; instead in the motor vehicles class the productivity decreases. There are also discrepancies between the increasing trend of the innovating enterprises and the total: in the industry of office machines and computers the productivity of the total decreases in the years, whereas the productivity of innovating enterprises increases.

Interesting are the results of table 5 where, for some economical activity, there are the concentration indexes previously described and the percentages (expressed in term of turnover and employees) of the innovating enterprises included in the fifth percentile of the total of the enterprises belonging to every class of economical activity.

Also this is an example of longitudinal analysis and allows to evaluate the structural changes of the industry in the period 1985–1992.

Significant is the case of the petroleum products where the innovating enterprises pass from 88.3% (of turnover) of weight on the fifth percentile of the total, in 1985, to 100% in 1992: this means that the fifth percentile (with a concentration index of 73% for the total) is composed by all innovating enterprises. On the contrary the trend of the class of machines for office and computers shows a decreasing change: it starts with the maximum value of

100% in 1985, it goes down till 1990 (76.9%) and in the last two years increases to 93.2%.

The class of food industry is characterised by the presence of small and medium enterprises and the concentration index is lower than the average but it shows an increasing presence of innovating enterprises in the fifth percentile, in fact it goes from 27.1% in 1985 to 55.5% in 1992. It is interesting to observe that, with the exception of the class of computers, in all the other classes the percentage of employees of the innovating enterprises on the fifth percentile increases.

The class of motor vehicles, very concentrated, presents a change similar to the class of petroleum products: the percentage of the turnover goes from 86.7% of the first year to 95% of the last year; also for this sector the fifth percentile is well represented by the innovating enterprises.

7. Conclusion

The analysis conducted in this study uses micro data collected by the Italian National Statistical Institute and it is an example of how the research, in economic statistics, can assume new aspects allowing the industrial statistics to increase their content of describing and understanding the dynamic of the economy.

The analysis of the data has showed that the enterprises that made technological innovation have better results than the total and that these results are different by economic sector. The information contents of the results could be higher if the period of the availability of the data should be longer.

It is evident that an important task of the National Statistical Institutes is to build data base of micro data on the enterprises to allow robust longitudinal analysis to investigate the changes of the economic system: it is therefore necessary to plan the statistical surveys to obtain data reliable for microeconomic analysis.

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Table 1. **Productivity, concentration and innovation – year 1992.**

Code and economical activity	P1	P2	P3	P4	C1	C2	K1	K2
14 – solid fuel	153.0	158.2	1130.5	1356.0	73.0	34.7	0.8	0.9
16 – coke-ovens products	176.1	189.1	366.1	371.3	86.1	90.6	1.7	2.0
17 – extr. petrol. nat. gas	72.8	60.4	179.4	166.3	41.9	–	0.6	4.9
22 – petroleum products	63.6	63.3	284.7	264.3	53.8	61.2	3.7	8.2
23 – extr. minerals	79.6	90.5	173.8	192.8	20.1	23.6	1.0	8.7
24 – non metal mineral prod.	79.8	86.7	200.2	209.1	42.6	41.1	1.8	5.1
25 – chemical products	101.1	99.4	311.0	315.2	51.6	45.9	3.0	5.0
26 – man-made fibres	71.6	70.4	220.2	207.6	38.0	30.1	3.0	3.9
31 – metal articles	61.6	65.8	169.6	175.4	34.6	37.1	1.6	5.2
32 – mech. engin. products	70.7	74.6	198.0	208.0	42.8	48.9	2.3	4.7
33 – office mach./data prod. mach.	153.2	180.7	140.0	156.6	91.7	62.8	6.5	7.5
34 – elect. engin. products	75.1	78.7	191.5	192.6	58.9	59.2	4.5	7.9
35 – motor vehicles	54.8	54.5	192.6	196.4	80.5	86.5	10.4	12.4
36 – other means of transport	57.7	49.2	153.9	153.7	76.9	56.9	4.7	10.7
37 – measur. prec. instrum.	67.9	78.9	150.3	163.2	42.6	41.6	4.1	8.4
41 – food	82.5	90.3	382.0	427.6	48.7	51.8	0.9	2.1
42 – sugar, drinks, tobacco	101.3	92.2	417.5	432.6	59.9	67.2	0.6	1.1
43 – textiles	59.4	70.4	191.3	219.5	36.9	42.5	1.2	4.2
44 – leather	59.3	72.5	232.6	288.0	28.1	22.4	0.5	2.9
45 – footwear	42.3	56.7	138.4	176.8	47.1	48.7	0.5	3.9
46 – artic. of wood and furnit.	55.5	60.5	187.0	209.9	31.5	34.0	1.1	4.3
47 – paper, print, publ.	85.0	91.4	228.1	232.9	50.9	56.9	1.9	4.8
48 – rubber and plastic	70.4	79.5	196.5	198.0	39.5	40.7	1.9	4.6
49 – other manufact.	38.5	63.2	163.8	286.5	37.4	30.7	0.9	3.8

P1 = value added per employee of total enterprises (millions of lire)
P2 = value added per employee of innovating enterprises (millions of lire)
P3 = value of production per employee of total enterprises (millions of lire)
P4 = value of production per employee of innovating enterprises (millions of lire)
C1 = index of concentration of total enterprises
C2 = index of concentration of innovating enterprises
K1 = cost for the innovation of total enterprises (% of turnover)
K2 = cost for the innovation of innovating enterprises (% of turnover)

Table 2. **Standardised productivity – year 1985.**

Code and economical activity	N1	N2	P1	P2	P3	P4
14 – solid fuel	76	18	224	196	919	969
16 – coke-ovens products	133	33	224	196	182	160
17 – extr. petrol. nat. gas	64	11	72	68	61	56
22 – petroleum products	510	105	88	79	125	103
23 – extr. minerals	333	19	93	87	61	62
24 – non metal mineral prod.	2 310	315	89	81	71	67
25 – chemical products	1 099	274	129	111	148	126
26 – man-made fibres	27	6	118	91	132	110
31 – metal articles	3 750	615	84	77	70	67
32 – mech. engin. products	3 499	874	95	83	81	71
33 – office mach./data prod. mach.	34	7	219	196	103	97
34 – elect. engin. products	1 770	415	92	81	70	60
35 – motor vehicles	495	118	82	78	79	75
36 – other means of transport	328	62	78	59	58	47
37 – measur. prec. instrum.	349	67	85	82	58	56
41 – food	1 442	180	89	92	165	168
42 – sugar, drinks, tobacco	709	115	107	85	158	153
43 – textiles	3 140	383	86	77	84	71
44 – leather	559	48	82	84	112	128
45 – footwear	4 148	150	59	65	56	68
46 – artic. of wood and furnit.	2 511	291	72	68	68	71
47 – paper, print, publ.	1 574	302	109	99	98	86
48 – rubber and plastic	1 517	312	91	81	83	72
49 – other manufact.	597	60	72	69	104	140

N1 = number of total enterprises
N2 = number of innovating enterprises
P1 = value added per employee of total enterprises (standardised)
P2 = value added per employee of innovating enterprises (std.)
P3 = value of production per employee of total enterpr. (std.)
P4 = value of production per employee of innovating enterpr. (std.)

Table 3. Standardised productivity – year 1992.

Code and economical activity	N1	N2	P1	P2	P3	P4
14 – solid fuel	87	24	202	180	512	541
16 – coke-ovens products	179	43	233	215	166	148
17 – extr. petrol. nat. gas	101	8	96	69	81	66
22 – petroleum products	677	152	84	72	129	105
23 – extr. minerals	361	31	105	103	75	74
24 – non metal mineral prod.	2 363	427	105	99	89	83
25 – chemical products	1 188	365	134	113	140	126
26 – man-made fibres	36	13	95	80	100	83
31 – metal articles	5 329	1009	81	75	75	69
32 – mech. engin. products	4 381	1278	93	85	88	82
33 – office mach./data prod. mach.	173	25	202	205	63	63
34 – elect. engin. products	2 836	697	99	89	86	77
35 – motor veichles	714	200	72	62	87	78
36 – other means of transport	432	95	76	56	70	61
37 – measur. prec. instrum.	441	99	90	90	67	65
41 – food	1 178	261	109	103	171	169
42 – sugar, drinks, tobacco	505	136	134	105	188	172
43 – textiles	3 513	532	79	80	85	86
44 – leather	895	76	78	82	102	112
45 – footwear	5 714	343	56	64	61	69
46 – artic. of wood and furnit.	2 659	437	73	69	82	82
47 – paper, print, publ.	2 121	456	112	104	102	92
48 – rubber and plastic	1 886	464	93	90	88	78
49 – other manufact.	681	85	51	72	72	111

N1 = number of total enterprises
N2 = number of innovating enterprises
P1 = value added per employee of total enterprises (standardised)
P2 = value added per employee of innovating enterprises (std.)
P3 = value of production per employee of total enterpr. (std.)
P4 = value of production per employee of innovating enterpr. (std.)

Table 4. Changes of standardised productivity – years 1985–1992 (*).

Code and economical activity	Year	N1	N2	P1	P2	P3	P4
14 – petroleum products	85	76	18	224	196	919	969
	86	69	18	175	216	822	720
	87	72	21	203	208	861	730
	88	77	22	191	200	686	659
	89	63	19	197	171	520	602
	90	61	21	220	211	622	734
	91	66	23	220	214	668	749
	92	87	24	202	180	512	541
33 – office mach./data prod.mach.	85	34	7	219	196	103	97
	86	44	10	202	184	95	93
	87	50	12	201	180	92	90
	88	50	13	198	181	103	101
	89	69	21	194	181	79	77
	90	70	21	202	227	100	97
	91	80	22	212	247	89	93
	92	173	25	202	205	63	63
34 – elect. engin. products	85	1 770	415	92	81	70	60
	86	1 789	424	91	80	73	65
	87	1 976	467	92	79	76	68
	88	2 082	515	93	80	77	69
	89	2 245	578	94	84	80	75
	90	2 209	627	97	89	82	75
	91	2 280	639	99	92	81	74
	92	2 836	697	99	89	86	77
35 – motor vehicles	85	495	118	82	78	79	75
	86	479	123	87	85	91	92
	87	497	136	92	86	94	90
	88	534	144	95	86	100	92
	89	550	151	98	89	103	95
	90	565	160	85	79	95	86
	91	580	169	77	68	85	79
	92	714	200	72	62	87	78
41 – food	85	1 442	180	89	92	165	168
	86	1 379	192	93	92	172	176
	87	1 406	209	88	83	162	162
	88	1 405	225	87	82	158	157
	89	1 415	243	89	86	167	166
	90	1 367	250	95	91	172	163
	91	1 385	259	103	96	178	167
	92	1 178	261	109	103	171	169
42 – sugar, drinks, tobacco	85	709	115	107	85	158	153
	86	672	121	114	91	170	178
	87	670	124	120	101	174	172
	88	640	129	112	94	161	158
	89	664	131	112	93	163	160
	90	636	135	114	90	163	150
	91	626	142	119	96	171	156
	92	505	136	134	105	188	172

Notation, see Table 3

Table 5. **Concentration and influence of innovating enterprises on the total.**

Code and economical activity	Year	C1	C2	P1	P2
14 – petroleum products	85	60.72	36.40	88.32	92.92
	86	51.20	39.47	81.35	84.30
	87	52.90	37.23	71.21	71.70
	88	55.92	36.34	85.02	84.70
	89	59.47	44.87	100.00	100.00
	90	74.03	37.18	100.00	100.00
	91	64.09	33.56	100.00	100.00
	92	73.04	34.67	100.00	100.00
33 – office mach./data prod. mach.	85	83.34	–	100.00	100.00
	86	82.76	49.04	100.00	100.00
	87	89.64	55.87	91.44	87.07
	88	87.69	57.30	91.70	87.01
	89	86.48	58.30	91.17	86.63
	90	84.38	74.51	76.91	64.18
	91	83.58	76.80	80.60	64.78
	92	91.67	62.81	93.18	87.07
34 – elect. engin. products	85	57.67	54.97	55.89	52.80
	86	57.02	54.10	57.99	53.98
	87	55.11	55.57	67.01	62.74
	88	56.10	58.32	65.86	63.65
	89	56.98	57.81	67.23	63.36
	90	56.20	58.91	71.57	69.53
	91	59.26	59.76	69.09	71.67
	92	58.95	59.15	71.40	74.16
35 – motor vehicles	85	83.52	87.08	86.66	78.20
	86	84.47	87.44	86.44	77.21
	87	85.74	88.87	77.68	71.88
	88	86.08	88.33	76.09	73.04
	89	86.06	88.80	74.62	73.47
	90	84.87	87.49	77.61	76.48
	91	81.26	86.52	96.09	94.74
	92	80.52	86.53	94.99	94.21
41 – food	85	44.10	40.69	27.07	21.37
	86	44.76	45.06	31.66	24.23
	87	43.57	42.48	33.50	29.27
	88	44.33	43.37	36.18	32.92
	89	43.73	45.74	43.61	39.63
	90	45.63	49.68	45.12	47.18
	91	45.83	51.30	48.41	50.05
	92	48.72	51.84	55.47	53.15
42 – sugar, drinks, tobacco	85	55.55	68.99	70.01	58.35
	86	58.18	67.23	69.97	58.36
	87	58.04	64.03	68.15	58.10
	88	58.48	63.29	70.72	61.79
	89	58.21	69.38	67.58	59.12
	90	57.86	68.33	66.61	61.37
	91	57.14	66.35	69.78	65.40
	92	59.89	67.25	72.86	67.31

C1 = index of concentration of total enterprises
C2 = index of concentration of innovating enterprises
P1 = % of turnover of innovating enterprises on the fifth percentile of the total enterprises
P2 = % of employees of innovating enterprises on the fifth percentile of the total enterprises

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THE IMPACT OF R&D ON PRODUCTIVITY: Evidence from Firm-Level Panel Data for Finland

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The study was concerned with the relationship between R&D and productivity in Finnish manufacturing firms. The analysis was based on the Cobb-Douglas production function modified to incorporate a variable describing R&D. Our specific concern was with estimating elasticities of production function parameters and particularly with analysing the productivity effects of R&D. The variable for R&D was R&D capital. The panel data covered the period from 1987 to 1993.

The methods used in the measurement of the production function differed in terms of whether the calculations were based on time-series or cross-sectional dimension of the data. The effect of the corrections for R&D double-counting on the estimates of R&D elasticity was examined. Also attention was paid to the effect of alternative depreciation rates of R&D capital on the estimates of R&D elasticity.

The results suggested that industrial R&D has a positive and statistically significant impact on productivity. For the entire set of firms, the within-firm estimates for R&D capital elasticity were within the range of 0.07 and 0.10 and the between-estimates within the range of 0.13 and 0.16. The differencies between different industry groups were quite clear. It was found that the productivity of R&D is significantly greater in the high-tech sector than in other branches. The relationship between R&D and productivity became stronger during the period under review, particularly in the early part of the 1990s. The same trend was evident in both the high-tech sector and other branches. The results were consistent regardless of the methods of measurement employed.

The effect of the depreciation rate of R&D capital on the estimated elasticity of R&D was found rather limited. However, the results indicate that,

when we use the 'perpetual inventory method', the differencies between the R&D elasticities based on different depreciation rates of R&D capital tend to grow as the time span gets longer from the starting point of the calculation of the R&D capital. The effect of the corrections on the R&D elasticity estimate was far clearer than the effect of different depreciation rates. When the corrections for double-counting of R&D were not made, the estimate of R&D capital elasticity was lower and the statistical significance of the estimate was weaker.

The generalizability of the results was undermined by problems of representativeness and the fact that the data comprised only a small portion of industrial companies with R&D activities. An important asset of the panel data was that it allowed an examination of the connections between R&D capital and productivity within the same firms over time.

Key words: R&D, Productivity, Panel Data, Manufacturing, Firm Level, Finland.

1. Introduction

This study is concerned with the dynamic performance of an information-intensive economy and, in particular, with the contribution of research and development (R&D) to the economic performance and productivity of Finnish manufacturing firms. The ongoing process of economic restructuration is reflected, specifically, in changing production procedures as well as in regional, industrial and firm-level changes in organisational structures. The major features linked with these changes are the increasing importance attached to the role of R&D and innovativeness, as well as the broad and rapid introduction of new technologies.

Manufacturing firms vary widely in terms of success and productivity and in terms of how they experience and respond to economic fluctuations. During the past decade, high-tech firms (businesses engaged e.g. in information technologies, new materials technologies, and biotechnologies) have represented a major growth sector. At the same time as the number of high-tech manufacturing firms and research activities has been growing, R&D has gained more attention in terms of company productivity and competitiveness. Although not all manufacturing firms operate in technology-intensive sectors, there are many good reasons for firms to emphasise the role of R&D. According to Rosenberg (1990, 171), there are numerous activities that are crucial to business success and that depend heavily upon a research capability.

This may be the case even if that capability does not play a direct role in solving industrial problems.

The dynamic role of research capability can be described as follows. Firstly, in order to evaluate the potential benefit of a given technology, firms need to obtain information about that technology. However, it is important that firms are capable both of understanding the value of the information that is available and of processing that information for their own purposes. And secondly, in order to be able to adopt and introduce a certain technology and in order to be able to manage the application of that technology, firms often need a vast pool of knowledge and R&D resources.

The point that needs to be stressed here is that R&D not only generates product and process innovations, but it also generates new information which enhances the firm's ability to make the best possible use of the knowledge available from the techno-economic environment (see Cohen & Levinthal 1989, 569). In short, it is essential for manufacturing firms to acknowledge the central long-term strategic productivity-related function of internal R&D. The effect of R&D on the overall activities of manufacturing firms can thus be very far-reaching.

2. Aims of the Study

The increasing use of new key technologies, the growing need for a highly skilled and competent workforce, and the growing requirements of carrying internal R&D have all generated a renewed and growing research interest in the question of productivity in manufacturing firms (see Science and Technology... 1994). It has become clear that we need more information about the fundamental preconditions for doing research and about its various effects. Studies concerned with the productivity of manufacturing firms and R&D have focused on the following questions: What has happened to productivity, what has happened to R&D, and what has happened to the relationship between productivity and R&D?

The theoretical framework for this study is provided by the Cobb-Douglas production function. The purpose is to investigate:

- The relationship between R&D and productivity and changes in this relationship in Finnish manufacturing firms during the period from 1987 to 1993.
- The effect of the rate of depreciation on estimates of R&D capital elasticity.
- The effect of the corrections for R&D double-counting.

The focus of the study is thus on the R&D variable of a production function model and on estimating the elasticity of R&D. Both cross-sectional and time-series estimates will be presented of R&D elasticity. The study is based on the new firm-level panel data compiled at Statistics Finland. The data include information on production, the labour force, physical capital and R&D activities in Finnish manufacturing firms.

3. Theoretical Framework

Model

For purposes of studying the impact of R&D on firm output or productivity, we need to modify the traditional Cobb-Douglas function by incorporating a variable that describes R&D capital (see Mairesse and Sassenou 1991, 11–12; Hall and Mairesse 1995, 268–269). The baseline assumption is that the production function of manufacturing firms can be written on the basis of the Cobb-Douglas function so that firm productivity Y_{it} (e.g. value added or labour productivity) is explained by three factors: L is labour input (e.g. the number of workers, person-years or working hours put in), C is physical capital and K is the amount of annual R&D expenditure or cumulative R&D capital. The function can be expressed as follows:

$$Y_{it} = Ae^{\lambda t} C_{it}^{\alpha} L_{it}^{\beta} K_{it}^{\gamma} e^{\varepsilon_{it}} \qquad i=1,...,N;\ t=1,...,T, \tag{1}$$

where A is constant and α, β and γ are the elasticity coefficients of physical capital, labour input and R&D capital. λ refers to the rate of disembodied technological change. ε is the error term of the equation, indicating the effect of factors that have not been taken in account in the structure of the model as well as other disturbance factors (see Griliches & Mairesse 1984, 344; Mairesse 1990; Baltagi 1995). The error term follows a normal distribution with a mean of 0 and a variance of δ^2. Subscripts i and t refer to the industrial firm and time. If the three dependent variables in the model produce constant returns to scale, the sum total μ of their elasticity coefficients is 1 (i.e., $\alpha + \beta + \gamma = 1$).

An important feature of the Cobb-Douglas function is that by taking logarithms from the variables, the function can be estimated as a linear regression equation:

$$y_{it} = a_{it} + \alpha c_{it} + \beta l_{it} + \gamma k_{it} + \varepsilon_{it} \ , \tag{2}$$

where the small letter stands for the variable's logarithm. The term $a_{it} = a_i + \lambda t$ is a firm- and time-specific indicator of technological level and other firm characteristics. In a panel material, this can be taken into account by calculating from the production function "within-firm estimates" based on firm-specific effects.

In the models above, the realisation of constant returns to scale can be studied on the basis of the sum total of the estimated elasticities of production factors. If we assume that the constant returns of scale do not materialise, equation 2 can be so modified that the effect of the labour input variable l is subtracted from both sides of the equation (e.g. Cuneo and Mairesse 1984; Griliches and Mairesse 1984, 1990; Hall and Mairesse 1995):

$$(y_{it} - l_{it}) = a + \lambda t + \alpha(c_{it} - l_{it}) + \gamma(k_{it} - l_{it}) + (\mu - 1)l_{it} + e_{it} \qquad (3)$$

The writing of the production function as in equation 3 is generally justified for interpretative reasons. If we subtract the effect of the labour input variable from both sides of the equation, we can explicitly measure any deviation from constant returns to scale. In this case the coefficient $(\mu - 1)$ of the logarithm of the labour input variable indicates the extent of the deviation from constant returns to scale. In the assumption of constant returns to scale $(\mu - 1)$ is left open or given the value 0. In this study, the theoretical framework for the analysis of the relationship between R&D and firm productivity is provided by models 2 and 3. In the results reported here, the estimates of labour elasticity refer to a situation where the coefficient of the logarithm of labour is $(\mu - 1)$.

Although the analysis here focuses on the variables' elasticity coefficients, it is important to recognise the meaning of the error term ε_{it}. The error term is usually interpreted to comprise all errors linked to the model's variables. These errors are based: a) on errors of measurement, b) on the different production functions of different firms; and c) on inadequate analysis and specification of the variables. However, a more detailed analysis of the contents of the information provided by the error term is a complex process. The most central component of the size of ε_{it} is probably related to the heterogeneity of the technologies and modes of production employed by the firms concerned. This firm-level difference which remains unmeasured is directly reflected in the model's disturbance or error component. Another important component with regard to ε_{it} has to do with changes in productivity over time, which are common to all firms. In the analysis of the error term, we must also take account of the errors related to the price deflators used as well as the effects of other factors that have a bearing on the real quantities of measured outputs and inputs (e.g. Mairesse 1990; Hall and Mairesse 1995).

Calculations have usually used the one-way error component model to take account of error and disturbance factors (see Baltagi 1995: 9–10). In this case the error term of consists of two separate components:

$$\varepsilon_{it} = \mu_i + \upsilon_{it} \ , \tag{4}$$

where the term μ_i is invariant in relation to time and refers to such firm-specific characteristics that have not been taken into account in the structure of the model. The component can be interpreted as describing such factors as management skills and strategic vision within the firm or its ability to make good use of communication channels outside the firm that are supportive of its R&D activities. υ_{it} describes the remaining perturbation and it varies in relation to firm and time. It may also be interpreted to comprise short-term changes in capacity utilisation (Griliches & Mairesse 1984, 344). With the exception of the within-estimates, we have used model 4 in this study. In the case of within-estimates, we employ a two-way model in which the structure of the error term is as follows (e.g. Baltagi 1992, 206–209; Baltagi 1995, 27–46, 219–220):

$$\varepsilon_{it} = \mu_i + \lambda_t + \upsilon_{it} \tag{5}$$

The error term in the model is divided into three components, of which μ_i is time invariant and describes unnoticed firm-specific characteristics. λ_t is invariant in relation to firms and it comprises an unnoticed time effect; it is thus the period-specific component. υ_{it} is the remaining stochastic error term, which can be regarded as the two-dimensional part of the measurement error. These error components are independent of each other. Based on model 5, the variability can be decomposed as follows:

$\sum_i \sum_t (x_{it} - \bar{x}_i)$ is the within-firm variability referring to μ_i,

$\sum_i \sum_t (x_{it} - \bar{x}_t)$ is the within-period variability referring to λ_t,

$\sum_i \sum_t (x_{it} - \bar{x}_i - \bar{x}_t - \bar{x})$ is the within period-firm variability referring to υ_{it},

where

$\bar{x}_i = \frac{1}{T} \sum_t x_{it}$ is the mean of the firm i,

$\bar{x}_t = \frac{1}{N}\sum_i x_{it}$ is the mean of the period t,

$\bar{x} = \frac{1}{NT}\sum_i \sum_t x_{it}$ is the overall mean.

The Accumulation of R&D Capital

A perpetual inventory method used for the measurement of physical capital is often applied for purposes of determining the amount of R&D or information capital in a given firm (e.g. Griliches 1979; Hall and Mairesse 1995). The equation for determining capital K for R&D activities is as follows:

$$K_t = R_t + (1-\delta)R_{t-1} + (1-\delta)^2 R_{t-2} + \ldots = R_t + (1-\delta)K_{t-1} \quad (6)$$

where K_t is the value of R&D capital in year t, R_t is the deflated R&D expenditure during year t and δ is the annual rate of depreciation for R&D capital. The method is useful enough for panel studies but it requires data on R&D expenditure over a very long period of time as well as appropriate indices for deriving real values of R&D capital and suitable depreciation rates. If data on R&D expenditure commence from year $t = 1$, for instance, the amount of cumulated R&D capital is obtained from equation 6. The problem here is that comprehensive data are not available on R&D expenditure over long periods. If data can be obtained on R&D expenses from the beginning of the time period concerned and R&D expenses have increased during the time preceding a certain measurement period at a rate of g, then the amount of R&D capital for the first year can be determined on the basis of the following equation:

$$\begin{aligned} K_1 &= R_0 + (1-\delta)R_{-1} + (1-\delta)^2 R_{-2} + \ldots \\ &= \sum_{s=0}^{\infty} R_{-s}(1-\delta)^s = R_0 \sum_{s=0}^{\infty}\left[\frac{1-\delta}{1+g}\right]^s = \frac{R_1}{g+\delta}. \end{aligned} \quad (7)$$

However, the measurement of the R&D capital variables involves certain problems associated with the characteristics of the variable that must be taken into account in interpreting the results. Firstly, research is very often a long-term process, and investments in research are not reflected in productivity very rapidly. Secondly, no exact data are available on the depreciation of

R&D investments. Thirdly, it must also be observed that the net increase in R&D capital reserves is not identical to the gross value of recent investments adding to capital reserves. And fourthly, when we consider a firm's intramural R&D expenditure as a measure of the R&D variable, this implies the assumption that the relationship between the firm's R&D and productivity depends on its own R&D expenditure, not on the amount it spends on foreign technology or on the amount spent on R&D elsewhere. Consequently, the amount of information in different companies and in different lines of industry cannot be directly inferred from the volume of their own R&D activities because it is very much influenced by technological diffusion in its various forms. All in all, the problems related to the determination of R&D capital are very complex. Other methods and applications apart from those used in the present study for determining the level of R&D capital are also available (e.g. Bartelsman et al. 1995; Klette & Johansen 1996).

Operationalization of Variables

The R&D capital stock (K) is calculated on the basis of Statistics Finland's figures for annual R&D expenditure. This still leaves us with the problem of the stock for the initial year. That can be estimated in accordance with equation 7 by using the long-term growth percentage g and depreciation coefficient δ. In principle, the depreciation rate is determined on the basis of the estimated average service life of the technology concerned as well as the form of its survival function (see Virtaharju & Åkerblom 1993, 28–33; Hall & Mairesse 1995, 287). However, there exists no unambiguous theoretical or empirical basis for setting this value. In addition, it may be assumed that depreciation rates will vary between individual firms. Therefore researchers have usually operated with assumptions that they have considered most appropriate. In this study, we have used the values of 0.1 and 0.3 for and compared the results obtained with these coefficients.

Data on R&D expenditure are available from 1971 onwards. The estimate used here for growth rate g is the same as the average real annual growth recorded for R&D expenditure in the private sector between 1971 and 1985, which was eight per cent. Since the figure for R&D expenditure R is only obtained for every other year, the interim years were estimated on the basis of the mean figure $(R_t+R_{t-2})/2$. For the operationalization of the other variables, there is the option of using either Statistics Finland's industrial statistics or final statements statistics (see Husso, Leppälahti, Niininen 1996, 20–21). In this study, the variables for value added (Y), labour input (L) and physical capital (C) are obtained from the industrial statistics. This is how the variables are defined:

Industrial statistics:

Y = gross value of production – value of production inputs,
L = number of personnel,
C = value of physical capital.

The problem here is that the value of physical capital is not obtained directly but it has to be estimated on the basis of acquisitions of machinery and equipment. Figures are only available on annual expenditure, i.e., investment in machinery and equipment. Since the value of the stock was not available, that has been estimated in the same manner as research capital. The choice of depreciation rate for physical capital involves similar problems as in the case of research capital: there are no straightforward grounds for the value of the physical capital coefficient, and researchers therefore often have to content themselves with picking a coefficient that seems appropriate. The value used here for the depreciation rate is 0.05. The values for the initial stock are based on data from the 1985 industrial statistics on the replacement value of fixed assets.

The overlap between physical capital and research capital has been regarded as one of the key problems in calculations based on production functions. In this study, the double-counting of physical capital (C) and research capital (K) was corrected by subtracting from physical capital the acquisition costs of fixed assets included in R&D expenditure. As for labour input (L), it has been considered problematic that it is not always possible to subtract R&D personnel from total personnel numbers in the firm. In this study, the effects of overlap between the R&D variable and the labour variable were examined by calculating the elasticity coefficients of R&D capital in corrected form without double-counting and in a situation where this correction was not made.

4. Description of the Panel Data

The research material for this study comprises Statistics Finland's R&D and industrial statistics for the period 1987–1993. These statistics have been linked together at the firm level. The data sets formed on this basis are divided into two main groups. A so-called balanced firm panel has been formed of the statistics so that both cross-sectional estimates and time-series estimates can be calculated. Since the questionnaires carried out in the 1980s for the R&D statistics involved only limited overlap in terms of the firms included, the number of firms in the panel is comparatively small. Because of the size of the panel data set, the firms were crudely divided into only two groups, viz. firms in high-tech branches and other industries. Hi-tech manufacturing industries included the manufacture of chemicals and chemical products (Nace Rev.1, mainly class 24), the manufacture of machinery and equipment (mainly class 29), the manufacture of electrical machinery and instruments (mainly classes 30, 31, 32 and 33), and the manufacture of transport equipment (mainly class 35). All other branches were combined into the single category of other industrial branches. The panel material was so processed that outlier firms were excluded. A more detailed description of the firms included in the panel and of the exclusion of outlier firms is presented in the study by Husso, Leppälahti and Niininen (1996), which uses the same data set.

The panel comprises a total of 74 companies, of which 40 operate in high-tech industries and 34 in other branches. Middle-sized and large firms are clearly overrepresented in the panel, indicating a skewed distribution. There are also clear differences in the volume and nature of company activities in different branches. In high-tech firms, R&D capital and R&D investment are at a higher level than in other companies. This, at least as far as R&D variables are concerned, was consistent with expectations. Firms in other industries, for their part, are clearly bigger when measured in terms of value added, staff numbers and physical capital.

Figures 1 and 2 describe the real development of key variables during the panel period. The decline in industrial output and above all the clear decrease in the use of labour inputs are also clearly in evidence in the panel. The combined value added of the firms decreased by 14.3 per cent from 1987 to 1993. This decrease was particularly sharp from 1989 to 1991. The decrease in staff numbers was even more dramatic, falling by 22.8 per cent during the period examined. The trend in the number of R&D personnel deviated throughout the period concerned from the trend in total personnel numbers, which remained unchanged until 1989, after which they began to decrease. On the other hand, staff numbers in R&D increased until 1989. The figures then began to decrease, but the decrease was not as dramatic as in the case of total personnel numbers. In 1993 the number of R&D personnel was 3.8 per cent higher than in 1987.

Figure 1. **Real development of panel variables, index 1987=100.**

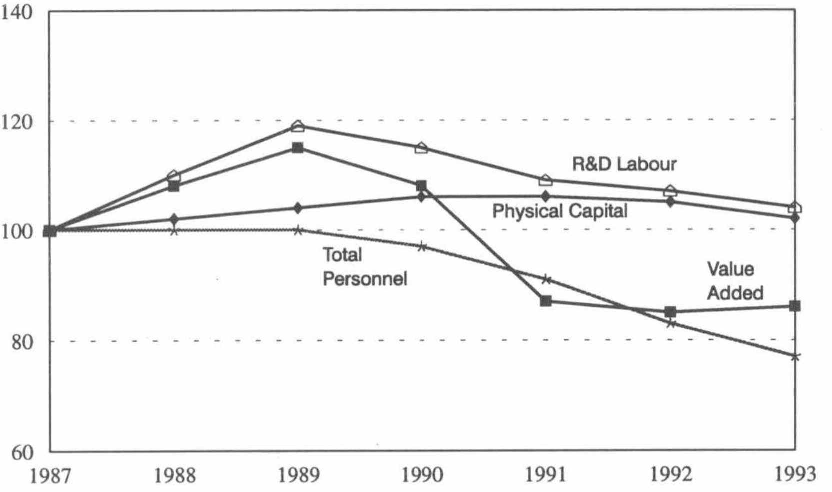
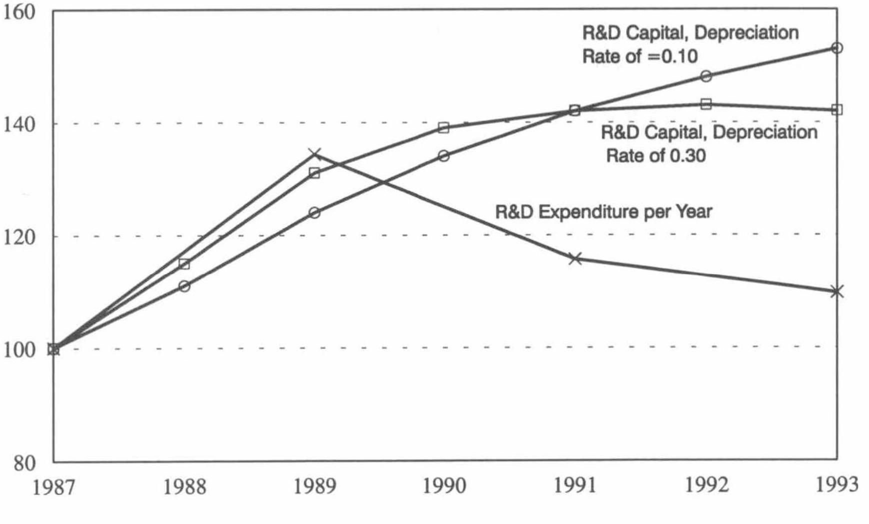


Figure 2. **Real development of R&D capital and annual R&D expenditure of the panel firms. Capital is calculated on the basis of depreciation rates of 0.10 and 0.30.**



During the period under review, the panel firms became much more intensive in terms of R&D capital. Calculated on the basis of a 0.10 depreciation rate, R&D capital increased from 1987 to 1993 by around 53 per cent, averaging 7.4 per cent a year. When the depreciation rate of 0.30 was used, R&D capital in the panel firms increased by around 42 per cent; average growth per annum was 6.0 per cent. During this period R&D expenditure increased by 9.7 per cent. Expenditure increased sharply until 1989, and then the real volume started to decline. Physical capital increased by only 2.2 per cent during the period under review. Overall the period can certainly not be described as one of steady growth, but rather as a more or less troubled period characterised by quite dramatic cyclic fluctuations. This is also reflected in the panel firm's variables.

The information about the development of productivity and R&D intensity (R&D expenditure/value added) in the panel firms and in the whole industry can be summarised as follows (see also Husso, Leppälahti & Niininen 1996, 23–32):

- The average real labour productivity has increased significantly during the period under review. Throughout this time labour productivity in the panel firms has been much higher than in the industry as a whole. Productivity decreased in the industry between 1989 and 1991, but then started to improve again. However, the trends in productivity have been consistent with those for the whole industry. In the panel data, the difference in the productivity between high-tech and other industries increased in the early 1990s with the onset of the recession.

- In high-tech branches, R&D intensity has remained at over 10 per cent throughout the panel. In other branches it has been at a clearly lower level, i.e. between 2–3 per cent. The difference between panel firms and the whole industry has decreased during the period under review.

Depending on the year examined, the panel firms account for 14.8–15.6 per cent of the entire industry's workforce, 23.1–31.1 per cent of its R&D expenditure and 17.7–21.0 per cent of its value added. Although the number of firms is relatively small, they cover a fairly large share of the industry's activities, at least in the light of these indicators. It has not been possible to present reliable calculations of the share of physical capital and R&D capital because comparable statistics on the whole industry are not available.

Judging by the parameters discussed, the panel firms differ from the manufacturing industry as a whole in terms of their higher R&D expenditure and intensity as well as in terms of their higher labour productivity. Large and medium-sized firms with R&D activities are overrepresented in the panel. Compared with the manufacturing industry as a whole, the volume of R&D activities is above average. Generally, however, the panel firms have responded to the changes taking place in the economy in a very similar fashion as other industrial companies. This is clearly seen if we look at the trends in staff numbers, value added, labour productivity and R&D activities in the panel firms and in the industry as a whole.

5. Results

Two basic statistical methods were used in his study to measure the production function. These methods differ from each other in terms of whether the estimates calculated are based on time-series or cross-sectional dimension of the data. The estimates are obtained using models 2 and 3, while deviations from constant returns to scale are obtained using model 3 (i.e., coefficient $\mu - 1$). Cross-sectional estimates are obtained by calculating the so-called between-firm regression. The between-firm estimates differ from the traditional annual cross-sectional estimates in that these estimates are based on time-series data and cover the whole period under review. The between-firm estimates are based on a "mean cross-section", i.e. they are performed on the individual firm means of variables over several years, i.e. $x_{i.} = 1/T \sum_{t=1}^{T} x_{it}$.

The estimates are based on between-firm differences in the levels (or values) of variables and they are calculated by the ordinary least squares method. Between-estimates usually come very close to so-called total estimates. On the other hand, they generally differ clearly from time-series estimates, i.e., from so-called within-estimates. This is explained by the fact that total variability comprises variability in the level of variables both within and between firms. Variability in the levels of the variables between firms is usually much greater than the variability within firms.

The within-estimates, for their part, take into account the changes in the level of variables within each individual firm. This means that the levels of the variables themselves are of no consequence. The estimates take into account the deviations of firm-specific variable levels from the mean figures of each variable for the whole period under review, i.e., $x_{it} - x_{i.}$.

The production function estimates of R&D capital elasticity were calculated by using the following three different construction methods of the R&D variable:

a corrections for R&D double-counting made, rate of depreciation of R&D capital 0.30;

b corrections for R&D double-counting made only in part (number of researchers is not subtracted from the total number of employees), rate of depreciation 0.30; and

c corrections for R&D double-counting made, rate of depreciation 0.10.

The purpose of constructing the R&D variable in different ways was to ascertain the effects of different rates of depreciation used in the calculation of R&D capital on the estimates of R&D elasticity and to find out what kind of effect double-counting of the R&D variable and the labour input variable has on the estimate of R&D capital elasticity.

The relationship between production factors and productivity was examined by cross-section estimates that cover the whole panel period from 1987 to 1993, i.e. the between-firm estimates based on a "mean cross-section" method. Two separate calculations were also made for the between-estimates (and for the within-estimates in Chapter 5.2.), of which the former covered the period from 1987 to 1990 and the latter the period from 1990 to 1993. The aim was to shed light on how the link between R&D activities and output, and, followngly, between R&D and productivitiy changed in the panel firms during these two, very different kinds of periods. The year 1990 was a sort of watershed in terms of economic development in the sense that in 1990 Finland was still enjoying an ongoing economic upswing, even though there were already signs of an imminent downturn.

Between-Estimates of R&D Elasticity

The production function between-estimates for the period 1987–1993 are shown in Tables 1, 2 and 3. We shall begin by looking at the results of the production function based on a R&D capital depreciation rate of 0.30 and with the corrections for R&D double-counting made (Table 1). The estimate of R&D capital elasticity for the whole period was 0.16. In high-tech industries, the estimate was comparatively high, i.e., 0.19, whereas in other branches it was 0.11. Judging on the basis of the R&D elasticity estimates of different branches, the links between R&D and productivity were considerably stronger in high-tech branches than in other industries. The p-values of the estimates were below 0.01, i.e., they were statistically very significant for the whole panel and for high-tech branches, whereas on the basis of the *p*-value (0.05), the estimate of R&D elasticity in other branches was statistically significant.

R&D elasticity estimate in the whole material for the period of 1987–1990 was 0.11 and for the 1990s period 0.19. The estimated elasticity thus increased by 0.08. An increase of the same magnitude also occurred in the

Table 1.
Between-firm estimates of production function for the 1987–1993 panel firms. Separate estimates are also given for the panel periods 1987–1990 and 1990–1993. The corrections for R&D double-counting are made, i.e., the number of researchers is subtracted from the total number of employees and physical capital devoted to R&D activities is deducted from total physical capital. The rate of depreciation of R&D capital is 0.30.

Dependent variable:
Log(Value added/Employee), constant returns to scale not imposed.

Time	1987–1993		1987–1990		1990–1993	
Physical capital log(C/L)	**0.145**	**(0.039)****	**0.162**	**(0.040)****	**0.121**	**(0.042)****
high-tech branches	0.143	(0.052)**	0.158	(0.051)**	0.134	(0.054)*
other branches	0.171	(0.070)*	0.209	(0.074)**	0.109	(0.078)
R&D capital log(K/L)	**0.156**	**(0.026)****	**0.107**	**(0.025)****	**0.186**	**(0.027)****
high-tech branches	0.194	(0.045)**	0.122	(0.043)**	0.240	(0.049)**
other branches	0.109	(0.048)*	0.059	(0.045)	0.142	(0.054)*
Labour log(L)#	**0.043**	**(0.059)**	**0.057**	**(0.061)**	**0.038**	**(0.062)**
high-tech branches	0.036	(0.083)	0.057	(0.082)	0.021	(0.086)
other branches	0.046	(0.094)	0.044	(0.103)	0.063	(0.103)
R^2	**0.959**	**(0.297)**	**0.954**	**(0.320)**	**0.953**	**(0.317)**
high-tech branches	0.964	(0.316)	0.963	(0.329)	0.962	(0.326)
other branches	0.948	(0.285)	0.936	(0.321)	0.938	(0.312)

Elasticity estimates and standard errors for all panel firms and for high-tech firms and other branches separately.

** p-value 0,01 < * 0,05 p-value ≥ 0,01 in other cases the estimate of physical capital or R&D capital is not statistically significant at below 5 % risk level.

R^2 = coefficient of determination; root mean standard error in parentheses.

= The coefficient of the logarithm of labour (L) measures here the departure from constant returns to scale (CRS), i.e. the difference of the sum of factor elasticities ($\mu = \alpha+\beta+\gamma$) from CRS value 1 ($\mu-1$). Standard error of L is for the elasticity estimates of the original value of log(L), not for ($\mu-1$).

The basic figure for the variable to be explained in the model (Y) is value added, which has been obtained from Statistics Finland's industrial statistics. The independent variables are as follows: labour input (L) is a firm's total personnel minus R&D personnel (industrial statistics and R&D statistics); the variable describing physical capital (C) is based on cumulated value of machinery and equipment acquisitions (industrial statistics); and the variable describing R&D capital (K) is based on cumulated intramural R&D expenditure (R&D statistics).

estimate of R&D elasticity in other industries (from 0.06 to 0.14). The most significant change was seen in the estimate of high-tech branches, with R&D elasticity estimate increasing from 0.12 to 0.24.

The estimates of R&D elasticity for the 1990s were considerably higher than the corresponding estimates for the 1980s. At the same time, the R&D elasticity for high-tech branches was considerably higher than in other branches. It is noteworthy that the between-estimates of R&D elasticity especially for the 1990s were in the expected range and consistent with the annual cross-section estimates published in the study by Husso, Leppälahti and Niininen (1996, 34). In addition, the between-estimates of physical capital elasticity corresponded even better with the results for annual cross-sections in the same study.

The results shown in Table 2 differ from those reported above in that no correction is made here for R&D double-counting. The estimate of R&D elasticity extending across the whole period was 0.13 for all firms. In high-tech branches, the figure was 0.15 and in other branches 0.09. During the

Table 2.
Between-firm estimates of production function for the 1987–1993 panel firms. Separate estimates are also given for the panel periods 1987–1990 and 1990–1993. The corrections for R&D double-counting are made only in part, i.e., the number of researchers is not subtracted from the total number of employees. The rate of depreciation of R&D capital is 0.30.

Dependent variable: Log(Value added/Employee), constant returns to scale not imposed.		
Time	1987–1993	1987–1990	1990–1993
Physical capital log(C/L)	**0.145 (0.037)****	**0.159 (0.038)****	**0.119 (0.040)****
high-tech branches	0.141 (0.049)**	0.153 (0.048)**	0.132 (0.052)*
other branches	0.169 (0.069)*	0.204 (0.073)**	0.106 (0.077)
R&D capital log(K/L)	**0.126 (0.025)****	**0.078 (0.025)****	**0.157 (0.027)****
high-tech branches	0.152 (0.045)**	0.078 (0.042)	0.203 (0.049)**
other branches	0.093 (0.047)	0.046 (0.044)	0.124 (0.053)*
Labour log(L)#	**0.047 (0.058)**	**0.063 (0.059)**	**0.040 (0.062)**
high-tech branches	0.040 (0.084)	0.065 (0.081)	0.025 (0.087)
other branches	0.051 (0.094)	0.051 (0.103)	0.066 (0.104)
R^2	**0.962 (0.287)**	**0.959 (0.305)**	**0.956** (0.307)
high-tech branches	0.967 (0.303)	0.968 (0.309)	0.964 (0.315)
other branches	0.949 (0.281)	0.939 (0.314)	0.939 (0.308)

Notation, see Table 1.

period 1987–1990 R&D elasticity for the whole material was 0.08 and during the period between 1990 and 1993 much higher at 0.16. In high-tech industries R&D elasticity estimate increased between the two periods even more, i.e., from 0.08 to 0.20. The R&D estimate for other branches increased from 0.05 to 0.12. The development of R&D elasticity estimate was very similar in all cases. The increase in the elasticity coefficient between the two periods was also of the same magnitude when the corrections for R&D double-counting were made. In both cases, the R&D elasticity coefficient for the period covering the 1990s was 0.07–0.13 higher than during the earlier period.

When the correction for R&D double-counting was not made, the estimate of R&D capital elasticity decreased by 0.01–0.04. This decrease in the elasticity coefficient was most clearly seen in high-tech branches. In addition to the effect of R&D double-counting on the level of the between-firm estimates of R&D elasticity, the results indicate that when the correction for R&D double-counting was not made, the statistical significance of the estimates of R&D elasticity was lower. This was not apparent in all figures, but in some of them.

The estimate of R&D capital elasticity based on the depreciation rate of 0.10 was 0.15 for all branches (Table 3). The estimate for high-tech industries was slightly higher at 0.17, in other industries 0.10. The p-values of the R&D elasticity estimates for all panel firms as well as for high-tech firms were below 0.01. Thus, the estimates were statistically highly significant. In other industries, the only estimate of R&D elasticity that was not significant (as judged on the basis of its p-value) was that for 1987–1990.

R&D elasticity for the whole group of panel firms during the 1980s period was 0.11; and for the 1990s period 0.17. The estimated elasticity increased between these two periods by 0.06. The rise in the estimate of R&D elasticity was roughly of the same order as in the case of other industries (from 0.06 to 0.11). The most significant change occurred in the R&D elasticity estimates of high-tech firms. The estimate of R&D elasticity increased from 0.11 to 0.21. The rise in the R&D elasticity estimate between the two periods was similar to the situation where the depreciation rate was 0.30. However, the choice of depreciation rate had some effect on the level of the estimates of R&D elasticity. Compared to the results based on the depreciation rate of 0.30, the estimates of R&D capital elasticity were for all firms by no more than 0.02 lower. In high-tech companies, the decrease in R&D elasticity estimate was between 0.01 and 0.03; in other industries, the change in elasticity estimate was between +0.01 and –0.03. The effect of the depreciation rate on the level of the estimate of R&D elasticity

Table 3.
Between-firm estimates of production function for the 1987–1993 panel firms. Separate estimates are also given for the panel periods 1987–1990 and 1990–1993. The corrections for R&D double-counting are made, i.e., the number of researchers is subtracted from the total number of employees and physical capital devoted to R&D activities is deducted from total physical capital. The rate of depreciation of R&D capital is 0.10.

Dependent variable: Log(Value added/Employee), constant returns to scale not imposed.			
Time	**1987–1993**	**1987–1990**	**1990–1993**
Physical capital log(C/L)	**0.149 (0.040)****	**0.163 (0.040)****	**0.125 (0.043)****
high-tech branches	0.148 (0.053)**	0.160 (0.052)**	0.140 (0.056)*
other branches	0.181 (0.070)*	0.206 (0.073)**	0.131 (0.080)
R&D capital log(K/L)	**0.145 (0.025)****	**0.105 (0.025)****	**0.171 (0.028)****
high-tech branches	0.174 (0.044)**	0.113 (0.041)**	0.212 (0.049)**
other branches	0.095 (0.046)*	0.064 (0.044)	0.112 (0.054)*
Labour log(L)#	**0.043 (0.060)**	**0.057 (0.060)**	**0.038 (0.064)**
high-tech branches	0.036 (0.085)	0.059 (0.082)	0.023 (0.089)
other branches	0.045 (0.095)	0.045 (0.103)	0.058 (0.106)
R^2	**0.957 (0.304)**	**0.954 (0.320)**	**0.949 (0.330)**
high-tech branches	0.962 (0.325)	0.963 (0.332)	0.958 (0.342)
other branches	0.946 (0.289)	0.937 (0.319)	0.933 (0.323)

Notation, see Table 1.

The basic figure for the variable to be explained in the model (Y) is value added, which has been obtained from Statistics Finland's industrial statistics. The independent variables are as follows: labour input (L) is a firm's total personnel minus R&D personnel (industrial statistics and R&D statistics); the variable describing physical capital (C) is based on cumulated value of machinery and equipment acquisitions (industrial statistics); and the variable describing R&D capital (K) is based on cumulated intramural R&D expenditure (R&D statistics).

was somewhat lesser than the effect of the correction for R&D double-counting. As expected, the results suggest that the choice of depreciation rate makes no difference in terms of the statistical significance of the estimates of R&D elasticity.

One of the special characteristics of the perpetual inventory method is linked with the fact that the start-point for the calculation of R&D capital and the start-point for the calculation of the estimates was the same year. The results suggest that the longer the time period for which the estimates of elasticity since the start-point of R&D capital calculations are calculated, the greater are the differences between the estimates of R&D capital elasticity calculated with different depreciation rates. These observations are at least partly explained by the way in which the R&D capital depreciation rate works when the perpetual inventory method is used. Although the values of capital stock vary with different depreciation rates, the relative differences between the capital stock figures for observation units in the start-year of the calculation remain constant. The differences between the observation units in the levels of capital value and their relative differences only begin to fluctuate after the start-year when the units' annual R&D expenditures are added cumulatively to the capital stock.

Notwithstanding the alternative depreciation rates of R&D capital and the alternative ways in which double-counting was handled, the different calculations shared the following features in common: Firstly, the different alternatives did not have a significant effect on the standard errors of the estimated elasticity coefficients. Secondly, they had hardly any effect on the deviations from constant returns to scale. And thirdly, the degree of explanation remained more or less unchanged (varying ± one percentage points) in spite of the different depreciation rates and methods of double-counting.

Time-series Estimates of R&D Elasticity

The within-firm estimates based on time-series data are shown in Tables 4, 5 and 6. When the depreciation rate of 0.30 for R&D capital was used and corrections for R&D double-counting were made, the within-estimate for R&D capital elasticity was 0.09 (Table 4). The difference between the estimates for different branches were significant: the figure for high-tech branches was 0.13 and for other branches only 0.04. The relationship between R&D and productivity in high-tech industries was thus clearly stronger. The estimates for all panel firms and for high-tech companies were statistically highly significant in contrast to the situation in other branches.

As in the case of the between-estimates, two separate calculations were made of the within-estimates; the first covered the period from 1987 to 1990, the second the period from 1990 to 1993. The within-estimates helped to throw light on how the links between R&D and productivity changed within firms during these two periods. The estimate of R&D elasticity for all the branches rose from 0.10 in the 1987–1990 period to 0.13 in 1990–1993, i.e., R&D elasticity went up by 0.03. In high-tech industries, the elasticity of R&D capital rose from 0.16 to 0.19. In other branches, the estimated elasticity was at a very low level during both periods and increased only from 0.03 to 0.04. According to the results, the estimates of R&D elasticity during

Table 4.
Within-firm estimates of production function for the 1987–1993 panel firms. Separate estimates are also given for the panel periods 1987–1990 and 1990–1993. The corrections for R&D double-counting are made, i.e., the number of researchers is subtracted from the total number of employees and physical capital devoted to R&D activities is deducted from total physical capital. The rate of depreciation of R&D capital is 0.30.

Dependent variable: Log(Value added/Employee), constant returns to scale not imposed.						
Time	**1987–1993**		**1987–1990**		**1990–1993**	
Physical capital log(C/L)	**0.150**	**(0.029)****	**0.182**	**(0.031)****	**0.154**	**(0.039)****
high-tech branches	0.163	(0.037)**	0.166	(0.038)**	0.157	(0.050)**
other branches	0.143	(0.055)**	0.189	(0.061)**	0.203	(0.074)**
R&D capital log(K/L)	**0.092**	**(0.019)****	**0.102**	**(0.020)****	**0.129**	**(0.026)****
high-tech branches	0.126	(0.031)**	0.163	(0.032)**	0.193	(0.047)**
other branches	0.039	(0.028)	0.028	(0.031)	0.035	(0.043)
Labour log(L)#	**0.033**	**(0.041)**	**0.021**	**(0.044)**	**0.016**	**(0.055)**
high-tech branches	0.037	(0.048)	0.019	(0.052)	0.019	(0.072)
other branches	0.051	(0.075)	0.039	(0.086)	0.012	(0.098)
Root MSE ja VCF	**0.246**	**(0.084)**	**0.174**	**(0.097)**	**0.252**	**(0.096)**
high-tech branches	0.250	(0.093)	0.166	(0.105)	0.259	(0.100)
other branches	0.234	(0.080)	0.172	(0.096)	0.241	(0.091)

Notation, see Table 1.

VCF=variance component fo firms.

The basic figure for the variable to be explained in the model (Y) is value added, which has been obtained from Statistics Finland's industrial statistics. The independent variables are as follows: labour input (L) is a firm's total personnel minus R&D personnel (industrial statistics and R&D statistics); the variable describing physical capital (C) is based on cumulated value of machinery and equipment acquisitions (industrial statistics); and the variable describing R&D capital (K) is based on cumulated intramural R&D expenditure (R&D statistics).

the 1990–1993 period were higher than in the period 1987–1990. In other words, the relationship between R&D and productivity grew closer during the recession, whereas the estimate of physical capital elasticity declined during the 1990s, pointing at a weakening of the link between physical capital and productivity.

The results in Table 5 differ from those discussed above in that the correction for the R&D double-counting is not made. The estimate for R&D elasticity covering the whole panel period was 0.07 for all firms; the figure for high-tech firms was 0.10 and for firms in other sectors only 0.03. During the 1987–1990 period, R&D elasticity estimate for the whole group of firms was 0.08 and during the 1990–1993 period slightly higher at 0.11. In high-

Table 5.
Within-firm estimates of production function for the 1987–1993 panel firms. Separate estimates are also given for the panel periods 1987–1990 and 1990–1993. The corrections for R&D double-counting are made only in part, i.e., the number of researchers is not subtracted from the total number of employees. The rate of depreciation of R&D capital is 0.30.

Dependent variable: Log(Value added/Employee), constant returns to scale not imposed.		
Time	**1987–1993**	**1987–1990**	**1990–1993**
Physical capital log(C/L)	**0.147 (0.029)****	**0.177 (0.030)****	**0.146 (0.038)****
high-tech branches	0.164 (0.036)**	0.165 (0.037)**	0.155 (0.048)**
other branches	0.130 (0.054)*	0.179 (0.060)**	0.185 (0.073)*
R&D capital log(K/L)	**0.072 (0.019)****	**0.079 (0.020)****	**0.106 (0.026)****
high-tech branches	0.100 (0.031)**	0.127 (0.032)**	0.162 (0.047)**
other branches	0.029 (0.028)	0.018 (0.031)	0.023 (0.042)
Labour log(L)#	**0.041 (0.041)**	**0.031 (0.044)**	**0.025 (0.056)**
high-tech branches	0.036 (0.050)	0.025 (0.054)	0.020 (0.074)
other branches	0.068 (0.075)	0.051 (0.086)	0.028 (0.099)
Root MSE ja VCF	**0.245 (0.076)**	**0.175 (0.087)**	**0.252 (0.088)**
high-tech branches	0.252 (0.083)	0.170 (0.092)	0.262 (0.092)
other branches	0.231 (0.077)	0.171 (0.091)	0.237 (0.088)

Notation, see Table 1.

VCF=variance component fo firms.

The basic figure for the variable to be explained in the model (Y) is value added, which has been obtained from Statistics Finland's industrial statistics. The independent variables are as follows: labour input (L) is a firm's total personnel (industrial statistics); the variable describing physical capital (C) is based on cumulated value of machinery and equipment acquisitions (industrial statistics); and the variable describing R&D capital (K) is based on cumulated intramural R&D expenditure (R&D statistics).

tech industries, the estimate of R&D elasticity increased between the two periods from 0.13 to 0.16. The estimate of R&D elasticity for the firms in other branches remained at the same level, i.e., 0.02. This estimate can be considered exceptionally low.

The effect of the correction for R&D double-counting was that when the correction was not made, the estimate of R&D elasticity fell by 0.01–0.03. The decrease in R&D elasticity was sharpest in high-tech firms. This result was consistent with the between-estimates of R&D elasticity. The results also indicate that the correction for R&D double-counting had no effect on the statistical significance of the estimates of R&D elasticity. The estimates were all statistically highly significant with the exception of the estimates for the firms in the other branches.

The estimate of R&D elasticity for the whole group of panel firms was 0.10 when the depreciation rate of 0.10 was used (Table 6). The estimate for high-tech companies was 0.13, for other branches 0.05. For all the panel firms, the R&D elasticity estimate for the 1980s period was 0.11 and for the 1990s period 0.13. The difference in comparison with all other corresponding results of this study was that the estimates of R&D elasticity in different groups of firms showed no noticeable increase during the periods. The R&D elasticity estimate of high-tech firms remained virtually unchanged, and there were no signs of significant change in the case of firms in other branches either.

Table 6.
Within-firm estimates of production function for the 1987–1993 panel firms. Separate estimates are also given for the panel periods 1987–1990 and 1990–1993. Corrections for R&D double-counting are made, i.e., the number of researchers is subtracted from the total number of employees and physical capital devoted to R&D activities is deducted from total physical capital. The rate of depreciation of R&D capital is 0.10.

	Dependent variable: Log(Value added/Employee), constant returns to scale not imposed.		
Time	1987–1993	1987–1990	1990–1993
Physical capital log(C/L)	**0.146 (0.030)****	**0.181 (0.031)****	**0.152 (0.040)****
high-tech branches	0.159 (0.038)**	0.173 (0.038)**	0.158 (0.051)**
other branches	0.134 (0.056)*	0.181 (0.061)**	0.194 (0.076)*
R&D capital log(K/L)	**0.103 (0.021)****	**0.112 (0.022)****	**0.134 (0.028)****
high-tech branches	0.127 (0.033)**	0.175 (0.035)**	0.173 (0.048)**
other branches	0.053 (0.033)	0.041 (0.035)	0.048 (0.048)
Labour log(L)#	**0.042 (0.041)**	**0.024 (0.044)**	**0.022 (0.056)**
high-tech branches	0.043 (0.048)	0.019 (0.052)	0.023 (0.072)
other branches	0.059 (0.075)	0.044 (0.086)	0.018 (0.099)
root MSE ja VCF	**0.244 (0.087)**	**0.174 (0.097)**	**0.250 (0.103)**
high-tech branches	0.250 (0.098)	0.167 (0.107)	0.258 (0.111)
other branches	0.234 (0.081)	0.172 (0.094)	0.239 (0.095)

Notation, see Table 1.

VCF=variance component fo firms.

The basic figure for the variable to be explained in the model (Y) is value added, which has been obtained from Statistics Finland's industrial statistics. The independent variables are as follows: labour input (L) is a firm's total personnel minus R&D personnel (industrial statistics and R&D statistics); the variable describing physical capital (C) is based on cumulated value of machinery and equipment acquisitions (industrial statistics); and the variable describing R&D capital (K) is based on cumulated intramural R&D expenditure (R&D statistics).

The estimates of R&D elasticity were at most 0.02 higher than those obtained by using the depreciation rate of 0.30. However, the effect of the depreciation rate on the level of the estimate of R&D elasticity may be considered relatively weaker than the effect of double-counting. Also, as expected, the choice of depreciation rate made no difference to the statistical significance of the estimates of R&D elasticity. According to Hall and Mairesse (1995, 287), the choice of depreciation rate in constructing R&D capital does not make much difference to the estimates of R&D elasticity, particularly on the within-firm dimension, although it does change the average level of measured R&D capital. The results of this study confirm this statement as far as the within-firm estimates of R&D elasticity are concerned. The situation was only slightly different when we examined the results of other regressions.

In the within-firm calculations, the estimate of physical capital elasticity was within the range of 0.13 and 0.20. The within-estimates of physical capital elasticity varied from case to case quite significantly. It is particularly noteworthy that the within-estimates of physical capital elasticity for the period 1990–1993 were clearly better and perhaps more credible than the corresponding results based on cross-section type estimates of physical capital elasticity. The within-regression estimates of physical capital elasticity may be regarded as better than others also in the sense that they were all statistically significant, with p-values clearly below 0.05. Of course, it needs to be stressed here that p-values are always approximations and that they are quite sensitive to the size of a sample.

In contrast to the situation with between-regressions, the within-regression estimates of physical capital elasticity were more often at a clearly higher level than the estimates of R&D elasticity. The differences between the magnitudes of R&D and physical capital elasticity estimates were particularly evident in the within-estimates for firms in other branches. In these calculations, the estimated elasticities of physical capital ranged between 0.13 and 0.20 and the estimated elasticities for R&D between 0.02 and 0.05.

The differences between different industry groups were not equally clear in estimates of physical capital elasticity as in the case of R&D capital. It is noteworthy that in the calculations covering the whole panel, the estimates of physical capital elasticity for high-tech industries were in fact higher than in other branches. However, in the results for the periods 1987–1990 and 1990–1993, the opposite is true: the estimates of physical capital elasticities in other branches were 0.02–0.04 higher than in the high-tech branches.

The estimated elasticities of physical capital generally remained fairly low. The productivity effects of machinery and equipment were excepted to be greater. We also expected that especially in other than high-tech branches the relationship between productivity and physical capital would have been more clearly visible through the estimates. After all, the stock of physical capital, for instance, was considerably higher in other branches than in the high-tech sector. In this regard, too, the results were somewhat surprising.

6. Conclusions

This study was concerned to explore the relationship between R&D and productivity from an econometric perspective. The focus was mainly on the estimation of production factors' elasticity coefficients and specifically on the productivity of R&D. Although different firm-level factors and general economic climate have a major influence on companies' R&D activities, output and productivity, these aspects remained very much in the sidelines in this analysis.

The results clearly indicate that in Finnish manufacturing firms, R&D activities have had a positive and statistically significant impact on productivity. Followingly, the results provide confirmation of the role of R&D capital as a statistically signifiant factor contributing to productivity differencies among firms. The productivity of R&D was relatively high in high-tech branches. In other branches, the estimates of R&D elasticity were often at a much lower level than in high-tech branches. Also, the estimates of R&D elasticity in other branches were not always statistically significant.

Regardless of the different techniques used for the calculations and the alternative values given to the variables, the results are largely consistent. The between-estimates for the whole period and for the entire panel ranged from 0.13 to 0.16. The time-series estimates, i.e., the within-estimates, were between 0.07 and 0.10.

The between-estimates and within-estimates of R&D elasticity for the periods 1987–1990 and 1990–1993 provided information on the changes that have occurred in R&D activities and productivity. According to the results, the relationship between R&D and productivity strengthened considerably during the 1990s. These results also supported the estimates of R&D elasticity obtained in the study by Husso, Leppälahti and Niininen (1996, 32–42). In this regard, the estimates of R&D elasticity calculated using different methods were all very similar. The results obtained with different production function specifications and alternative ways of constructing variables also pointed at significant differences in the productivity of R&D between high-tech and other firms.

The depreciation rate of R&D capital was found to have rather limited effect on the estimated elasticity of R&D. However, the within-estimates of R&D elasticity tended to be slightly higher when a depreciation rate of 0.10 was used. In the case of cross-sectional estimates, R&D elasticity coefficient tended to be higher when a depreciation rate of 0.30 was used. The effect of the depreciation rate was somewhat weaker in the within-estimates. The results also indicate that, when we use the perpetual inventory method, the differences between the R&D elasticity estimates based on different depreciation rates of R&D capital tend to grow as the time span gets longer from the point at which the calculation of R&D capital is started. The effect of the corrections on R&D elasticity estimates was far clearer. When the corrections were not made, the estimate of R&D elasticity was lower (at most 0.05 lower) and the statistical significance of the estimate was often weaker.

It needs to be stressed that the generalizability of our results is undermined by problems with representativeness and the small size of the panel. The panel included only a very small proportion of all manufacturing firms in Finland with R&D activities. In this sense, the results must be read and interpreted with caution. In any event, the magnitude of the estimates of R&D elasticity was certainly affected by the fact that the most of the companies included in the data showed a clearly higher than average R&D intensity. Measured in terms of labour productivity, the panel companies also had a better than average productivity. If calculations could have been made of all companies with R&D activities, these calculations would have included companies with very low levels of R&D activities and whose R&D productivity could have been estimated as being on average lower than in the companies included in the material of this study. In this situation, the estimates of R&D elasticity would probably also have been somewhat lower.

The crude classification we used in this analysis serves to iron out some of the differences between industry groups in terms of their volume of R&D activities. This is due to the fact that there may be firms in the high-tech sector that are not very R&D intensive or that have no high-tech R&D activities. Accordingly, in the category of other industries we may find firms that do meet these criteria of high-tech industry. However, the crude classification we had clearly helped to provide an overall picture of the firms in each industry group. A more detailed classification might have led to a straightforward, clear-cut result as regards the elasticity coefficients for different variables: the estimates for technology-intensive firms would have been extremely high, whereas in other companies the estimates of R&D elasticity would probably have been close to zero.

It can be briefly observed that the estimated elasticities of physical capital varied greatly depending on the specification of the model and on the construction of the variables. The estimates of physical capital elasticity were mostly within the range of 0.11–0.20. In order to find explanations for these "deviations", the figures need to be examined more carefully in the future. Overall, the estimates were somewhat lower than was expected; in some calculations, the estimates of physical capital elasticity came very close to or were even below the level of the estimate of R&D capital elasticity. This is explained at least in part by the specific characteristics of the companies included in the data. The analysis included firms that showed a stronger than average commitment to R&D activities. However, this is not to say that machinery and equipment capital are of no major consequence to productivity. Nonetheless the results did not clearly highlight the productivity of physical capital. To address this issue, we will need in the future to devote closer attention to model specification and to constructing the variable for physical capital. In analysing the total amount of physical capital in the panel firms, and particularly in other than high-tech firms, our attention is drawn to the large amount of that capital. This gives reason to assume that the method we employed or the rate of depreciation we used was not the best possible. On the other hand, it must be noted that the operation of R&D intensive firms is not nearly as often so heavily dependent on machinery and equipment capital as is the case in traditional manufacturing industry.

7. Discussion

Cross-sectional estimates (or between-estimates) of R&D capital elasticity have typically varied in different studies between 0.07 and 0.26; and time-series estimates of R&D capital elasticity between 0.07 and 0.16 (e.g. Griliches 1980; Cuneo and Mairesse 1984; Griliches and Mairesse 1984; Mairesse and Sassenou 1991; Hall and Mairesse 1995; Husso, Leppälahti and Niininen 1996). The results show that the productivity and the output effects of R&D activities have mostly been statistically significant and positive. In spite of the different specifications of models and alternative ways of constructing variables in different studies, the results have been quite consistent. However, as far as comparability is concerned, it must be noted that the data sets and the representativeness of these data sets may vary quite considerably from one case to the next. Estimates of elasticity coefficients are very much influenced by how well different types of firms (in terms of R&D activities) are represented in the sample: obviously, we may get higher R&D estimates if the sample includes large numbers of technology-intensive firms. For these and other reasons, we must be very cautious in comparing the results of different studies. In very general terms, however, it may be noted that the results obtained by different researchers for R&D capital elasticity estimates come relatively close to each other.

An important question in the interpretation of estimates calculated in alternative ways has to do with the estimates that best describe the relationship between R&D and productivity. The fact that there are significant disparities between estimates arising from the cross-sectional and time-series dimensions is a common feature of panel data econometrics. In spite of the fact that time-series estimates may themselves be biased and less robust, the common view is to give preference to the time-series (i.e. within-firm) estimates. The reason for this is that these are not affected by the biases caused by the omission of firm effects (see Mairesse and Sassenou 1991, 23).

On the other hand, Hall and Mairesse (1995, 277) argue that both within-firm estimates and between-firm estimates are informative indicators of the relationship between R&D and productivity, even though they describe the phenomenon studied from different angles. Within-estimates provide a more accurate description of what goes on in a firm as it allocates resources to R&D; between-estimates, on the other hand, provide a better picture at the national economy level of the effect of R&D activities or public technology subsidies, for instance, on productivity or on output. However, in comparing estimates calculated in alternative ways, it needs to be stressed that there exists no single correct or superior method for measuring the productivity of R&D. Different ways of constructing R&D variables and model specifications all serve to generate additional information that is necessary in studying the complex phenomenon of productivity.

One of the difficulties with the production function is that the form of this function constrains reality. Another major problem is that the models often assume that a firm's productivity or output depends only on its own R&D expenditure, not on the amount it spends on technology made by others (i.e. technological spillovers) (see Mansfield 1990, 344). Given the shortcomings of the models, the results must always be approached with caution. The difficulties in the measurement of productivity or growth in productivity are closely associated with difficulties in constructing the R&D variable. R&D capital usually consists of a weighted sum of past R&D expenditure, in which the weights reflect both the delayed effects of R&D expenditure on output and the consumption of investments over time. Consequently, one of the major questions has to do with the time lag of R&D to commercialisation. R&D expenditure is not normally reflected very rapidly in value added or sales. Also, the misspecification biases (f.ex. selectivity problem, simultaneity of labour and output), as well as issues of the comprehensiveness and reliability of data obtained from R&D activities have proved problematic.

We need to emphasise that firms obtain and use technology from several different sources, and often the various forms of technology complement one another rather than being substitutes for each other (see Vuori 1995, 54). Thus, the estimates of R&D elasticity only tell us one side of the "productivity story". We need to bear in mind the multidimensional effects of R&D on productivity or on output in manufacturing firms. The whole story is that, in order to stay in business, firms invest in R&D so that they can generate product and process innovations, but the indirect effects of R&D must also be stressed – R&D helps firms to develop their capacity to adopt, introduce, and gain economic benefit from the knowledge produced elsewhere.

To sum this all up, we would like to lend our support to the following words by Mairesse and Sassenou (1991, 35): *The issue at stake is not so much the question of whether or not a relationship exists between R&D and productivity. Individual case studies and other factual knowledge in the field, as well as the fact that firms do indeed undertake research, leave little room for doubt on this score. The question is whether or not econometric studies can characterise such a relationship in a satisfactory and useful manner.* The production function model and the estimates of its parameters allows us to study some of the mechanisms between R&D and productivity. However, in order to gain a deeper understanding of the relationship and interaction between R&D and productivity, a great deal of research in this field of science still remains to be done.

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TECHNOLOGY SUBSIDIES, R&D INVESTMENT AND PRODUCTIVITY

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This paper focuses on the effect of public technology subsidies on research and development investment as well as the productivity of the firm. We make use of a new firm level database consisting of financial statement data and information on subsidies. The objective is to analyse the determinants of R&D investment, especially how technology subventions affect R&D investment. In addition to that, the effect of liquidity constraints and ordinary investment are estimated. The second issue in the paper deals with the effect of subsidies on a more fundamental issue, a firm's profitability and productivity.

The results suggest that the firm's financial position has a significant effect on R&D investment. An increase in long term debt curtails R&D investment while cash flow has a positive effect on R&D. Ordinary investment and R&D investment appear to be complementary. The data confirm the role of public technology subsidies: both direct subsidies and loans have a positive and statistically significant effect on R&D outlays. On the other hand, subsidies were not found to have a conclusively positive effect on profitability or productivity.

Key words: R&D, Subsidies, Productivity, Panel Data, Firm Level.

1. Introduction

The broad consensus of opinion among economists is critical of subsidies. However, under circumstances where private incentives are lower than the social ones, the use of public subsidies may be optimal. Research and development is an example of an activity which is characterised by externalises; unlike production subsidies, R&D subsidies often improve not only the profitability of the subsidised firm but also the profitability of rival firms. Due to information problems related to R&D investment, i.e. moral hazard and asymmetric information, the role of financing the R&D investment becomes crucial. Therefore, the firm may prefer internal finance in high risk investments such as R&D. Even if the decline in investments is profit maximising in the current capital structure, the economy as a whole may lose due to positive externality issues in R&D investments. Hall (1992) found that increased leverage in a firm's balance sheet was immediately followed by substantial reductions in investment and R&D. These reductions in the manufacturing firms amounted to a decrease of 2.5 percent in the private industrial R&D spending in the U.S.A. (p.1).

The predicted outcome for a high leverage firm is that the leverage results in higher interest expense which crowds out investment expenditure. This problem can be even more pronounced in R&D investment than in ordinary investment due to creditors' preference of tangible collaterals. As a result, the role of marginal q in the neo-classic investment theory as the only determinant of investment has been under criticism. As Kaplan and Zingales (1995, 4) point out, internal cash flow is a proxy for investment opportunities not captured by measured q which is an average q in empirical applications, as opposed to marginal q posited by the theory.

Other theoretical rationales for the R&D – leverage dynamics include tax treatment and future expectations. The relative price of debt is higher for the firms which have high R&D expenses and thus, *ceteris paribus,* lower taxable income (Hall 1992, 14). Changes in expectations affect the correlation between investment and liquidity. Finally, the economic setting is likely to have an impact on R&D investment decisions. At the beginning of a recession, the composition of R&D outlays is likely to change so that the share of labour costs increases while material and fixed costs attributed R&D decreases. This stems from the fact that most of the R&D investment consist of salaries to research personnel which cannot be adjusted quickly.

On the basis of the above discussion, it is reasonable to assume that leverage and liquidity constraints may have an effect on firm's R&D investment decision. The effect of cash flow has been examined thoroughly and many studies have found cash flow to be associated with higher levels of R&D intensity (see e.g. Cohen and Levin (1989, 1072) for the review of the literature). As cash flow is likely to correlate with other attributes of financing an R&D investment, it should be examined in conjunction with other sources of financing. The estimated model is the following:

$$RD_{it} = \beta_0 + \beta_1{'}A_{it} + \varepsilon_{it} \ , \tag{1}$$

where RD is the annual R&D investment expenditure of firm i and $\boldsymbol{A}$ is matrix of firm's characteristics, including received subsidies which are the main issue of this paper. Ordinary investment is included to indicate whether complementaries between ordinary investments and R&D investments exist. It can also be thought of as a control variable. The extended model is augmented by adding squared terms of subsidy variables.[1]

A majority of studies on the relationships between productivity and R&D conducted recently are based on firm data. Many of them are specified in terms of Cobb-Douglas production function with R&D capital, e.g. Griliches and Mairesse (1984), Griliches (1986) and Jaffe (1986) for the U.S. data. According to Mairesse (1991, 13), the differences between these studies are slight and they may be seen as a series of econometric experiments. Husso (1996) has used this approach with the Finnish data and found a clear positive connection between productivity and R&D investment. Since there is a large body of literature on R&D – productivity dynamics, we concentrate on the impact of public subsidies. R&D and ordinary investment variables are included in our model as control variables. Therefore, we use the panel data method by regressing the following model:

$$PROD_{it} = \beta_0 + \beta_1'\boldsymbol{B}_{it} + \varepsilon_{it} \ , \tag{2}$$

where $PROD$ is productivity, defined as value added divided by the number of personnel. Matrix $\boldsymbol{B}$ denotes alternative sets of firm's characteristics, including subsidy, leverage and investment variables.

Throughout the analysis, we assume that the error component model for the disturbances is one-way. This is a standard assumption with panel data which proposes the following structure for error term ε_{it}:

$$\varepsilon_{it} = \mu_i + \upsilon_{it} \ , \tag{3}$$

where μ_i is the time-invariant, unobservable individual specific effect and υ_{it} is the remaining white noise disturbance (see e.g. Baltagi 1995, 9–10). The fixed effects model used in this paper assumes that μ_i are fixed parameters. This assumption can be tested by Hausman (1978) statistic. Under the null hypothesis of the Hausman test, the fixed effects model is appropriate. Large values in the

1 The description of variables can be found in the appendix. Financial variables have been calculated using the convention of the Committee for Corporate Analysis. Ordinary investment is corrected to avoid double accounting; ordinary investment includes also increase in fixed assets that are devoted to R&D. To avoid double accounting, we have subtracted R&D investment in fixed assets from ordinary investment. This yields corrected ordinary investment, INV.

Hausman test argue in favour of fixed effects model over the random effects model (Greene 1991, 165, 303).

Instead of the fixed firm effects model we could have controlled for industry characteristics by using separate regressions for each industry. There are two reasons why pooled data were used. First, there is no theoretical rationale for a firm in one industry to behave differently than a firm in another industry. Second, the definition of an industry is not clear for big firms operating in a variety of industries. At the two-digit SIC level used in this data, the variety within each class makes some industries rather aggregated. If a more detailed industry classification could be used, there would be another kind of measurement problem: most large firms would have considerable degree of operation outside their designated industry.

2. Data

The studies of R&D subsidies are scarce: finding relevant data have hampered empirical applications. Throughout the analysis, we use a unique firm level database consisting of both financial statement data set and detailed data on received subsidies. To our knowledge this kind of data has not been available before at the firm level.

Financial statements databank contains financial statements and some other accounting information. R&D databank includes information on R&D outlays and sources of R&D financing. Since the sample has not remained the same over the years, i.e. it partly consists of different firms from year to year, the number of firms in the dataset shrinks considerably in a long sample. Therefore, we allow each firm to have one missing value between 1985 and 1993. The resulting unbalanced panel has 134 firms and a total of 605 observations over five years (odd years between 1985–1993).

Barring employment, all variables have been deflated by industrial output price index. By employing only one index, the problems of double deflating such as potential bias in the deflated series can be avoided. Sample statistics of the panel dataset can be found in table 1. The ranges of the classifying variable are chosen so that the classes are approximately of equal size.

Even in a basic data such as the above, one can notice an analogy to Schumpeterian relationship between innovation and firm size, at least in a way that the empirical literature has interpreted it: the R&D intensity is highest in the in the middle category (see e.g. Scherer(1965). The share of public technology subventions declines with firm size. The same holds both for direct subsidies and loans. The amount of total public subsidies ranges from

Table 1. R&D Expenditures by Sales.

	1985–1993					
	Outlays			Financing		
Sales Mio FIM.	R&D, % of sales	Salaries & Wages %	Other outlays %	Direct subsidies %	R&D loans %	Public subsidies tot. %
– 50	1.9	58.1	41.9	4.2	5.5	9.7
50–100	2.0	57.9	42.1	5.8	5.3	11.1
100–200	2.5	56.2	43.8	4.2	4.3	8.4
200–500	1.5	57.0	43.0	3.5	4.0	7.6
500–	1.7	48.3	51.7	3.0	2.0	5.0

5 percent (sales over FIM 500 million) to over 11 percent (firms with sales between FIM 50 and 100 million). By and large, public subsidies are equally distributed between direct subsidies and loans. Barring the smallest category, the share of labour costs declines with firm size.

3. Results

Table 2 presents the results of the R&D investment regressions. Subsidies have been subtracted from R&D investment outlays before estimation since R&D investment automatically increases by the amount of subsidy. Alternatively, we could have compared the regression coefficients of subsidies to one. Now the null hypothesis is that the coefficients are not statistically different from zero. In order to test whether R&D and ordinary investment decisions are endogenous, ordinary investment was regressed on the set of all other right hand side variables except R&D investment and the squared terms of variables. The resulting fitted value of investment was then used in estimating the original models. Since the coefficient of the fitted value of investment turned out to be statistically significant, investment decisions were indeed endogenous. Thus, the fitted value of investment is used in all R&D investment regressions.

The hypothesis that R&D investments are sensitive to liquidity constraints is supported, as can be seen in the signs of CFLOW and DEBTL. Cash flow has a positive effect on R&D investment while the long term debt curtails

R&D. Hall (1992, 19) reports similar findings in the U.S. data. The coefficients for public subsidies – both direct subsidies and loans – are statistically significant at five percent confidence level, and positive in both equations. The extended equation with squared terms SPUBL and SLOAN reveals that public subsidies exhibit diminishing rate or return. The t-value of SLOAN is marginally significant at ten percent confidence level. Ordinary and R&D investments seem to be complements; an increase in ordinary investment is associated with an increase in R&D investment as well. This would imply that ordinary investment does not crowd out research and development outlays. As a whole, the explanatory power of both the basic and the extended model is high. The adjusted R^2 is almost 0.8 and most of the determinants of RD are statistically significant at ten percent confidence level, the signs of the coefficients being economically justifiable.

Table 2. **Estimation Results for Type of Subsidies Equation**

DEPENDENT VARIABLE: RD

	Basic Model		**Extended Model**	
Variable	**Coefficient**	**t-value**	**Coefficient**	**t-value**
Constant	17865.	0.027	–0.60862E+06	–0.913
INVF	0.31789E-01	8.181	0.29409E-01	7.695
CFLOW	0.12221	20.026	0.12148	20.285
DEBTL	–0.13742E-01	–6.039	–0.13711E-01	–6.152
PUBL	7.4559	11.582	11.260	10.108
LOAN	3.3290	3.638	5.8614	2.982
SPUBL			–0.22540E-06	–2.980
SLOAN			–0.53271E-06	–1.612

Basic Model	Extended Model
Observations = 605	Observations = 605
Deg.Fr. = 599	Deg.Fr. = 597
R-squared = 0.77470	R-squared = 0.78583
Adjusted R-squared = 0.77282	Adjusted R-squared = 0.78331
Model test: F[5,599] = 411.95	Model test: F[7,597] = 312.92
Prob value = 0.00000	Prob value = 0.00000
Log-L = –10865.2035	Log-L = –10849.8909
Restricted(ß=0) Log-L = –11316.0326	Restricted(ß=0) Log-L = –11316.0326
Hausman-test = 161.10 (5 df, prob value = 0.000000)	Hausman-test = ***

The results from productivity regressions are presented in table 3. In the first model, productivity is regressed on ordinary and R&D investment as well as direct subsidies and subsidised loans (columns one and two in table 3). When explanatory variables are lagged by one period, both investment have positive and statistically significant effect on productivity while direct

***Table 3.* Estimation Results for Type of Subsidies Equation**

DEPENDENT VARIABLE: PROD
Observations=605

Variable	Coefficient t-statistics	Coefficient t-statistics	Coefficient t-statistics	Coefficient t-statistics	Coefficient t-statistics
CONSTANT	0.211E+06	0.212E+06	0.211E+06	0.210E+06	0.213E+06
	32.813	32.976	32.354	32.678	32.883
RD[1]	0.634E-03		0.764E-03	0.431E-03	
	2.247		2.050	1.401	
INV[1]	0.259E-04		0.205E-04	–0.260E-05	
	2.056		1.496	–0.122	
PUBL[1]	–0.137E-01		–0.857E-02	–0.114E-01	
	–2.057		-1.189	–1.685	
LOAN[1]	0.161E-02		–0.169E-02	0.654E-03	
	0.183		–0.179	0.074	
DEBTL[1]				0.206E-04	
				1.657	
RD[2]		0.373E-03	–0.312E-03		0.388E-03
		1.315	–0.650		1.252
INV[2]		0.284E-04	0.228E-04		0.304E-04
		2.241	1.655		1.418
PUBL[2]		–0.167E-01	–0.102E-01		–0.169E-01
		–2.508	–1.438		–2.478
LOAN[2]		0.869E-02	0.859E-02		0.876E-02
		0.983	0.936		0.988
DEBTL[2]					–0.148E-05
					–0.118
R^2	0.028	0.022	0.037	0.033	0.022
Adjusted R^2	0.022	0.016	0.025	0.025	0.014
Model test:F[x,n]	4.380	3.430	2.900	4.060	2.750
Prob value	0.002	0.009	0.004	0.001	0.018
Log-L	–8061.369	–8063.225	–8058.525	–8059.986	–8063.218
Restricted(ß=0) Log-L	–8070.073	–8070.073	–8070.073	–8070.073	–8070.073

Table 4. Estimation Results for Type of Subsidies Equation.

DEPENDENT VARIABLE: GROSS PROFIT RATIO
Observations=605

Variable	Coefficient t-statistics	Coefficient t-statistics	Coefficient t-statistics	Coefficient t-statistics	Coefficient t-statistics
CONSTANT	0.105	0.104	0.103	0.104	0.104
	27.414	27.415	26.767	27.282	27.295
RD[1]	–0.105E-10		0.115E-09	–0.122E-09	
	–0.063		0.520		–0.667
INV[1]	0.976E-11		0.816E-11	1.006	–0.582E-11
	1.305		1.006	–0.460	
PUBL[1]	–0.159E-08		–0.311E-09	–0.363E-09	
	–0.405		–0.073	–0.090	
LOAN[1]	0.628E-08		0.225E-08	0.575E-08	
	1.201		0.401	1.100	
DEBTL[1]				0.113E-10	
				1.525	
RD[2]		–0.733E-10	–0.281E-09		–0.125E-09
		–0.437	–0.988		–0.686
INV[2]		0.809E-11	0.665E-11		0.785E-12
		1.083	0.813		0.062
PUBL[2]		–0.377	0.115E-09		–0.903E-09
		–0.148E-08	0.027		–0.225
LOAN[2]		0.106E-07	0.949E-08		0.104E-07
		2.038	1.743		1.985
DEBTL[2]					0.529E-11
					0.716
R^2	0.007	0.011	0.015	0.011	0.012
Adjusted R^2	0.001	0.05	0.001	0.003	0.004
Model test:F[x,n]	1.090	1.690	1.110	1.340	1.460
Prob value	0.362	0.149	0.354	0.246	0.202
Log-L	613.192	614.401	615.482	614.364	614.659
Restricted(ß=0) Log-L	611.007	611.007	611.007	611.007	611.007

subsidies have a negative effect on productivity. With lag 2, R&D investment is no longer statistically significant.

In another specification of the first model, the right hand side variables include both ordinary and R&D investment with lags 1 and 2 as well as lagged values of direct subsidies and subsidised loans as before. The results can be found in column three. The effect of R&D investment remains positive and statistically significant with lag1 while the coefficient of public subsidies is no longer statistically significant.

In addition to the earlier set of models, leverage as measured by long term debt is included in the right hand side. Since investment variables and long term debt capture similar effects, i.e. increased investment usually results in increased debt, the inclusion of leverage should weaken the effect of R&D and ordinary investment. Also, if R&D investment is mainly financed internally instead of external debt, it should not be affected as much as ordinary investment. Looking at the last two columns of table 3, the effect of investment is weakened, and as expected, the coefficient of ordinary investment suffers more than R&D investment. The effect of direct subsidies remains negative in both lag1 and lag2 models. To sum up, direct subsidies had either negative or no effect on productivity. Subsidised loans did not have any statistically significant effect in the above specifications.

Using the same methodology as above we look at the effect of technology subsidies on the profitability of the firm. The definition of profitability is not as straightforward as was the case with productivity. Several variables are used to measure profitability: gross profit, profit before depreciation and net profit ratios as well as return on investment (ROI) and return on equity (ROE).

For the sake of comparison we keep the right hand side of the following regressions identical to the set of models in the productivity equations. Thus, in the first set of models, gross profit ratio is regressed on R&D and ordinary investment as well as direct subsidies and subsidised loans (table 4). Again, the right hand side variables have been lagged by one and two periods. The only statistically significant regression coefficient in these equations is subsidised loans whose coefficient is positive in lag 2 model. Once variables with lags one and two are combined, R&D loans still remain the only statistically significant explanatory variable in the statistically significant explanatory variable in the model (column 3). In the other specification, leverage or long term debt is added to the right hand side (columns 4 and 5). The effect of R&D loans still remains statistically significant in the lag 2 model.

Profit before depreciation and net profit ratios were also used as a measure of profitability. Both of these measures of profitability yielded very similar results. Only ordinary investment with lag 1 turned out to be statistically significant. Once leverage was included in regressions, it replaced ordinary investment as a statistically significant variable. Both leverage and ordinary investment coefficients were positive. Finally, balance sheet based measures of profitability, ROI and ROE, did not respond to the right hand side variables. None of the explanatory variables in the above models had statistically significant coefficients in ROI and ROE equations. The results of these regressions are not reported here.

4. Summary and Conclusions

The purpose of this paper was to analyse the determinants of R&D investment, especially public subsidies and financial constraints for investment, and further the effect of subsidies on productivity and profitability. The dataset allowed us to carry out the analysis on a firm level data in a period from 1985 to 1993. A panel data analysis with fixed effects model was used; this choice was also supported by test statistics which favours fixed effects model over random effects model.

Strong evidence was found to support the claim that a firm's financial position has a significant effect on R&D investment. Both leverage and liquidity, measured here by long term debt and cash flow, respectively, clearly affected R&D investment outlays. The effects had signs similar to the correlations obtained in section one; long term debt curtails R&D investment while an increase in cash flow has a positive effect on R&D. These findings are in line with the study by Hall (1992) which was carried out on U.S. data.

The data strongly confirm the role of public technology subsidies. The subsidies were divided into direct subsidies and loans. Both types of subsidies induce R&D investment, with direct technology subsidies having a larger impact than loans. The squared terms in the extended model would imply that technology subsidies exhibit diminishing rate of return.

Subsidised loans did not have any statistically significant effect on productivity but appeared to be more effective than direct subsidies when gross profit ratio was used as a profitability measure. Direct subsidies had either negative or no effect on productivity, and no effect on profitability measured by any of the financial ratios. Thus, subsidised loans might seem to be a less risky choice of the two types of subsidies However, the effect of subsidies on profitability depended considerably on the choice of profitability measure and there was only a weak evidence on the effect of subsidised loans. It should be stressed that the results apply only to a time span of six years; in addition to lags 1 and 2 reported in the above tables, models with lag 3 were estimated as well but the results were not significantly different.

To sum up, neither form of subsidies did conclusively improve productivity or profitability. It seems that technology subsidies induce new R&D projects but do not have a positive effect on productivity or profitability. At the same time, however, R&D investment has a positive effect on productivity. This might imply that the firms use subsidies to finance the riskiest R&D projects or basic research projects which take a long time to yield any results. A more detailed analysis of this question is left for the further research.

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Appendix:
Variable descriptions and Sample Statistics

Sample statistics have been calculated directly from the panel dataset after deflating the variables to 1985 Finnmarks.

Variable	Description	Sample Mean	Variance
CFLOW	after tax cash flow, defined as profit + change in reserves + depreciation difference + depreciations + additional depreciations	51785797	2.90E+16
DEBTL	long term debt	311159978	1.17E+18
EITEKES	direct subsidies and loans from public sources other than Technology Development Centre (TEKES)	107641	2.56E+11
GROSS PROFIT RATIO	gross profit/sales	0.1070	0.0078
INV	ordinary investment, defined as increase in fixed assets - proceeds from sold fixed assets - fixed R&D investments	146891433	3.43E+17
LOAN	R&D loans mainly from public sources.	261852	8.63E+11
NET PROFIT RATIO	(gross profit - depreciations - financial expenses + depreciation difference) / sales	0.0765	0.0106
PROD	productivity (value added / number of employees)	216937	150369
PROFIT BEFORE DEPRECIATION RATIO	(gross profit - financial expenses) / sales	0.1330	0.0127
PUBL	public direct R&D subsidies. Includes subsidies from international organizations, e.g. the EU, and subsidies from domestic non profit organizations.	348065	2.05E+12
RD	R&D investment performed by the firm	10701196	1.10E+15
ROE	(gross profit - depreciations - financial expenses + depreciation difference) / (equity + reserves + valuation items)	0.6089	77.7518
ROI	(gross profit - depreciations - financial expenses + depreciation difference + interest expenses + other expenses from debt + exchange rate difference) / (interest paying debt + valuation items + reserves + equity)	0.0428	0.0105
SLOAN	square of LOAN		
SPUBL	square of PUBL		

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PLANT LEVEL EXPLANATIONS FOR THE CATCH UP PROCESS IN FINNISH MANUFACTURING
A Decomposition of Aggregate Labour Productivity Growth

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The Finnish manufacturing sector has experienced exceptionally rapid labour productivity growth since the mid 80's until recently due to which the average labour productivity level has climbed to the international top group as described in Maliranta (1996). In the comparison of the aggregate labour productivity between Finland and the United States it appeared that the increase of the Finnish labour productivity level relative to the United States was accompanied by an increase in relative capital intensity in Finland. The period from 1990 to 1993 was a period of considerable downsizing in Finnish manufacturing contrary to the US manufacturing sector where labour input has been quite stable.

Plant-level explanations of the accelerated labour productivity growth in the Finnish manufacturing sector are studied in this paper. Aggregate annual labour productivity changes are decomposed into various components. The entry-exit effect is defined as a difference in annual change between two different samples of plants: one including all plants in each year and the other covering only those plants that existed in the both successive years. It turned out that since the mid 80's the entry-exit element played a role in Finnish manufacturing. Especially, an increase in exit-rate has been an influential factor.

The second source of aggregate labour productivity change, related to the previous one, arises from the fact that the relative labour input shares of the staying plants change. Plants with above average labour productivity level has increased their relative labour input share so that employment reallocation has a positive effect on the aggregate labour productivity growth. Furthermore, this effect has been increasing during the time span from 1976 to 1994 and was about 2 % per year in the early 90's.

The third determinant is a combination of employment reallocation and productivity growth within plants and it is called cross-term. This factor has had a negative effect on aggregate productivity growth, i.e. the relative labour input shares have decreased in plants with above average labour productivity growth.

Entry-exit, labour input reallocation and cross-term together had a minor effect on aggregate labour productivity from 1975 to 1985. In other words, aggregate labour productivity growth and labour productivity growth within plants, which is the fourth component of the aggregate productivity growth, nearly coincided in this period. Since the mid 80's, on the other hand, the three first components together have played an essential part in aggregate growth. The sustained increase of the labour productivity growth rate since the mid 80's in Finnish manufacturing is based mainly on factors other than plant level growth.

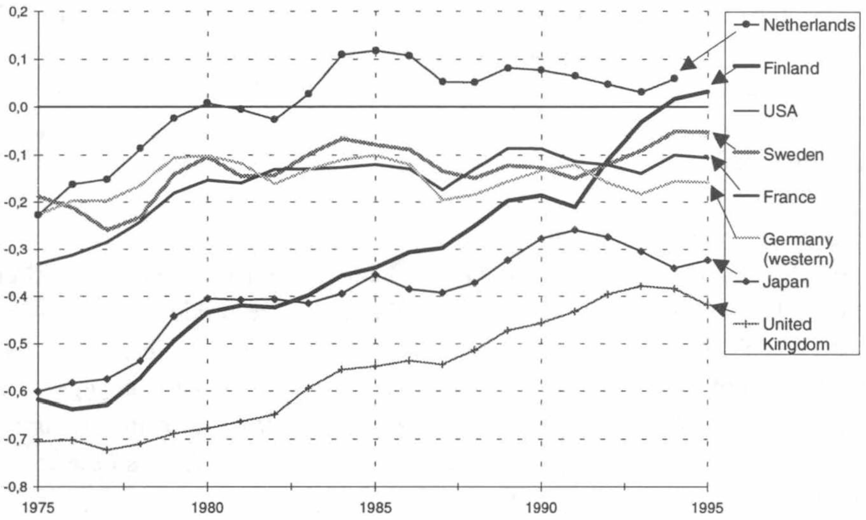
Key words: Manufacturing, Productivity, Plants, Decomposition.

1. Introduction

One of the major reasons for carrying out this study is illustrated in Figure 1, which seems to indicate a notable catch-up process in Finnish manufacturing especially in the early 90's. While the improvement of labour productivity level in relation to the United States stagnated in the leading European countries in the early 80's, the speed of the catch-up in Finland remained quite steady at least until quite recently.[1]

1 These results are based on the studies on comparative productivity levels by sector using the methods developed in the International Comparison of Output and Productivity (ICOP) project in Groningen University. So-called industry-of-origin approach is applied in t hese studies, where value added by manufacturing industry is converted to a common currency on the basis of average unit value ratios for product samples. Each country's census of production and industrial survey was used as the basic data source for measurement of labour input, value added in own currency and conversion factors required in the measurement of real relative labour productivity (see van Ark 1993).

Figure 1. **Real Value Added / Hour, Log Differences, USA = 0 , 1975–1995.**



Source:
Maliranta (1996, updated) based on the following results: the level comparisons (with the United States) of Netherlands, France, Western Germany, Japan and the United Kingdom obtained in the ICOP project (see van Ark 1996), the level comparisons of Finland and Sweden in Maliranta (1996). In addition, the series of labour productivity growth rates in the countries in question for extrapolations were obtained from the Bureau of Labour Statistics in the United States, Finnish national accounts and van Ark (1996).

The findings from the international comparisons of manufacturing labour productivity are significant in many respects. The manufacturing sector still accounts for a significant share of the total employment and output in developed countries and therefore the labour productivity in this sector is fairly closely linked to the prosperity of the nation, which is commonly measured by the GDP per capita ratio. Especially for small open economies as Finland and Sweden, the (average) performance level of the manufacturing sector is important, as a dominant share of the country's export derives from the manufacturing sector. Although labour productivity is only a so-called partial productivity measure, it is usually a suitable indicator of real competitiveness. A practical advantage of focusing on the manufacturing sector lies in the fact that in most of the other sectors data problems are even more serious than in the manufacturing sector.

The factors affecting relative international labour productivity levels in Finnish manufacturing and in its industries is studied in Maliranta (1996) by means of various aggregate data sets. It appeared in the study that the difference in labour productivity levels between Finland and the United States in the late 80's cannot be explained by capital intensity, industry structure or plant size. Skill levels of the workforce do not seem a probable explanation either.

As the international comparisons of labour and total productivity seem to indicate, there was a considerable productivity gap between Finnish manufacturing and the so-called international first best practice frontier before the late 80's. If we assume that technology is common in all countries at a given point in time, this finding could be interpreted as an indication of inefficiency in the Finnish manufacturing sector. Aggregate evidence seems to suggest that Finnish manufacturing firms and plants began to make better use of production possibilities, in other words they improved their efficiency. An explanation for this could be the tightening of economic environment with increasing real interest rates, deteriorating price competitiveness and diminishing demand. In other words, it could be argued that although the problems became apparent in the 90's, the roots of Finnish disastrous experiences in the early 90's trace back to the weak productivity performance of the past as emphasised by Pohjola (1996).

One reason for the decrease in labour inputs in Finland during the slump seems rather obvious. Since enterprises and plants were previously inefficient they employed a large amount of labour force in relation to output quantity. As the market environment became tougher, enterprises and plants focused on efficiency with the result that employment declined.

In this paper this hypothesis is assessed by means of plant level evidence. It is demonstrated that there is very little if at all indication of a sustained increase in the labour productivity growth rate among manufacturing plants. The economic environment in the early 90's may well have become tougher, but this did not, however, seem to boost the productivity of manufacturing plants significantly. In sum, micro level evidence concerning labour productivity does not give a lot of support to the view that inefficiency among plants in operation improved substantially or exceptionally fast[1].

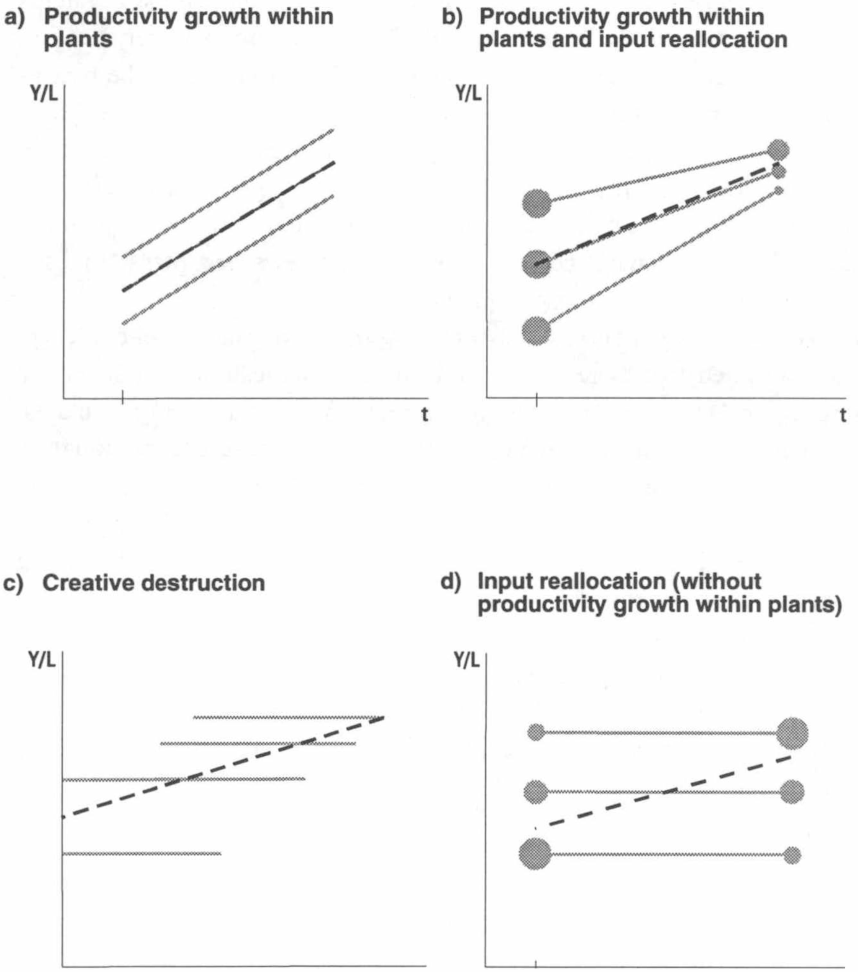
Micro level findings show that the connection between the productivity level and employment is positive. Plants with above average labour productivity increased their relative labour input share. The positive effect of high productivity level for the plant's employment became pronounced especially after the mid 80's and was strongest in the 90's.

1 In order to obtain a more reliable view on the behaviour of efficiency, capital input should be taken into account too. The scope of this paper, however, does not allow the inclusion of capital input and capital productivity measurement. The extension of this analysis in that direction is straightforward.

2. Micro-Level Occurrences and Macro-Level Appearance

Figure 2 describes different kinds of connections between the micro and macro level. Diagram (a) presents a realisation where productivity growth within plants (solid lines) coincides with aggregate productivity growth (broken line) and in this case the 'representative plant' model is suitable for the analysis of the growth.

Figure 2. **Plant-level heterogeneity and the aggregate development of productivity.**



In diagram (b) there is heterogeneity among plants on both levels and in the growth rates of productivity. The spots illustrates the magnitude of the labour input. The diagram illustrates that the swifter the downsizing of the labour input is, the faster the productivity growth. Because the determinant of aggregate growth presented in (b) is a combination of the changing labour input shares and the different growth rates among plants, this effect is henceforth called the cross effect, as described by Baily et al (1996).

In diagrams (c) and (d) there is no labour productivity growth within plants even though aggregate data show positive growth. In case (c) the aggregate growth arises from the entry-exit process which can be described as 'creative destruction' according to Schumpeter (1942). In case (d) the entry-exit process does not occur but the average growth is brought forth as the relative shares of labour input increase in the plants with an above average productivity level.

3. The Components of Aggregate Labour Productivity Growth, 1975–1994

Data set

The Finnish manufacturing census of production for the period from 1975 to 1994 is made use of in this paper. The data set consists, in principal, of all Finnish manufacturing plants having at least 5 persons. In addition, only those plants that create positive value added are included in the following analysis. Thus, if a plant performs negative value added or its total employment drops below 5 persons in some year, it is interpreted as a closed down plant. This plant may re-entry later, as it meets again the requirements stated above.

There are alternative means of measuring a plant's output. Since the so called double counting is not a problem at the plant level, gross product could be used as an output measure. The problem is, however, that this output measure is heavily dependent on intermediate input. The advantage of value added measure is that it avoids double counting at the aggregate level. Since our focus is on the link between micro and macro level explanations of productivity growth, value added is a natural choice as a means of measuring the output of a plant.[1] Nominal value added of a plant is converted into 1990

1 In this study we employ the so-called census value added concept which ignores non-industrial services. The advantage of this concept over the so-called total value added concept used in national accounts is that the latter is more robust over the time span in the Finnish census of production. The census value added type measure is also applied in the international comparisons presented in Figure 1.

prices with the corresponding implicit industry deflator obtained from Finnish national accounts[1].

Although this study makes use of the implicit price indices of national accounts and although the manufacturing production census is the basic data source used for national accounts, aggregate productivity results do not coincide precisely with the results of the national accounts. On the contrary to national accounts, some of the manufacturing labour input and output is excluded here as mentioned above. Secondly, the census value added measure may overestimate the growth of total value added in manufacturing to some extent as manufacturing plants use an increasing amount of non-industrial services from sectors other than manufacturing.

The purpose of this paper is to measure the significance of the factors described in Figure 2 for Finnish manufacturing. The factors under investigation are:

1 Entry and exit (entry-exit)

2 Heterogeneity in labour productivity levels and re-allocation of labour input shares among plants (share effect)

3 Heterogeneity in labour productivity growth rates and re-allocation of labour input shares (cross effect)

4 Labour hours weighted average of labour productivity growth at the plant level (within plants effect)

Entry and exit

In order to measure the effect of plant turnover for the aggregate productivity growth, the productivity growth is measured with two different data sets. One consists of plants existing both at the beginning and at the end of the defined period (two years or more) and another set includes all plants in each year. Here the effect of the entry-exit is defined as a difference of the labour productivity growth rate measure obtained from these two different data sets (see below). (See also Baily et al. 1992.)

One of our ultimate issues of interest is how the relative importance of different factors change in different periods and under different business conditions. In order to evaluate the tendencies and the regularities in the process during the time span, we are interested in year to year changes. Although productivity measure usually indicates noticeable short term variation in

1 The deflator could be defined for 15 manufacturing industries.

growth rates because of the changes in business conditions or inaccuracy, we should however, make a long term view on the productivity as emphasised by Baumol et al (1989) since only sustained growth makes difference to the standard of living of a nation. For this reason it is well grounded to extend the period to cover ten years, for example.

The measurement of entry-exit effect (*ENTEX*) in the period from the year t-s ($s \geq 1$) to the year t can be measured as follows

$$\left(\frac{LP_t^A}{LP_{t-s}^A}-1\right)-\left(\frac{LP_t^S}{LP_{t-s}^S}-1\right)=\frac{LP_t^A}{LP_{t-s}^A}-\frac{LP_t^S}{LP_{t-s}^S}=ENTEX \quad , \tag{1}$$

where LP is labour productivity (real value added per hour worked), A refers to the data set containing all the plants in the year in question, S refers to the data set comprising the plants existing both in t–s and in t (the survivors).

The effect of entry-exit component to on annual changes (s=1) of the aggregate growth is shown in Figure 8 and in the table in the appendix. Until the year 1984 the entry-exit effect had played an insignificant role, but the importance of this effect rose to a higher level in 1985 and has been crucial ever since. Figure 9 indicates that the entry-exit have had an increasing and substantial long-term (s=9) effect. During the period from 1985 to 1994 labour productivity growth was 17 percentage points lower among those plants existing both in 1985 and in 1994 than the average growth in the total data set.

The effect of the entry-exit consists of four component:

1 The relative productivity level of the plants exiting in the next period

2 The relative labour input (hours) share of the plants exiting in the next period

3 The relative productivity level of the entering plants

4 The relative labour input share of the entering plants.

The effect of these factors can be presented and measured in the following way. Let us turn to the log differences. We redefine the entry-exit effect by using log-differences (*entex*)[1]

1 In small changes, log differences approximate ordinary percentage differences quite closely.

$$entex = \log\left(\frac{LP_t^A}{LP_{t-s}^A}\right) - \log\left(\frac{LP_t^S}{LP_{t-s}^S}\right)$$

$$= \underset{(I)}{\log\left(\frac{LP_{t-s}^S}{LP_{t-s}^A}\right)} + \underset{(II)}{\log\left(\frac{LP_t^A}{LP_t^S}\right)}, \tag{2}$$

where the log refers to natural logarithm.

The term *(I)* — exit-effect — can be developed further by realising that

$$LP_{t-s}^A = (1 - w^D)LP_{t-s}^S + w^D \cdot LP_{t-s}^D, \tag{3}$$

where $w^D = \frac{L_{t-s}^D}{L_{t-s}^A}$, $0 \le w^D \le 1$.

L indicates the amount of labour input and D refers to the data set containing only those plants disappearing before the year t. By inserting (3) in the term *(I)* we obtain

$$\log\left(\frac{LP_{t-s}^S}{LP_{t-s}^A}\right) = -\log\left(1 - w^D\left(1 - \frac{LP_{t-s}^D}{LP_{t-s}^S}\right)\right) . \tag{4}$$

Normally the labour productivity level is low among the plants disappearing in the near future, thus $\frac{LP^D}{LP^S} < 1$.

Under these circumstances, the lower LP^D or the higher w^D, the greater is the positive effect of exit for aggregate labour productivity growth.

In a similar way we can render the term *(II)* — entry-effect — in the following formula:

$$\log\left(\frac{LP_t^A}{LP_t^S}\right) = \log\left(1 - w^E\left(1 - \frac{LP_t^E}{LP_t^S}\right)\right) , \tag{5}$$

where $w^E = \frac{L_t^E}{L_t^A}$ ($0 \le w^E \le 1$) is the labour input share of the plants entering in the year t and E refers to the data set including only the plants entering after the year t–s.

Usually $\dfrac{LP^D_{t-s}}{LP^S_{t-s}} < \dfrac{LP^E_t}{LP^S_t} < 1$ at least with small values of s and thus the term *(II)* is generally negative, because then the term inside the outer brackets on the right side of equation (5) is less than one. In addition, as $w^E < w^D$ in Finnish manufacturing since the mid 80's then the sum of the terms *(I)* and *(II)* were positive in that period.

Figure 3 illustrates the decomposition of the entry-exit effect for Finnish manufacturing. Taken as a whole, the entry effect has been quite stable and slightly negative, excluding a few exceptions. The exit effect, in turn, has been positive and in addition quite noteworthy and stable since the mid 80's.

Figure 4 reveals that the increase of the exit effect in 1985 was based mainly on the increase in the share of labour hours in the plants disappearing the next year. In general, labour productivity among the plants which no longer operated the next year was 20 – 40 per cent lower than among the plants which operated also next year. On the average, labour productivity among newly entered plants was 80 percent of the level of plants that were at least two years old. Thus the relative labour productivity level of newly en-

***Figure 3.* Decomposition of the entry-exit effect on the aggregate labour productivity growth in Finnish manufacturing, log differences.**

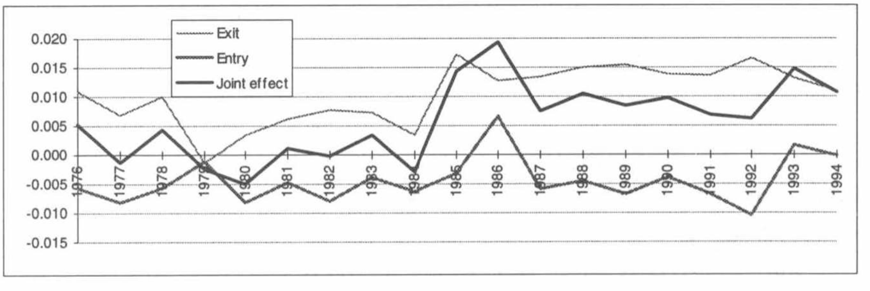


***Figure 4.* The components of exit effect.**

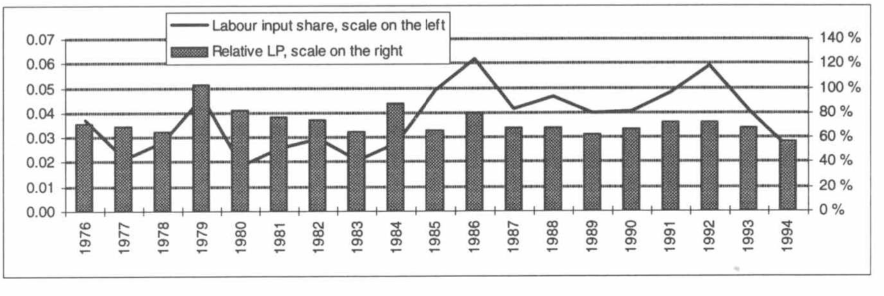
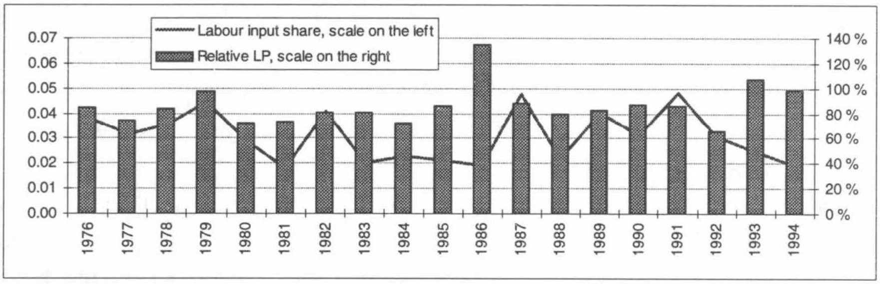


Figure 5. The components of entry effect.



tered plants was clearly higher than the relative level among those disappearing the next year.

In previous graphs 3 to 5 annual changes were studied. However, the process of the disappearance and entry may be long and complex. In this context, however, this issue is dealt with only briefly. Figure 6 indicates that the plants show clearly below average labour productivity three and two years before disappearance. In addition, the relative labour productivity level seems to decrease as 'doomsday' approaches.[1]

As can be seen in the Figure 6, the relative labour productivity level was rather high in preceding three years among plants which disappeared in 1992 or 1993, when the economic conditions were harsh. On the other hand, in 1994 mainly those plants which had been quite weak in terms of relative labour productivity in the near past were the ones to disappear. This could be expected as the economic situation was normalised by 1994 and was not as severe than earlier. In this respect the year 1994 resembles 1989, when the previous boom in the Finnish economy occurred.

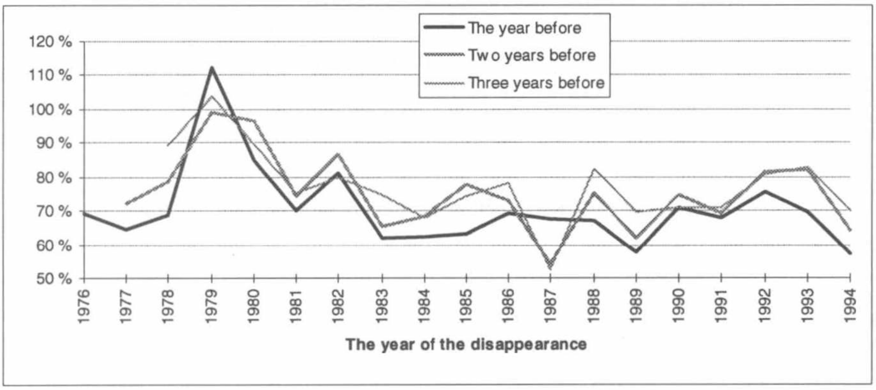
In this context it is worth of considering the issue of data quality to some extent. As can be seen in the Figure 4, a considerable amount of plants disappeared in 1979. A recession in that year provides partial explanation for this. Two things, however, give rise to some doubts. Firstly, in 1978 the relative labour productivity level was exceptionally high among the that dis-

1 The relative levels in Figure 6 and 7 do not always coincide with the results shown in Figure 4 and 5. Firstly, the reference levels are defined differently (see text). Secondly, entry and birth do not necessarily mean the same thing. Here birth is defined as the first ap-pearance during the period from 1975 to 1994. Sometimes a plant disappears and makes a new entry later.

appeared in 1979. Secondly, there was a vast amount of entries in 1979 (see Figure 5).

A closer look at the data reveals that the plant code changed for a large number of plants in 1979. It was possible to match the older and proper code for 660 plants with the help of the enterprise code, address and some other variables.[1] It appears, however, that not all miscodings could be corrected. On the other hand, the plants that disappeared covered about 4 % of the total labour hours, which is about 2 percentage points above the normal level of those times. Thus this kind of defect may have some effect on an annual change but is of a little importance in long term considerations. Other defects that may explain year to year variation in aggregate labour productivity components at least partly can also exist[2]. One should, however, pay attention mainly on the tendencies and long term effects when interpreting the results.

***Figure 6.* The labour productivity level of the plants with zero, one or two years left relative to the plants with at least three years left.**



Note: The productivity level of the disappearing plants is compared with the plants in operation for at least three more years, except for 1992 and 1993 the disappearing plants are compared with those in operation in 1994.

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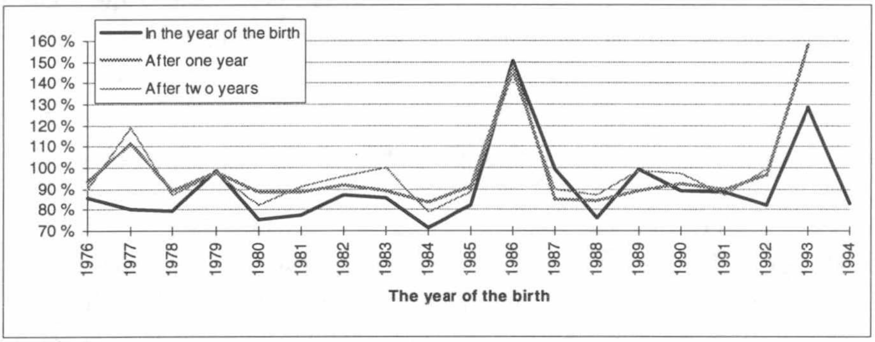
1 Some breakoffs could also be recognised and corrected between 1975 and 1976 (some 400 cases) and between 1979 and 1980 (about 50 cases) but these were usually small plants and thus had no significant effect on the results. The whole period was checked but no flaws could be detected in the plant codes.

2 At varying intervals the Finnish manufacturing census of production is supplemented by plants found in other registers. This hap-pened, for example, in 1991. This explains why there was a big increase in the number of plants in spite of the severe economic slump at the time. There was also an increase in the labour input share of the plants that appeared in that year (see Figure 5).

Figure 7. **The labour productivity level of the plants in operation one year, two years and three years relative to the plants in operation more than three years.**



Note: The productivity level of the newly born plants is compared with the plants in operation already three years earlier except for plants that were born in 1976 or 1977, where the comparison is made with the plants that existed already in 1975.

Labour input shares, labour productivity levels and labour productivity growth among staying plants

Thus far we have studied how the aggregate labour productivity is affected by the fact that the sample changes due to the disappearance and the appearance of plants. Next we will look at what has happened among staying plants. Henceforth we make use of a decomposition method applied by Baily et al (1996) for a full panel of US manufacturing plants from 1972 through 1988. Unlike Baily et al, we are not making use of one full panel of the plants over a long period, but at the first stage several full panels are constructed, each consisting of the plants in two successive years. (See also Baily et al 1992.)

Three components of annual labour productivity change are 'within plant' effect, an labour input share component and a cross term. These can be calculated by following formula:

$$\frac{\Delta LP_t}{LP_{t-s}} = \frac{\sum_i \phi_{t-s,i} \Delta LP_{t,i}}{LP_{t-s}} + \frac{\sum_i \Delta\phi_{t,i} LP_{t-s,i}}{LP_{t-s}} + \frac{\sum_i \Delta\phi_{t,i} \Delta LP_{t,i}}{LP_{t-s}} \quad , \tag{1}$$

where LP is real value added per hour, $\phi_{t,i}$ is the labour input share of plant i, $t–s$ refers to the first period and t refer to the last period.

The results of this decomposition with s=1 is shown in Figure 8 and in the table in the appendix. The effect of the labour input share shows a clear upward trend and this effect contributed from 2 to 4 percentage points to the annual aggregate productivity growth in the 90's. The entry-exit effect (ENTEX) varied to some extent hand in hand with the labour input share effect. The cross term, on the other hand, seems to be some kind of mirror image to the entry-exit effect.

The changes between 1992 and 1993 deserve some further attention. A recovery from the economic slump was already emerging in the Finnish manufacturing at the time. As can be seen in Figure 3, the exit effect still existed but what is interesting is that some new high productivity plants emerged in 1993 but which accounted for a relatively small share of the labour hours. Figure 7 seems to suggest that those plants were even stronger in 1994. On the other hand, the labour input share of those plants was relatively small and thus the possibility that a random effect or some kind of measurement error plays some role should not be ruled out.

However, the labour input share component seems to confirm that something real and exceptional happened between 1992 and 1993. Figure 7 suggests that there was an outstanding re-allocation of labour input shares among surviving plants. Firstly, the plants with an above average labour productivity level had increased their labour input share to a greater extent than before. Secondly, the cross-term was significantly negative, indicating that the plants with an above average growth rate accounted for a declining share of labour input[1]. These results seem to suggest that in the period from 1992 to 1993 the gainers were those plants which had managed to reach high labour productivity performance earlier as well as those low productivity plants which were able to adjust their labour input. These results bear a resemblance to what happened in the US manufacturing sector in 1981, but these results are economically even more significant than in the United States (see Baily et al 1996, page 7).

The time series of the labour productivity within plants follows closely a log-linear trend over the period from 1975 to 1994. The aggregate level time series, on the contrary, drifts away from this trend since the mid 80's (see Figure 10). Without structural factors, Figure 1 would have been quite different as far as Finland is concerned. For the sake of comparison, factors other than plant level growth contributed less than 3 percentage points during the period from 1975 to 1984 while this figure was 22 percentage points for the period from 1985 to 1994. There may also be differences in the relative

1 When interpreting a particular year to year change as in this case one should bear in mind that problems with data may bias the results. We could not locate any such data problems that could give rise to the results reported above, unlike in the case of the year 1979 or 1991, where some explanations for the surprising results could be traced.

Figure 8. **The effect of entry-exit, labour input share and cross term for the annual aggregate labour productivity growth rate.**

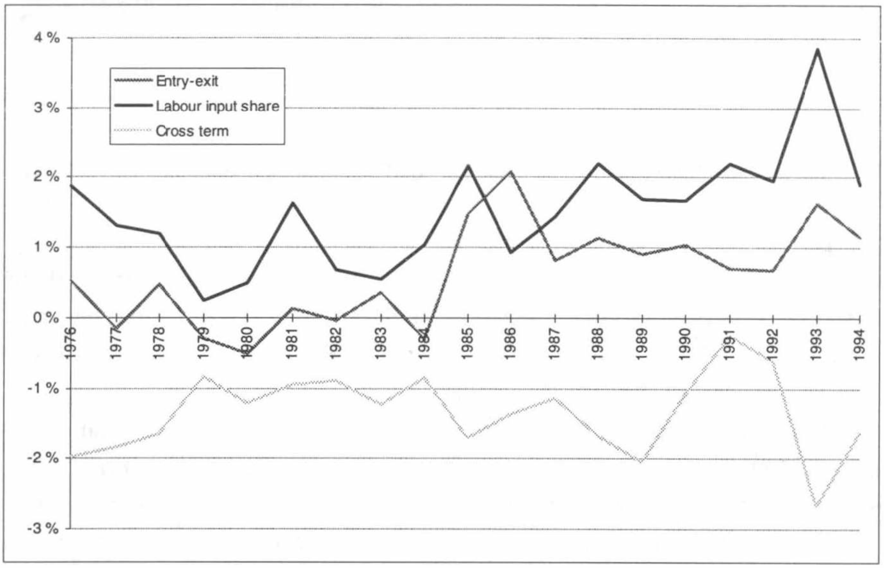
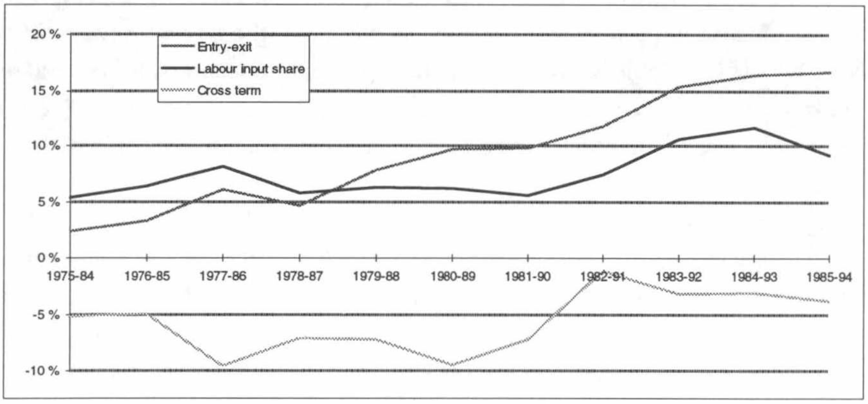
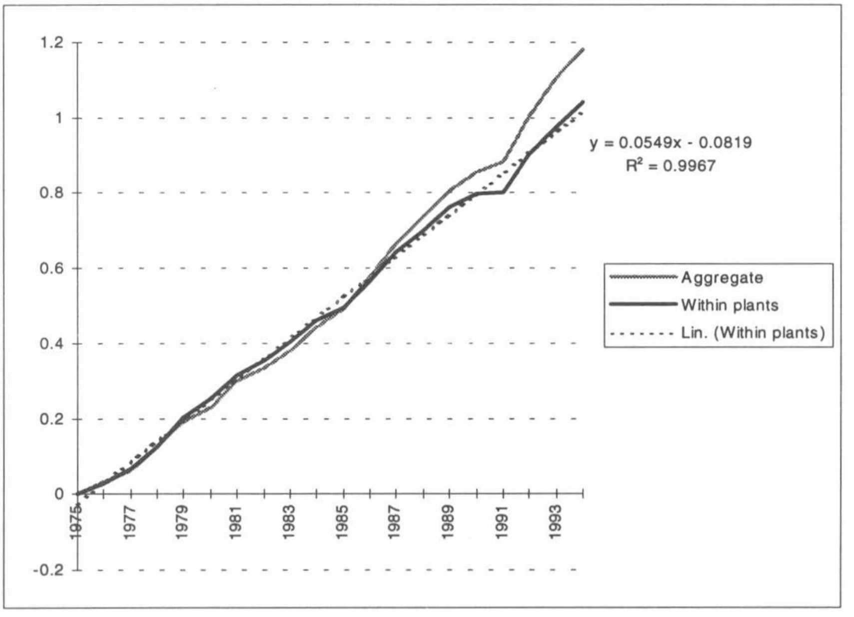


Figure 9. **Structural factors of aggregate labour productivity growth in decade.**



importance of the structural factors not only between different periods but also between different countries. The comparison of the results obtained here and by Baily et al (1996) seems to indicate that structural factors have played a bigger role in Finland than in the United States at least as far as the labour input share effect is concerned.

Figure 10. **Labour productivity from 1975 to 1994, log differences, 1975=0.**



4. Conclusions

This paper demonstrates that the understanding of the factors behind macro level observations requires the use of micro level data. There are several micro level determinants which affect aggregate results. As the results for the Finnish manufacturing sector indicates, the absolute and relative size of different components of aggregate productivity growth may vary considerably during the time span. Thus, for example, the interpretations concerning plant level growth or technical change made on the basis of aggregate series should be looked at with reservation.

As the importance of different components has changed in the course of time, it is quite possible that there may have been substantial differences in the relative shares of different components between countries. Therefore the results of international productivity differences based on aggregate data sets should be interpreted with care. As the results of this paper point out it is quite possible that there is a long-lasting difference in the growth rates of aggregate productivity between so-called leader and follower countries in favour of the latter which, however, have nothing or very little to do with technology transfer, for example. Consequently, it would be very useful from the point of view of international productivity comparisons if the decomposition of productivity growth were available for each country. The comparison of the magnitudes of different components between countries could also give a wider understanding of the process of entry-exit and the re-allocation of labour hour shares among plants.

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Appendix: Annual aggregate labour productivity and its components

Year	Aggregate productivity	Within plants	Entry-exit	Labour input share	Cross-term
1976	3.2 %	2.7 %	0.5 %	1.9 %	–2.0 %
1977	3.4 %	4.0 %	–0.1 %	1.3 %	–1.8 %
1978	6.2 %	6.2 %	0.5 %	1.2 %	–1.7 %
1979	7.1 %	7.9 %	–0.3 %	0.2 %	–0.8 %
1980	3.8 %	5.1 %	–0.5 %	0.5 %	–1.2 %
1981	7.3 %	6.5 %	0.1 %	1.6 %	–0.9 %
1982	3.4 %	3.6 %	0.0 %	0.7 %	–0.9 %
1983	4.8 %	5.2 %	0.4 %	0.5 %	–1.2 %
1984	6.2 %	6.4 %	–0.3 %	1.0 %	–0.9 %
1985	5.2 %	3.3 %	1.5 %	2.2 %	–1.7 %
1986	8.9 %	7.2 %	2.1 %	0.9 %	–1.4 %
1987	9.2 %	8.0 %	0.8 %	1.4 %	–1.1 %
1988	7.5 %	5.9 %	1.1 %	2.2 %	–1.7 %
1989	7.0 %	6.5 %	0.9 %	1.7 %	–2.1 %
1990	5.2 %	3.6 %	1.0 %	1.7 %	–1.1 %
1991	2.9 %	0.2 %	0.7 %	2.2 %	–0.3 %
1992	12.6 %	10.6 %	0.7 %	2.0 %	–0.6 %
1993	10.8 %	8.0 %	1.6 %	3.8 %	–2.7 %
1994	7.8 %	6.4 %	1.1 %	1.9 %	–1.6 %

Note: See text

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GROWTH PATTERNS AND ECONOMIC PERFORMANCE OF FRENCH MANUFACTURING FIRMS IN 1993

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The aim of this article is to identify specific types of economic behaviour and to relate them to companies' investment, and particularly intangible investment, decisions. It is first of all necessary to define competitiveness and to suggest a measurement indicator suited to aggregated accounting data. The link between competitiveness and profitability will be specified and the diversity of the companies will then be highlighted.

We use an unbalanced sample of more 12 000 manufacturing firms belonging to the Banque de France balance sheet data base from 1991 to 1993.

Key words: Productivity, Competitiveness, Profitability, Behaviour of Firms, World of Production

1. Measurement of Corporate Performance

Assessing a company's economic situation involves looking at how the management uses resources and *measuring the results obtained* with reference to the objectives set (Jacot 1990).

Three stages in the assessment have then to be identified, *"namely, the recognition of levels that are too often confused in economic assessments: the "physical" level, the "market" level, and the "financial" level* (Jacot 1990, 65).

The "physical" level corresponds to the productivity (or yield) of labour and capital. It is the level of the concrete implementation of the combination of factors of production. It covers both the technological and organisational dimensions of the production process, along with human resources

1 The opinions and analyses offered in this article are the author's.

management. As a result, the productivity stemming from this "physical" level depends as much on quantitative factors (staff numbers, capital, etc.) as on qualitative factors (training, working conditions, etc.). One can say that this productivity is one factor in a company's competitiveness, since it is the outcome of the production process from the point of view of factors of production.

Competitiveness in the strict sense of the term corresponds to the "market" level. In addition to the productivity of labour and capital, it depends on the "excellence of production", i.e. quality, reliability, fluidity (zero stocks), flexibility, safety, etc. *Using accounting data, and in the absence of information on the company's environment,* the pertinent indicator of the market outcome is the profit margin. This is because the profit margin is the result of cost control, via the company's pricing policy and the quality of customer service, and of the Organization of production and of human resources.

The third, "financial", level, brings return on assets[1] into play. It is thus possible to dissociate competition issues (competitiveness) from profitability. This is because the formation of profit can differ greatly according to the firm, not only in terms of its market, but also through the specific choices in relation to labour and/or capital productivity and price and non-price competitiveness. This therefore influences the investment decisions that shape the company's combination of factors of production and the corresponding financial structure.

This *a posteriori* accounting assessment of the underlying economic dynamics is only valid if it concerns all the players in the firm in terms of the conditions that need to be met or reproduced to continue, strengthen, and improve competitiveness and, in a wider sense, the current and future efficiency of the company.

2. The Importance of a Good Assessment of Profitability

Analysing a firm's ability to generate funds involves studying the type of environment in which it operates and the organisational methods it uses to manage its environment. By referring to the typology established by Salais and Storper (1993), one can study the range of choices made by the company that determine the formation of profitability.

1 It is also possible to use return on equity.

"Maximising the return on capital does not in itself define a hierarchy of choices between the production models. All the production models are in fact profitable if they are implemented coherently (Salais and Storper 1993, 74; Paranque 1992, 1994a, 1994b)."

The different "production models" can be studied on the basis of return on assets, which is expressed as:

$$GRI = \frac{Overall\ gross\ cash\ flow}{Capital\ employed}\ Gross\ return\ on\ investment^{1}.$$

Several variations of the ratio "reflecting" the choices made by the firm are possible, according to the market and production process dimensions:

*"**The first formula puts the accent on the market,** in other words on the choice of product and Organization compatible with a market-driven optimisation of return on assets".*

$$GRI = \frac{OGCF}{T} \times \frac{\dfrac{T}{Production\ equipment}}{\dfrac{Capital\ invested}{Production\ equipment} + \dfrac{WCR}{T} \times \dfrac{T}{Production\ equipment}} \quad (1)$$

T = turnover
$OGCF$ = overall gross cash flow
WCR = Working capital requirement
Capital invested = capital employed minus the working capital requirement (gross fixed assets)

In this case, the vectors are the overall gross profit margin, the rate of turnover of production equipment (adaptability/sensitivity of the company to short-term demand) and the frequency of operating working capital requirement turnover. *"This market-driven optimisation gives priority to the flow, i.e. to short-term Organization".*

*"**The second two formulae stress the Organization of production,** in other words the **technology-driven optimisation of profitability**. This optimisation based on technology gives priority to capital invested in equipment and labour, i.e. to medium-term Organization".*

The first of the formulae is expressed as:

1 According to the financial analysis method used by the Banque de France Balance Sheet Data Centre: gross operating cash flow + non operating financial income and net expenses; capital employed, either own self-financing + financial debt, or fixed assets + working capital requirement + cash and cash equivalents + leasing.

$$GRI = \frac{(1 - \frac{PC}{VA}) \times \frac{VA}{N}}{\frac{K}{N} + \frac{WCR}{N}}, \qquad (2a)$$

VA = value added
PC = personnel costs (wages plus social security costs)
N = number of employees
K = capital invested (capital employed minus working capital requirement)

*"**The underlying technological direction here is increasing labour productivity,** VA/N, based on the substitution of capital for labour, K/N, and on the relative savings on personnel costs, PC/VA; PC/VA diminishes if labour productivity rises faster than personnel costs per employee".*

The second formula is expressed as :

$$GRI = \frac{(1 - \frac{PC}{VA}) \times \frac{VA}{K}}{1 + \frac{WCR}{K}}. \qquad (2b)$$

*"**The underlying technological direction is improving capital efficiency,** VA/K. It corresponds to combinations of factors of production based on specific qualities of labour or intangible investment intended primarily to develop the capacities of the work force"*[1].

This approach thus makes it possible to define a yardstick for assessing how well profitability is managed, i.e. how the "dynamic equilibrium" is controlled.

3. Different Types of Behaviour in the 1993 Recession[2]

In 1993, the constraint of financing fixed asset formation made a clear distinction possible between firms. First of all, firms differ in their investment policy and how it is financed, taking into account their activities and their own ability to improve their competitiveness in times of recession.

1 Here, work force is used in the wide meaning of the term to refer to all employees, and those involved in or responsible for investment efficiency.

2 See annex 1 description of the sample.

Companies can also be distinguished according to their combination of factors of production and its efficiency. It emerges that small- and medium-sized manufacturing firms with fewer than 100 employees can be contrasted with large companies with fewer than 2000 employees.

On the basis of this initial approach, six classes of behaviour can be identified[1]:

The first so-called "autonomous" class of behaviour includes mainly small- and medium-sized manufacturing firms with fewer than 100 employees and intermediate goods manufacturers. They are slightly more competitive than average but suffer from a deficit on the "physical" level, which could jeopardise their future (Coriat and Taddeï 1992; Ochs 1995).

The second class of behaviour, called "exporter" behaviour, covers companies that belong mainly to the business equipment sector. They are firms that employ between 100 and 2000 people. Their competitiveness is based on high labour productivity despite the fact that their capital efficiency is the lowest in the typology and adversely affects their return on assets. Their ratio of intangible investment is high, even during the two previous years, and must thus have contributed to their performance.

Typology of companies in 1993.

Average of ratios	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	
	Autonomous	Exporting	Profitable	Investor	Non-capital intensive	Ailing	All
Share of the class in the sample (%)	44.9	13.3	10.1	9.3	9.5	12.9	100.0
Active ratios							
Debt servicing costs (%)	77.9	77.1	53.6	96.9	66.5	526.6	133.8
Overall VA/Capital employed (%)	57.4	48.0	NS	55.7	130.5	54.9	63.0
Fixed asset formation rate (%)	1.0	7.0	12.1	18.5	22.8	- 20.3	3.8
Change in VA (%)	NS*	0.0	NS	12.5	2.3	- 25.4	- 3.2
Change in employee numbers (%)	- 3.8	NS	1.6	8.2	- 1.1	- 11.6	- 3.2
Change in capital (%)	1.3	4.6	NS	27.3	5.1	- 10.7	3.1
WCR turnover (days)	86.0	102.5	NS	71.1	28.3	96.6	81.8

1 Factor analysis was used to classify types of behaviour in ascending order.

Average of ratios	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	
	Auto-nom-ous	**Expor-ting**	**Profit-able**	**Investor**	**Non-capital inten-sive**	**Ailing**	**All**
Export rate (%)	7.5	55.4	NS	11.7	8.2	NS	16.4
Investment rate (%)	7.4	NS	6.8	32.2	4.8	7.6	9.8
Shareholders' rate of return (%)	1.6	1.9	9.2	1.9	NS	1.2	2.5
Lenders' rate of return (%)	12.5	12.5	13.6	10.0	NS	NS	15.3
External financing rate (%)	46.8	38.1	33.9	77.7	25.2	96.5	51.6
Production employees/total employees (%)	8.0	NS	49.2	80.7	81.9	73.8	76.1
Labour costs (FRF 000s/p)	181.2	210.4	278.2	190.2	179.6	NS	197.8
Illustrative ratios							
Return on equity (%)	2.5	3.6	8.6	3.1	6.1	- 24,4	0,2
GRI (%)	12,3	NS	17,5	15,2	18,0	- 4,4	11,5
OGCF/Overall VA (%)	23.3	26.5	30.6	29.4	17.6	- 7.8	20.5
Total investment rate (%)	9.2	NS	10.4	38.4	5.8	NS	12.5
Capital employed / personnel costs (%)	NS	357.7	317.6	336.9	140.3	246.7	280.8
VA/employee numbers (FRF 000s/p)	244.0	301.0	436.1	289.6	227.7	187.0	266.4
Rate of turnover of production equipment (%)	298.6	311.6	644.3	296.5	647.4	NS	376.5
376.5							
Equity/total assets (%)	37.7	42.4	42.6	32.1	NS	16.9	35.4
Average cost of external financing (%)	11.6	10.7	11.0	9.0	19.6	NS	11.9
Ordinary bank financing/external financing (%)	NS	24.7	23.0	23.1	16.0	37.4	26.9
Rate of intangible investment	1.7	3.6	5.2	NS	1.3	1.7	2.6
Proportion (%)							
Intermediate goods	42.5	NS	23.4	44.4	25.2	NS	37.1
Consumer goods	NS	27.2	42.6	NS	44.4	30.0	35.7
Business equipment	17.0	33.6	31.3	16.1	27.6	29.0	23.1
Household goods	NS	NS	NS	NS	NS	NS	0.6

Average of ratios	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	
	Auto-nom-ous	Expor-ting	Profit-able	Investor	Non-capital inten-sive	Ailing	All
Automotive sector	NS	NS	1.7	NS	NS	NS	3.4
Small manufacturing firms	68.8	41.8	54.1	70.4	79.0	NS	64.4
Medium manufacturing firms	NS	39.1	NS	NS	18.4	NS	28.2
Large companies	3.4	15.7	12.9	3.0	1.9	NS	6.2
Very large companies	NS	NS	NS	NS	NS	NS	1.2

Source and production: Banque de France – Companies Observatory. Last update October 1994
* *NS:* non significant relative to the average or the frequency with which they appear in the sample.

The third class includes, in particular, companies with between 500 and 2000 employees in the business equipment and consumer goods sectors. This class of behaviour is called "profitable" because it is characterized by what may be termed a "virtuous" pattern: high labour productivity and average capital efficiency go hand in hand with a high profit margin. Beginning in 1991, this pattern was based on a very high and sustained rate of intangible investment.

The fourth, *so-called 'investing'*, class consists mainly of small- and medium-sized manufacturing companies and of firms in the intermediate goods sector. These companies are *more competitive than average but suffer from a deficit in capital efficiency which is probably due to the time lag in return on investment.* The rate of intangible investment is average[1].

Class 5 includes small- and medium-sized manufacturing companies and firms in the consumer goods and business equipment sectors. These companies are *'non-capital-intensive', and are uncompetitive but make up for this handicap by a high degree of capital efficiency which gives them a clear advantage on the 'financial' level.* They have the lowest rate of intangible investment but this must be assessed in the light of the specific features of these companies and of the limits of the indicator, which does

1 It is probably undervalued given the accounting methods since a large part of the accompanying expenses and the costs of implementing tangible investments are not isolated and are therefore considered as intangible investments.

not take into account "incorporated" intangibles such as know-how acquired "on the job".

"Ailing" companies are included in class 6. This class has no specific features in terms of size. Only firms in the business equipment sector are slightly more numerous. *These are companies whose debt servicing costs are five times greater than that of the rest of the sample.* Their intangible investment rate is slightly above average.

The wide range of situations that emerges may be explained by different degrees of sensitivity to the recession and the fall in activity. This would be a rather simplistic view if one did not take into account the specific characteristics of each company in terms of technology, marketing policy, strategy and work Organization.

4. Various Types of Environment

The wide range of economic structures reflects the wide variety of market positions and production processes.

The typology set out above shows that companies encounter four main situation types:

- the first is characterized by a high level of debt servicing costs (class 6) and highlights the solvency constraint linked, in particular, to the decline in activity
- the second concerns the profitability constraint linked to the investment policies that have been implemented (classes 4 and 5, and to a lesser extent, class 3)
- the third stresses the specific features of a growth pattern based on increasing labour productivity (class 3), which may be achieved at the expense of capital efficiency (class 2)
- the fourth type of situation, encountered by class 1, is a synthesis of the three preceding situations and, while low investment levels help preserve financial autonomy and a certain degree of profitability, this may be at the expense of future competitiveness.

In other words, the constraints appear to be specific to the firms in each of these classes and the sensitivity of their profitability to their economic and financial situations seems therefore to vary. This takes us back to the idea developed by

R. Salais and M. Storper concerning the existence of "worlds" characterized by particular constraints, whose main features are as follows :

- the "interpersonal world" (MARSH) is that of specialised and dedicated products, which renders companies extremely sensitive to changes in demand due to the high level of uncertainty. Profitability will therefore be highly dependent on the profit margin and on control of the combination of factors of production (labour and productivity costs and capital efficiency). Competition is on quality and therefore depends on investment policy. It is a world of uncertainty and differentiation
- the "market world" (MARCH) is that of standard and dedicated products in which competitiveness is based first on price and then on quality. Standardisation leads to higher than average capital intensiveness as well as higher labour productivity; it is a world of uncertainty and of economies of scale
- the "industrial world" (IND) is that of mass production. Here too, standardisation leads to increased capital intensiveness and high labour productivity but profitability will depend less on the profit margin than on control of the operating cycle (turnover of working capital requirement and equipment turnover) ; it is a world of predictability and of economies of scale
- the "intangible world" (INNOV) is that of innovation. Like the "interpersonal" world, it is therefore characterized by high labour costs corresponding to the high level of skills required and a high degree of capital efficiency which, as in the "industrial" world, is due to a constraint linked to the risk of slower working capital requirement turnover (development of new products) and the need for a high rate of equipment turnover. It is a world where uncertainty becomes certainty: "the company has no choice but to act as though it were producing for an existing and known market".

It is interesting to try to establish links between the typology set forth previously with the "worlds" thus defined.

5. Specific Growth Patterns

The purpose is to *analyse,* other things being equal, a *possible configuration,* reasoning along the lines of "if the company fulfils these conditions, then we can assume that it belongs to this world", with the proviso that several "worlds" can coexist within one company.

Frequen-cy**	Personnel costs/value added or value added/ capital		Capital/numer of employees or value added/number of employees		Market
Overall gross cash flow/overall VA	Class 1 (63.6) Class 2 (59.1) Class 3 (72.9)*	Class 4 (76.1)* Class 5 (97.7)* Class 6 (30.6)	Class 1 (34.2) Class 2 (60.8) Class 3 (90.2)	Class 4 (53.9) Class 5 (26.4) Class 6 (9.0)	Un-certainly
	Marsh (63.4)		March (41.3)		
WCR turn-over or Rate of turnover of production equipments	Class 1 (56.9) Class 3 (54.8) Class 3 (75.3)	Class 4 (54.4) Class 5 (91.2) Class 6 (43.6)	Class 1 (52.4) Class 2 (73.8) Class 3 (96.9)	Class 4 (66.8) Class 5 (73.8) Class 6 (47.2)	Pre-dicta-bility
	INNOV (59.8)		IND (62.5)		
Technology and process of production	Economy of differentiation		Economy of scale		

Source and production: Banque de France, Companies Observatory, October 1994

*more important than the world in the sample.
** χ^2 test, world/class ; frequency of the world by class/frequency of the world in the sample. Ho rejected.

Clearly, this is not a demonstration but a series of questions concerning the diversity of situations encountered by companies and the diversity of solutions they find to achieve profitability.

Using the Salais and Storper criteria, one can then assess the importance of the six classes in each "world" independently of the others.

"Autonomous" companies (class 1) and "ailing" companies (class 6) are not linked to any particular "world". Thus, there is no determinism in the difficulties of "ailing" companies or in financial autonomy. A common point emerges between these two classes, namely a deficit on the "physical" level. This may result from either a fall in activity or a more or less serious loss of control over the implementation of the combination of factors of production, which is generally a prelude to the company's coherence coming under threat.

"Profitable" companies (class 3) and "exporting" companies (class 2) resemble each other in their underlying technology policy, which is based on increasing labour productivity as a factor of their competitiveness. These companies in general, and particularly "profitable" companies, trade on economies of scale (MARCH or IND). "Profitable" companies may nevertheless trade on differentiation (MARSH and INNOV), where their competitiveness results partly from a higher degree of capital efficiency than "exporting" companies, and therefore from a different technology policy.

"Investing" companies (class 4) are more frequently positioned on an uncertain market selling standard products – economies of scale – (MARCH) or dedicated products – differentiation – (MARSH). We saw that they are, on average, more competitive than other companies, but that they could suffer from a deficit in capital efficiency, probably linked to the lag in return on investments, particularly in the case of companies belonging to the "market" world (MARCH).

For the last three classes mentioned, the underlying technology policy tends to be increasing labour productivity by substituting capital for labour. "Non-capital-intensive" companies (class 5) mainly belong to the "world" of differentiation (MARSH and INNOV), with a technology policy based on capital efficiency. This allows them to compensate for their lack of competitiveness. They are sometimes found in the "industrial" world.

This breakdown of typologies makes it possible to identify constraints corresponding to the company's concrete situation, and therefore to a possible range of management approaches, depending on its size, product range, geographical market, technologies used, etc.

This approach shows just how illusory it is to generalise and forget that, even though the company forms a homogenous whole, it can only do so if it manages to make the lines of reasoning found within it coexist coherently. If the lines of reasoning are in conflict, the company faces a crisis, if they are not, the company is competitive.

6. Conclusion

In the recession, the extent of the decline in investment and profitability and the strengthening of financial autonomy varied according to the company.

Most companies, i.e. "autonomous" companies, were able to preserve their profitability and reduce their debts by cutting back investment. The choices made in response to short-term pressures may jeopardise past gains in competitiveness. One may therefore wonder, as does Artus, whether such a policy is effective, *"Reducing investment does limit short-term debt in a period of recession, but if this shortfall in fixed assets is thought to be (at least partially) irreversible, the decision leads to an insufficient, sub-optimal capital stock that may reduce profits in the long term"* (Artus 1994).

In contrast, "profitable" companies, and above all "investing" companies and "non-capital-intensive" companies, trimmed their investment in fixed assets to a lesser extent. This may increase their financial constraints but enhances their competitiveness, providing the recovery comes early enough to allow them to make the expected gains.

In simple terms, both these scenarios show a dividing line defined by fixed asset formation and the market constraint. On one side, there are companies faced with a tighter market constraint but which can nevertheless loosen their financial constraint by reducing investment even if this means accepting lower profitability. On the other side of the line, there are companies that benefit from an increase in activity. This enables them to reduce their profitability constraint, but the counterpart to their accumulation of fixed assets is a loss of financial autonomy.

The range of firms' economic and financial situations thus reflects specific economic approaches and not simply different types of behaviour in response to a similar environment. The company that produces standard products and seeks economies of scale does not have the same constraints as a firm whose activity is based on innovation and meeting specific needs. The ways these constraints are managed are different too. The management approaches are based, depending on the case, on greater labour intensiveness, or else, on improved overall efficiency in the use of capital, and particularly of human capital.

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Appendix: Description of the Sample in French

L'échantillon constitué pour la présente étude rassemble des entreprises adhérant à la Centrale de bilans, présentes de 1991 à 1993, relevant du secteur de l'industrie manufacturière. Quatre tranches de taille d'entreprises définies selon le nombre de salariés ont été définies.

SEUILS D'EFFECTIFS RETENUS ET STRUCTURE DE L'ÉCHANTILLON PAR TRANCHE DE TAILLE EN 1991

Tranches de taille	Seuils	pourcentage d'entreprises	pourcentage d'effectifs
1 (PPMI)	100 salariés	63.3	12.9
2 (GPMI)	de 101 à 500	28.8	25.7
3 (GE)	de 501 à 2.000	6.6	25.4
4 (TGE)	plus de 2.000 salariés	1.3	36.0
Ensemble		100.0	100.0

Source et réalisation: Banque de France – Observatoire des entreprises. Mise à jour octobre 1994

STRUCTURE DE L'ÉCHANTILLON COMPARÉE À CELLE DE L'INDUSTRIE NATIONALE EN 1991*

(en pourcentage)	Échantillon de l'étude		Industrie *		Taux de couverture	
	Nombre d'entreprises	Effectifs	Nombre d'entre-prises	Effectifs	Nombre d'entreprises	Effectifs
PMI (moins de 500 salariés)	92,1	38,6	98,9	55,5	9,2	32,8
GE	7,9	61,4	1,1	44,5	62,6	65,0
Biens intermédiaires	37,1	33,1	28,3	32,0	11,8	48,7
Biens de consommation courante	35,8	22,5	38,7	28,0	8,3	38,0
Biens d'équipement professionnel	23,1	26,3	21,4	28,0	9,7	44,1
Biens d'équipement ménager	0,6	1,6	0,5	1,6	10,8	49,8
Construction automobile et autres matériels de transport	3,4	16,5	1,8	10,3	16,7	75,2
Ensemble	**100,0**	**100,0**	**100,0**	**100,0**	**9,0**	**47,1**

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AIRLINES, ENVIRONMENT AND TECHNICAL EFFICIENCY: An International Comparative Study[1]

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The principal aim of this paper is to measure the efficiency of international airlines. We obtain measures of technical efficiency from stochastic frontier production functions which have been adjusted to account for environmental influences such as network conditions, geographical factors, etc. We observe that two alternative approaches to this problem have been proposed in the efficiency measurement literature. One assumes that the environmental factors influence the shape of the technology while the other assumes that they directly influence the degree of technical inefficiency. In this paper we compare the results obtained when using these two approaches. The two sets of results provide similar rankings of airlines but suggest differing degrees of technical inefficiency. Both sets of results suggest that Asian and Oceanic airlines are technically more efficient than European and North American airlines but that the differences are essentially due to more favourable environmental conditions. Nevertheless, it is among Asian companies that the major improvements in managerial efficiency (technical efficiency with environmental factors netted out) took place over the sample period (1977–1990).

Key words: Frontier Production Function, Asian, Oceanic, European and North American Airlines.

1 The authors wish to thank Philippe Barla and Pierre Pestieau for stimulating discussions.

1. Introduction

Over the past two decades, international airline companies have faced many changes. In particular they have been exposed to a major deregulation process which began in North America and has since spread across the Atlantic and Pacific Oceans to the rest of the world. This reform process has been primarily argued for on the basis of improving competition and hence efficiency in the provision of air transport services. To shed some light on the success, or otherwise, of these policies, the primary objective of this paper is to estimate and compare the evolution of airlines performance during this period.

There are many ways in which one may define and measure performance of industrial activities such as air transportation. Forsyth, Hill and Trengove (1986) provide a review of a variety of financial and productivity related alternatives. In this study we focus upon the measurement of technical efficiency[1] and concentrate our attention on the flying operations that represent the heart of the airlines companies activities. Using annual physical data on output and input quantities, we specify a stochastic frontier production function and estimate its unknown parameters using maximum likelihood (ML) methods [see Aigner, Lovell and Schmidt (1977) for more on this methodology). Technical efficiencies are then measured relative to these estimated frontiers.

One of the main assumptions underlying frontier analysis and technical efficiency measurement is that all the firms in an industry share the same production technology and face similar environmental conditions. We know, however, that this is not generally the case and, for the case of airlines companies, factors such as geography, institutional regulations, market structure, etc. may influence performance measures obtained.

Two conflicting views exist in the efficiency measurement literature regarding the way that the issue of environment should be addressed. The first approach assumes that the environmental factors influence the shape of the technology and hence that these factors should be included directly into the production function as regressors (e.g., Good et al. 1993). The second approach assumes the environmental factors influence the degree of technical inefficiency (and not the shape of technology) and hence that these factors

1 There is a strong case for the use of technical efficiency measures in performance assessment in regulated or public enterprises. It is evident that in many instances financial measures, such as cost or profit efficiency, can be quite misleading when prices are difficult to define, quotas and subsidies are rife, and cost-minimization or profit-maximization objectives are unlikely to apply across all companies. Support for this argument may be found in Pestieau and Tulkens (1993).

should be modelled so that they directly influence the inefficiency term (e.g., Battese and Coelli 1995). Both approaches appear reasonable depending upon ones philosophical perspective. We therefore present and compare the results obtained under the two alternative approaches.

One of the first points that must be made regarding the above two approaches is that the first approach (hereafter termed Case 1) produces technical efficiency scores which are *net* of environmental influences, while the second approach (Case 2) produces technical efficiency scores which incorporate the environmental effects and hence may be termed *gross* technical efficiency scores. To make these scores comparable we propose a method that may be used to convert the Case 1 net technical efficiency scores into gross measures and an additional method that may be used to convert the Case 2 gross technical efficiency scores into net scores. The latter approach is based upon the efficiency decomposition procedure proposed by Gathon and Pestieau (1995) for instances when a two-stage estimation method is used to estimate the Case 2 model.[1]

Measuring net efficiency is an important issue as it allows one to predict how companies would be ranked if they were able to operate in equivalent environments. We argue that the net efficiency indicators may be viewed as being primarily indicators of managerial performance, given that the gross efficiency predictions have been "purged" of the major environmental influences. Furthermore, these measures allow us to estimate the expected impact on efficiency of a change in the environmental context when this environment is, at least partially, under the control of national or international authorities or, indirectly, modifiable by the company itself.

The production frontiers are estimated using annual data on inputs and outputs corresponding to 32 international airlines observed over the period 1977 to 1990. These airlines are taken from four different regions (America, Asia, Europe and Oceania) and hence operate in rather different environmental conditions. We attempt to account for these differences using three variables: the average stage length, the average load factor and the average aircraft size. All data is taken from the annual published reports of the International Civil Aviation Organisation (ICAO, 1977–1990).

The remainder of the paper is organised into sections. In Section 2 we discuss the two alternative approaches to accounting for environment factors in stochastic frontiers. In Section 3 we provide a brief review of recent studies of airline efficiency before describing the data and the model specifi-

1 In this study we use the single-stage estimation procedure discussed in Battese and Coelli (1995) to estimate the Case 2 model.

cations. Empirical results and discussion are presented in Section 4 and the final section contains some concluding comments.

2. The production frontier and the environment

Following Aigner, Lovell and Schmidt (1977), a stochastic production frontier is specified with a composed error term. For the purpose of simplifying the presentation, let us assume here a simple Cobb-Douglas production technology of the form[1]:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{k,it} + v_{it} - u_{it} \tag{1}$$

where y_{it} and x_{it} indicate the output and the inputs, respectively (i=1,2...N firms and t=1,2,...T periods); β_0 and the β_k are parameters to be estimated; v_{it} is a random error term and u_{it} is a non-negative random variable assumed to represent technical inefficiency in production.

To estimate the parameters of this model using maximum likelihood one must select distributional forms for the two error terms (v_{it} and u_{it}). The most commonly made assumptions are that the random error term, v_{it}, is independently and identically distributed as $N(0,\sigma_v^2)$, and that the non-negative inefficiency random variable, u_{it}, is distributed independently of the v_i, and has a half-normal distribution. That is, it has a distribution equal to the upper half of the $N(0,\sigma_u^2)$ distribution.

The intuition behind the error component specification is that any deviation from the frontier caught by the technical efficiency term, u_{it}, is the result of factors under the firm's control, such as the will and effort of the producer and his employees, and factors such as defective and damaged product (Aigner, Lovell and Schmidt 1977). However, the frontier itself can vary randomly across firms due to the random error v_{it}. On this interpretation, the frontier is stochastic, with random disturbance v_{it}, being the result of favourable or unfavourable external events such as luck or climate. Moreover, errors of observation and on measurement of production constitute another basis for the presence of v_{it} in the frontier model.

Given the definition of the stochastic frontier production function in equation (1), we note that the realisations of the u_{it} are not observable. That is,

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1 From this point forward we shall define all models assuming panel data because the empirical section of this paper involves panel data. Note that the cross-sectional form of this models may be easily obtained by removing the time subscript.

following the estimation of the unknown parameters of the model defined in equation (1), the residuals of the model will be realisations of $\varepsilon_{it} = v_{it} - u_{it}$, not of u_{it}. Battese and Coelli (1988) observe that an appropriate predictor for the technical efficiency involves the conditional expectation of $\exp(-u_{it})$, given the random variable ε_{it}. That is, one may define the technical efficiency predictor using

$$TE_{it} = E[\exp(u_{it})|\varepsilon_{it}], \tag{2}$$

The above defined frontier model does not attempt to account for the possibility that different firms may experience different environmental conditions which may subsequently have an influence upon their technical efficiency levels.

In order to take into account this situation we consider two alternative approaches:

- *Case 1:* assume that environment conditions affect the shape of the production technology, or
- *Case 2:* assume that environment conditions influence the firm's technical efficiency.

We shall now deal with each of these cases in turn.

Case 1

In Case 1 we consider that the environment has a direct influence on the production structure and model the technology by introducing some representative variables aside the production factors. It is assumed that in this case each firm faces a different production frontier. In terms of equation (1) and assuming that M factors representing the environment, $z_{j,it}$, enter in a simple log-linear way in the production frontier[1], we will have a modified production frontier:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{k,it} + \sum_{j=1}^{M} \theta_j \ln z_{j,it} + v_{it} - u_{it} , \tag{3}$$

where the θ_j are parameters to be estimated.

1 If interactions between the environmental variables and the production factors were considered, then the shape may also vary with differing environmental conditions. In that case output-input production elasticities as well as substitution elasticities may be influenced by the environment.

When equation (2) is used to define predictors of technical efficiency relative to the frontier model defined in equation (3) the technical efficiency measures obtained will be net of environmental influences. One may also obtain measures of gross efficiency (i.e., inclusive of environmental influences) by re-evaluating the technical efficiency predictors with $\sum_{j=1}^{M} \theta_j z_{j,it}$ replaced with $\max\left[\sum_{j=1}^{M} \theta_j z_{j,it}\right]$. Thus all firms will be compared with the frontier associated with the most favourable environment.

Case 2

In other studies (e.g., Kumbhakar 1991, and Battese and Coelli 1995) environmental factors are assumed to directly affect technical efficiency. Then the underlying hypotheses is that all firms share the same technology represented by the production frontier (1) and that the environmental factors have an influence only on the distance that separate each firm from the best practice function.

Some early empirical papers (e.g., Pitt and Lee 1981, and Kalirajan 1989) also took the view point that the environmental factors have an influence upon efficiency. These papers adopt a two-stage estimation approach, in which the first stage involves the specification and estimation of a stochastic frontier production function [such as equation (1)] and the prediction of the technical efficiency scores of the firms. The second stage of the analysis then involves the specification of a regression model where the technical efficiencies are regressed upon certain explanatory factors (such as environmental or management factors).

There is an inconsistency, however, in the above two-stage method. As noted by Battese and Coelli (1995), the stochastic frontier production function is estimated in the first stage under the assumption that the inefficiency effects (error term) are identically distributed, while in the second stage the predicted technical efficiencies are regressed upon a number of factors, hence suggesting the inefficiency effects are *not* identically distributed. A more appropriate approach involves the specification of a model in which both relations are estimated in a single stage. Models of this form have been proposed by Kumbhakar (1991) and others for cross-sectional data and have been applied to panel data by Battese and Coelli (1995). These authors present a stochastic frontier production function in which the technical inefficiency effects are a function of firm characteristics. This is the stochastic frontier model used in the Case 2 analysis in this study.

The Battese and Coelli (1995) model is identical to model (1) with the one exception that the inefficiency term is made an explicit function of a vector of environmental characteristics, z_{it}, by specifying that the u_{it} are independently (but not identically) distributed as non-negative truncations of a general normal distribution of the form:

$$N(m_{it}, \sigma^2) \text{ or } N\left[\delta_0 + \sum_{j=1}^{M} \delta_j z_{j,it}, \sigma^2\right], \tag{4}$$

where δ_0 and the δ_j are parameters to be estimated.

Within this framework, the values of the unknown parameters in (1) and (4): β_0, β_k, δ_0, δ_j, σ_u^2 and, σ_v^2 are obtained simultaneously using maximum likelihood estimation. The expressions for the likelihood function and first partial derivatives are presented in Battese and Coelli (1993). The estimates are calculated using the computer program FRONTIER (Coelli, 1992 and 1994). This program uses the reparametrisation $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma^2$ which has advantages during estimation because the value of γ must lie between zero and one. Also presented in Battese and Coelli (1993) is an expression for the conditional expectation of $\exp(-u_{it})$, given ε_{it}. This is equal to

$$TE_{it} = E\left[\exp(-u_{it}) | \varepsilon_{it}\right] = \left\{\exp\left[-\mu_{it} + \frac{1}{2}\sigma_*^2\right]\right\} \left\{\Phi\left[\frac{\mu_{it}}{\sigma_*} - \sigma^*\right] / \Phi\left[\frac{\mu_{it}}{\sigma^*}\right]\right\}, \tag{5}$$

where $\Phi(.)$ denotes the distribution function of the standard normal random variable,

$$\mu_{it} = (1-\gamma)\left[\delta_0 + \sum_{j=1}^{M} \delta_j z_{j,it}, \sigma^2\right] - \gamma\varepsilon_{it}, \text{ and } \sigma_*^2 = \gamma(1-\gamma)\sigma^2.$$

By replacing the unknown parameters in equation (5) with the maximum likelihood estimates we obtain an operational predictor for the technical efficiency of the i-th firm in the t-th time period.

As opposed to the situation in Case 1, in Case 2 the technical efficiencies are gross measures, in that they include the influence of environmental factors. To obtain measures of net technical efficiency (net of environmental factors) we replace the $\sum_{j=1}^{M} \delta_j z_{j,it}$ in equation (5) with $\max\left[\sum_{j=1}^{M} \delta_j z_{j,it}\right]$ and then re-calculate the technical efficiency predictions. These adjusted predictions may then be interpreted as net efficiency scores because they involve predictions of efficiency levels when all firms are assumed to face identical environmental conditions (i.e., the most favourable).

Note that the differences between the gross and net technical efficiency measures of the i-th firm may be viewed as the contribution of these environmental factors to the inefficiency of that firm. Furthermore, given that we can assume that all major environmental factors have been accounted for, then the net efficiency measure may then be interpreted as a measure of managerial performance.

Furthermore, we note that the above proposed decomposition of technical efficiency for Case 2 is similar in spirit to that proposed in Gathon and Pestieau (1995), who decompose technical inefficiency in European railways into managerial and regulatory components. The method of parameter estimation and hence the decomposition method, however, differ between the Gathon and Pestieau study and the present analysis. The present study uses the recently developed single-stage estimation methods as opposed to the two-stage estimation method used by Gathon and Pestieau.

3. The Airline Industry

Numerous studies have been dedicated to the measurement of airline performance. These studies have gone beyond simple partial productivity measurement. Forsyth, Hill and Trengove (1986) aim to discuss the adequacy of some commonplace measures of airline efficiency and to illustrate an alternative productivity indicator. Some authors, Caves, Christensen and Thretheway (1984) and Sickles (1985) estimate airline total factor productivity on the basis of an econometric study of airline cost functions. More recently, Kumbhakar (1990) and Good, Nadiri and Sickles (1993), combined the estimation of airline cost and factor demand functions with frontier analysis and proceeded to conduct technical and allocative efficiency comparisons. Schmidt and Sickles (1984), Barla and Perelman (1989), Distexhe and Perelman (1994) and Good et al. (1993) measured technical efficiency using either stochastic parametric or non-parametric techniques and panel data.

The airline data used in this study consists of a panel of 32 airlines, involving 15 European airlines, (including the four majors: Air France, Alitalia, British Airways and Lufthansa), eight North American carriers (including American, Delta, Pan Am and TWA) and nine Asian or Pacific companies. We have annual observations during the period 1977 to 1990. The primary data source is the *Digest of Statistics* from the International Civil Aviation Organisation (ICAO, 1977–1990, a).

An output measure and two input measures, labour and capital, are constructed using this data. Labour input is an aggregate of two separate categories of employment used in the production of air travel. These categories include pilots, as well as co-pilots and other cockpit crew, and flight attendants. It is important to omit all other labour because the sub-contracting of certain ground operations make it difficult to make relevant comparisons across carriers. Such an assumption may seem too restrictive, but the analysis is carried out on core flying activities. Information on the annual number of employees are available from ICAO's *Personnel Series* (ICAO, 1977–1990, b).

Capital input information is provided by ICAO's *Fleet Digest.* (ICAO, 1977–1990, b). We construct a capital variable which is defined as the sum of the maximum take-off weights of all aircraft multiplied by the number of days the planes have been able to a operate during a year (defined as the total number of flying hours divided by average daily revenue hours). With such a capital variable definition, we avoid performance prediction bias due to maintenance operations.

A number of previous production function analyses of airlines have included an energy measure as an additional input. We attempted to obtain information on energy consumption but were unsuccessful. International airline associations are not willing to publish or divulge information on fuel consumption because several European airlines consider this data as strategic information. We are confident, however, that this omission is unlikely to have a large impact upon our econometric work because of the high degree of complementarity we expect to observe between fuel consumption and the capital measure we have specified (see above).

Information regarding the carrier's output quantities are obtained from ICAO's *Commercial Airline Traffic Series* (ICAO, 1977–1990, c). While the source allows several possible output measures, we consider the sum of the two components of airline output: passenger service and cargo operation which are measured in available tonne-kilometres (ATK). Following Barla and Perelman (1989), we choose this variable as a measure of production rather than performed tonne-kilometre (PTK). This choice is justified by the fact we are mainly concerned with the measurement of technical efficiency of flying operations and not of the ticketing and marketing functions of these airlines.

In order to take into account the environment in which these firms operate, we include three variables that are above all proxies of the market and network characteristics, namely, the average load factor, the average stage length and a measure of average aircraft capacity.

Stage length, defined as the ratio of total performed aircraft kilometres to the total number of aircraft departures, is a measure of the network size. This variable is expected to have an negative effect on inefficiency as flying short distances implies aircraft will be unproductive for a longer time periods.

Aircraft capacity, is proxied by the weighted mean number of seats in each aircraft. It is assumed on the one hand that a wide-body aircraft requires proportionally less crew, and on the other hand it increases ATK more than proportionally. This variable thus considers the advantages that equipment size and route volume may have on performance.

Load factor is defined as the ratio of performed tonne-kilometres to available tonne-kilometres, and is considered as a measure of market demand. Airlines operating with high load factor coefficient would expect an additional need in labour, essentially in cabin crew. Hence such a characteristic would be expected to be positively related to inefficiency.

Table 1 provides an illustration of the evolution across time of these variables. What clearly appears from this table is that, on average, Asian and Oceanic companies operate in different environment conditions compared with European and North American companies. For the three variables, and for almost all companies, the average values observed are higher for the Asian and Oceanic group. In particular, stage lengths are 50% higher for Asian and Oceanic companies that at the same time reached seventy percent occupation rates for the last years of the period. European carriers clearly close the gap with North American carriers in terms of stage lengths and aircraft sizes while maintaining higher rates of aircraft occupation for near all the observed airlines and periods.

It must be argued, however, that the variables that we consider here as environmental factors are at the same time potentially under the control of the firms. This is certainly true up to a certain degree. However, for the purpose of model estimation, we will consider them as exogenously determined, as has been assumed in the majority of previous studies.[1]

The production technology is specified by a translog production frontier with non-neutral technological progress:

1 Note that essentially the same variables have been considered as exogenous in many past studies, such as Forsyth, Hill and Trengove (1986), Schmidt and Sickles (1984) and Distexhe and Perelman (1993).

$$\begin{aligned}\ln y_{it} &= \beta_0 + \beta_1 \ln x_{1,it} + \beta_2 \ln x_{2,it} + \beta_{11} (\ln x_{1,it})^2 + \beta_{22}(\ln x_{2,it})^2 \\ &+ \beta_{12}(1n\, x_{1,it} \ln x_{1,it}) + \beta_\tau\, t + \beta_{\tau\tau}\, t^2 + \beta_{1\tau} (\ln x_{1,it}\, t) \\ &+ \beta_{1\tau} (\ln x_{1,it}\, t) + v_{it} - u_{it} \\ &= TL(\beta_k, \ln x_{k,it}, t) + v_{it} - u_{it}\ , \end{aligned} \tag{6}$$

where y_{it} indicates the output, in available tonne-kilometres, $x_{1,it}$ and $x_{2,it}$ are labour and capital inputs defined as above, t is a time trend; the v_{it} are normal random errors and the u_{it} are the technical inefficiency effects with a truncated $N(m_{it}, \sigma_U^2)$ distribution.

As discussed in Section 2, two alternative models will be estimated in order to take into account the environmental factors. For Case 1 we assume that these factors may influence the shape of the translog frontier. Hence equation (6) becomes:

$$lny_{it} = TL(\beta, 1nx_{it}, t) + \sum_{j=1}^{3} \theta_j z_{j,it} + v_{it} - u_{it}\ , \tag{7}$$

where $z_{1,it}$, $z_{2,it}$ and $z_{3,it}$ indicate the average stage length, aircraft capacity and weight load factor, respectively, and the have a truncated distribution, with m_{it} equal to a constant value, δ_0. However, for Case 2 we have the translog frontier (6) with $m_{it} = \delta_0 + \sum_{j+1}^{3} \delta_j \ln z_{j,it}$.

4. Estimation and Results

The estimated coefficients of three different model specifications are presented in Table 2. The first column contains estimates of the translog model without environmental factors; in the second column environmental factors are assumed to affect the production technology (Case 1) and in third column they are introduced as explanatory variables of technical efficiency (Case 2).

The simple translog model in column 1, which does not incorporate environmental variables, is rejected in favour of the Case 1 and 2 models on the basis of likelihood ratio tests. We also observe that an unexpected negative coefficient appears associated with the labour factor[1]. These results seem to confirm the belief that environmental variables cannot be neglected without

1 Note that first order coefficients for labor and capital correspond to average partial output elasticities, given that all the variables were normalized with respect to their mean before calculating second order terms.

introducing a bias in the estimation of production functions for airlines activities.

Turning now to the Case 1 and 2 models, we observe that they produce quite similar information concerning the structure of the translog production technology. The constant returns to scale hypothesis (evaluated at the sample means) cannot be rejected in either of these models; the majority of the second order terms do not have t-ratios larger than 2 in absolute value[1], and average technological progress for the whole sample was estimated to be close to 1.0% per year over the period.

The estimated coefficients of the environmental variables have the expected signs in both Case 1 and 2 models. Network characteristics represented by the average stage length and aircraft size, have a positive and significant affect on the production/efficiency of companies, while the load factor influence is negative, but not significant. These results imply that firms with low density networks benefit from a more favourable environment and hence perform better when no attempt is made to take into account this advantage.

But before turning to the technical efficiency results, it is also interesting to remark from Table 2 that the coefficients that correspond to the estimated share of the inefficiency term in the variance of the composed error term is higher than 0.95 in Case 1 but less than 0.60 in Case 2. The difference between these results is most likely explained by the way in which the environment variables are included in these models. As indicated in Section 2, Case 1 produces a measure of technical inefficiency *net* of the influence of environment, while Case 2 gives us a *gross* inefficiency measure.

In Table 3 the technical efficiency measures (both net and gross) calculated from the estimation of both models are listed. Three different remarks can be made from Table 3. First, the airlines efficiency scores obtained under Case 1 are generally lower than those obtained under Case 2. The average level of (gross) technical efficiency varies from 66.3% in Case 1 to 86.7% in Case 2. Second, the gap between net and gross measures of technical efficiency is lower under Case 2 than in Case 1. The ratio of net/gross gives 1.31 on average for the model with environment variables in the production frontier against 1.09 for the model with environment explaining inefficiencies. Third, as expected, the Asian and Oceanic airlines companies perform better on average when differences in environment are not taken into ac-

1 The different models presented here were compared with alternative Cobb-Douglas specifications using a likelihood ratio test but in all cases the Cobb-Douglas technology was rejected.

count. In terms of net efficiency the results differ among models. In Case 1 European and North American airlines perform marginally better than Asian and Oceanic airlines when gross efficiency is purged from environmental factors in Case 1, while in Case 2 the net scores are close for the three groups of companies but with the order unchanged among them.

On the basis of these results we proceed to a correlation analysis among the four measures obtained. The results appear in Table 4. In this table we observe a high correlation between the gross measures of efficiencies obtained from the two models as well as between the gross and net scores obtained in Case 2. The lowest correlations are those associated with the net scores Case 1, that is, the model that includes environmental factors in the production set of variables.

Summing up, it appears that, in the specific case of airlines, the two methods of accounting for environmental influences provide similar rankings of the airlines in terms of both net and gross efficiency. However, the net scores obtained from the Case 1 model provide larger estimates of the impact of environmental differences and show a more widespread range of efficiency scores. The key point to make is that the selection of method does have a large influence upon the size of the efficiency scores obtained. This is important information for people who are about to embark upon an efficiency study which involves environmental variables.

The ex ante selection of one method over the other is difficult task. From a philosophical standpoint, we prefer the Case 2 model because we believe the estimated frontier represents the outer boundary of the production possibility set, irrespective of environmental issues. The gross efficiency measures obtained from this procedure seem closest to the intuitive notion of efficiency being about converting physical inputs into physical outputs. One can then decompose these gross efficiency measures into managerial and environmental components if additional data is available.

However, if one does not have a strong preference for one approach over the other, one can always turn to the data for guidance. Since the Case 1 and 2 models are not nested in each other we have used a non-nested testing procedure to attempt to discriminate between the two models. To do this we have constructed an artificial nested model that includes environmental variables both in the production function and also as factors explaining inefficiency (see column 4 in Table 2). Using likelihood-ratio tests we test the null hypotheses associated with the Case 1 and Case 2 models against the alternative nested model. The results of these two tests indicate that the Case 1 null hypothesis is not accepted, while the Case 2 null is accepted.[1] This implies that, in the airlines example treated here, the model including environmental variables as explanatory factors of technical inefficiency (Case 2) provides a better fit to the sample data.

The dynamics of technical efficiency in airlines

In this section we provide a description of the evolution of technical performances over time and, in particular, investigate the difference between the gross and net scores obtained from the application of the Battese and Coelli (1995) approach (Case 2).

As indicated before, over the period covered by our sample the airlines transportation market experienced several modifications. Other than technological progress, that was estimated here to be approximately 1.0% each year, the undergoing deregulation process induced a series of changes in the organisation of airline activities. In order to be able to face a more competitive environment most airlines were forced to restructure their aircraft fleet and their network of flights and destinations.

In Table 5 we reproduce the results obtained by each company in the first and last three-year time periods: 1977–79 and 1987–90. The ratios between the scores obtained in both periods are also presented in order to facilitate comparison.

On the one hand, some companies like Malaysian Airlines, British Caledonian and Finnair present the best improvement in gross technical efficiency over the period, followed by several Asian companies. On the other hand, four European airlines present important losses in technical efficiency over the period: AUA, Iberia, and particularly Sabena and SAS. On average, the relative situation of European and North American companies stay unchanged for the whole period.

The comparison between the evolution of gross and net efficiency scores allows us to measure the relative weight of changes in pure managerial efficiency and changes in efficiency due to environment. We recall that managerial efficiency is measured by net efficiency while environment efficiency corresponds to the difference between gross and net efficiency.

On the one side, some firms appear to have benefited from changes in environmental conditions over the period: Cathay, Singapore Airlines, Air France, and specially British Caledonian and Finnair. On the other side, two

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1 For Case 1 the LLR test versus the nested model is equal to 33.2 (d.f.=3) and for Case 2 it is equal to 7.8 (d.f.=3).

companies, Sabena and SAS, experienced losses as the result of changes in network characteristics that have to be added in this case to losses due to managerial inefficiency.

On average, the Asian companies have realised the best improvements in efficiency over the period, but mainly as a result of gains in managerial efficiency.

Finally, in Table 6 we present the annual variations of average efficiency for the three geographical regions of America, Europe and Asia/Oceania. These results illustrate the evolution of a cycle, which is more pronounced for the European and North American airlines than for the Asian companies, with negative rates observed in the earlier and latter years of the eighties. Given the definitions of output and capital that are used in this study, this cyclical behaviour is most likely a consequence of demand conditions reflecting the under utilisation of the labour force.

5. Conclusions

In this paper we estimate the technical performances of 32 international airlines over the period (1977–1990). We obtain measures of technical efficiency from stochastic frontier production functions which have been adjusted to account for environmental influences such as network conditions, geographical factors, etc. We consider two alternative approaches to this problem. Case 1 assumes that the environmental factors influence the shape of the technology, while Case 2 assumes that they directly influence the degree of technical inefficiency. In comparing the results obtained when using these two approaches, we observe that the two sets of results provide similar rankings of airlines but suggest differing degrees of technical inefficiency. For example, we observe that the average level of (gross) technical efficiency varies from 66.3% in Case 1 to 86.7% in Case 2.

Both sets of results suggest that Asian and Oceanic airlines are technically more efficient than European and North American airlines but that the differences are essentially due to more favourable environmental conditions. Nevertheless, it is among Asian companies that the major improvements in managerial efficiency (technical efficiency with environmental factors netted out) took place over the sample period (1977–1990) during which significant deregulation of international air transportation took place.

It is important to include in these conclusions the observation that this study is by no means a perfect empirical analysis. Some points worth noting, include the observation that information on certain inputs, such as fuel, were not available. Furthermore, we note that the three environmental variables we have used are unlikely to fully capture all environmental influences. Hence the net measures of technical efficiency that we obtain are unlikely to be completely free of all environmental effects. We also re-iterate our concern that some of the "environmental" variables we have included are arguably endogenous to the management process and hence may introduce some degree of simultaneous equation bias to our estimates (although we argue that, at least in the short run, these variables are approximately exogenous).

Finally, we observe that this study is, to our knowledge, the first empirical analysis to apply these two approaches (to the inclusion of environmental variables into frontier functions) to the one data set. We are comforted to find that the ranking of efficiencies do not vary greatly with the method selected but are concerned to find that the sizes of the estimated efficiencies do differ significantly. We thus hope that a number of similar comparative analyses are conducted in the near future so as to shed some light upon the generality of the results obtained in this study.

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Table 1. Environment factors in airline activity[1].

Airlines and regions	Average stage length		Average aircraft size		Average weight load factor	
	1977–80	1987–90	1977–80	1987–90	1977–80	1987–90
Cathay (Hong Kong)	1,841	2,490	238	341	65.1	72.9
Indian Airlines	524	635	107	109	69.7	73.9
Japan Airlines	2,151	2,524	216	231	61.8	69.7
Korean Airlines	1,405	1,449	227	224	64.3	75.3
Malaysian Airlines	449	580	150	208	66.1	73.6
Pakistan Airlines	1,094	971	193	187	50.8	58.1
Qantas (Australia)	3,532	4,032	269	317	60.8	68.8
Singapore Airlines	2,099	3,338	210	287	70.9	73.5
Thai (Thailand)	2,026	2,149	212	245	64.1	68.1
Asia and Oceania	1,680	2,018	202	239	63.7	70.4
Aer Lingus (Ireland)	873	-------	178	-------	64.7	------
Air France	1,203	1,323	200	226	61.0	66.2
Air Inter (France)	484	509	114	122	58.5	60.3
Alitalia	1,088	1,055	185	232	60.5	66.4
AUA (Austria)	768	907	102	104	46.2	49.2
British Airways	1,238	1,337	178	198	61.3	67.9
British Caledonian	1,163	1,665	154	272	58.6	59.5
Finnair (Finland)	649	875	141	138	55.5	64.5
Iberia (Spain)	772	989	175	214	55.9	64.4
KLM (Netherlands)	1,502	1,875	205	246	59.7	72.5
Lufthansa (Germany)	1,010	1,141	201	209	62.0	66.6
Sabena (Belgium)	1,173	1,198	193	224	61.7	71.4
SAS (Scandinavian)	778	740	176	126	56.2	62.9
Swissair	988	1,122	186	220	57.6	64.9
UTA (France)	2,599	3,598	194	341	58.5	58.2
Europe	1,086	1,310	172	205	58.5	63.9
Air Canada	1,069	1,286	176	197	49.7	55.3
American (U.S.)	1,331	1,284	178	170	54.3	53.3
CP Air (Canada)	1,558	1,243	194	160	60.6	56.4
Delta (U.S.)	748	1,063	169	146	51.8	52.6
Eastern (U.S.)	834	1,010	134	160	58.1	54.8
Pacific Western (Canada)	438	--------	131	-----	47.8	-----
Pan American (U.S.)	2,515	1,644	254	220	57.3	60.9
TWA (U.S.)	1,482	1,362	177	163	51.9	55.4
North America	1,247	1,271	177	174	53.9	55.5
All	**1,293**	**1,513**	**182**	**208**	**58.8**	**63.9**

1 Means values over the period weighted by tons-km available.
Source: OACI (1977–1990)

Table 2. **Alternative production frontier models**[1].

		Translog without environment (1)		Environment in production Case 1 (2)		Environment in inefficiency Case 2 (3)		Nested model (4)	
β_0	constant	0.179	(6.7)	0.190	(9.2)	0.195	(11.2)	0.183	(5.9)
β_1	ln x_1 (labor)	–0.054	(1.2)	0.344	(7.8)	0.297	(5.6)	0.282	(5.6)
β_2	ln x_2 (capital)	1.062	(23.7)	0.666	(15.0)	0.693	(13.8)	0.707	(5.9)
β_τ	t (trend)	0.009	(4.7)	0.009	(5.3)	0.010	(6.1)	0.010	(14.5)
β_{11}	$(\ln x_1)^2$	–0.312	(2.1)	0.129	(1.2)	0.039	(0.3)	0.009	(5.7)
β_{22}	$(\ln x_2)^2$	–0.426	(3.0)	0.006	(0.1)	–0.078	(0.7)	–0.107	(0.8)
$\beta_{\tau\tau}$	t^2	0.000	(0.5)	0.000	(0.5)	0.001	(1.2)	0.001	(1.1)
β_{12}	$\ln x_1 . \ln x_2$	0.704	(2.4)	–0.151	(0.7)	0.040	(0.2)	0.105	(0.5)
$\beta_{1\tau}$	$\ln x_1 . t$	0.025	(2.3)	0.023	(2.8)	0.017	(1.9)	0.019	(2.1)
$\beta_{2\tau}$	$\ln x_2 . t$	–0.013	(1.3)	–0.016	(2.0)	–0.013	(1.5)	–0.016	(1.9)
θ_1	ln z_1 (stage length)	–		0.177	(7.7)	–		0.058	(1.1)
θ_2	ln z_2 (aircraft size)	–		0.135	(2.9)	–		–0.146	(1.6)
θ_3	ln z_3 (load factor)	–		–0.043	(0.7)	–		0.323	(2.7)
δ_0	constant	–1.163	(0.5)	0.090	(1.6)	3.269	(7.7)	0.108	(2.0)
δ_1	ln z_1 (stage length)	–		–		–0.319	(7.4)	–0.247	(3.4)
δ_2	ln z_2 (aircraft size)	–		–		–0.246	(3.6)	–0.456	(3.3)
δ_3	ln z_3 (load factor)	–		–		0.102	(1.1)	0.501	(3.0)
σ		0.205	(0.7)	0.032	(4.3)	0.018	(7.7)	0.019	(7.1)
γ		0.961	(18.7)	0.964	(46.1)	0.597	(5.2)	0.654	(6.6)
LLF(d.f)		192.0	(382)	273.3	(375)	286.0	(375)	289.9	(372)
d		388		388		388		388	

1 t-tests appear into brackets.

Table 3. **Airlines gross and net technical efficiency** [1]**.**
(Average scores over the period 1977–1990)

Airlines	**Case 1 : Environment in production**			**Case 2 : Environment in inefficiency**		
	Gross	**Net (%)**	**Net/Gross**	**Gross**	**Net (%)**	**Net/Gross**
Cathay (Hong Kong)	74.8	83.6	1.12	94.7	96.3	1.02
Indian Airlines	52.0	86.0	1.65	64.5	83.5	1.30
Japan Airlines	70.2	81.4	1.16	93.2	95.8	1.03
Korean Airlines	72.0	90.4	1.25	93.0	96.5	1.04
Malaysian Airlines	56.3	87.9	1.56	71.3	88.5	1.24
Pakistan Airlines	58.1	79.6	1.37	77.5	89.4	1.15
Qantas (Australia)	67.7	69.0	1.02	94.8	95.1	1.00
Singapore Airlines	80.0	89.2	1.12	96.2	97.3	1.01
Thai (Thailand)	72.0	83.6	1.16	93.7	96.0	1.02
Asia and Oceania	70.3	82.0	1.17	91.6	95.0	1.04
Aer Lingus (Ireland)	50.3	73.7	1.46	66.7	81.2	1.22
Air France	70.4	91.3	1.29	91.4	96.2	1.05
Air Inter (France)	37.7	62.8	1.67	51.6	67.3	1.30
Alitalia	56.3	75.6	1.34	78.6	89.8	1.14
AUA (Austria)	54.0	82.2	1.52	66.8	82.7	1.24
British Airways	57.6	76.6	1.33	79.5	90.6	1.14
British Caledonian	67.8	89.4	1.33	87.3	94.8	1.09
Finnair (Finland)	55.7	84.5	1.52	70.7	86.0	1.22
Iberia (Spain)	57.0	80.3	1.41	76.8	89.9	1.17
KLM (Netherlands)	76.5	95.0	1.24	95.0	97.3	1.02
Lufthansa (Germany)	70.1	95.3	1.36	90.8	96.5	1.06
Sabena (Belgium)	66.8	88.9	1.33	86.3	93.5	1.09
SAS (Scandinavian)	50.6	76.4	1.51	68.2	84.0	1.23
Swissair	64.3	87.5	1.36	85.1	94.4	1.11
UTA (France)	77.7	84.7	1.09	96.2	96.9	1.01
Europe	64.3	85.9	1.34	84.4	92.7	1.11
Air Canada	67.1	89.5	1.33	88.4	95.4	1.08
American (U.S.)	66.2	87.3	1.32	87.3	94.8	1.09
CP Air (Canada)	73.4	94.4	1.29	93.0	96.8	1.04
Delta (U.S.)	63.6	91.0	1.43	83.0	94.4	1.14
Eastern (U.S.)	56.8	82.2	1.45	75.6	89.9	1.19
Pacific Western (Canada)	74.5	88.6	1.19	94.0	96.6	1.03
Pan American (U.S.)	55.5	91.5	1.65	67.6	86.7	1.28
TWA (U.S.)	66.0	85.6	1.30	87.9	94.6	1.08
North America	66.1	87.7	1.33	86.4	94.4	1.10
All	**66.3**	**86.0**	**1.31**	**86.7**	**94.0**	**1.09**

1 Means values over the period weighted by tons-km available.

Table 4. Spearman rank correlations among alternative efficiency measures.

	Case 1 Environment in production		Case 2 Environment in inefficiency	
	Gross	Net	Gross	Net
Case 1: *Environment in production*				
Gross	1.000	0.645	0.965	0.992
Net		1.000	0.451	0.660
Case 2: *Environment explaining inefficiency*				
Gross			1.000	0.960
Net				1.000

Table 6. Technical efficiency growth by region[1].

Case 2: environment explaning inefficiency

	Gross efficiency			Net efficiency		
Years and periods	Asia Oceania	Europe	North America	Asia Oceania	Europe	North America
1978/1977	0.50	1.59	1.23	0.53	0.80	0.50
1979/1978	2.31	0.09	1.80	1.12	− 0.04	0.68
1980/1979	2.05	1.30	− 2.39	1.45	0.51	− 1.24
1981/1980	− 0.39	− 2.38	− 0.12	− 0.78	− 1.37	− 0.28
1982/1981	0.88	0.68	− 0.22	0.54	0.35	− 0.26
1983/1982	− 0.12	− 0.10	1.12	− 0.20	− 0.04	0.62
1984/1983	1.15	0.75	− 0.35	0.62	0.30	− 0.09
1985/1984	0.54	1.07	1.76	0.54	0.43	0.72
1986/1985	0.44	0.38	− 2.00	0.28	0.11	− 0.72
1987/1986	0.35	− 2.21	− 1.35	0.28	− 1.57	− 0.49
1988/1987	0.61	0.75	0.66	0.39	0.78	− 0.30
1989/1988	− 1.25	1.18	− 1.79	− 1.02	0.26	− 0.68
1990/1989	− 1.59	− 2.53	− 3.14	1.37	− 1.18	− 1.69

1 Geometrical means weighted by tons-km available.

Table 5. **Technical efficiency evolution[1].**

Case 2 : environment explaning inefficiency

Airlines and regions	Gross efficiency			Net efficiency		
	1977-79	1987-90 (%)	1987-90 / 1977-79	1977-79	1987-90 (%)	1987-90 / 1977-79
Cathay (Hong Kong)	84.7	95.3	1.12	91.6	96.4	1.05
Indian Airlines	60.9	64.9	1.07	80.0	83.6	1.05
Japan Airlines	87.1	95.3	1.09	92.7	96.9	1.05
Korean Airlines	94.0	93.1	0.99	97.0	96.7	1.00
Malaysian Airlines	61.2	72.5	1.18	79.5	88.7	1.15
Pakistan Airlines	74.9	81.3	1.08	86.9	93.0	1.07
Qantas (Australia)	95.9	94.7	0.99	96.5	95.0	0.98
Singapore Airlines	90.2	97.6	1.08	94.8	97.9	1.03
Thai (Thailand)	96.5	94.9	0.98	97.7	96.8	0.99
Asia and Oceania	82.8	87.7	1.06	90.7	93.9	1.04
Aer Lingus (Ireland)	71.6	------	------	86.1	------	------
Air France	89.3	93.7	1.05	95.7	97.0	1.01
Air Inter (France)	46.1	51.2	1.11	60.4	66.5	1.10
Alitalia	77.5	80.0	1.03	89.9	91.1	1.01
AUA (Austria)	71.7	63.9	0.89	89.2	79.1	0.89
British Airways	77.8	80.1	1.03	89.6	90.8	1.01
British Caledonian	77.9	94.2	1.21	90.7	96.6	1.07
Finnair (Finland)	57.5	79.2	1.38	72.1	93.4	1.29
Iberia (Spain)	80.5	74.2	0.92	93.6	86.9	0.93
KLM (Netherlands)	94.6	96.2	1.02	97.2	97.6	1.00
Lufthansa (Germany)	89.3	90.8	1.02	96.1	96.4	1.00
Sabena (Belgium)	88.5	74.8	0.85	95.4	86.1	0.90
SAS (Scandinavian)	75.9	63.0	0.83	90.6	79.0	0.87
Swissair	86.0	84.1	0.98	95.1	93.6	0.98
UTA (France)	96.2	96.4	1.00	97.4	96.5	0.99
Europe	78.7	80.1	1.02	89.3	89.3	1.00
Air Canada	89.4	89.2	1.00	96.1	95.6	0.99
American (U.S.)	87.7	85.5	0.97	95.0	94.1	0.99
CP Air (Canada)	90.8	91.2	1.00	95.8	96.6	1.01
Delta (U.S.)	83.4	82.4	0.99	95.1	93.8	0.99
Eastern (U.S.)	76.5	71.9	0.94	91.8	85.3	0.93

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APPROACHES TO A LONG-TERM FORECASTING OF MAJOR R&D INDICATORS IN RUSSIA

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The paper is focused on the methodological approaches based on the analysis of population of institutions performing research and development (R&D) in Russia and longitudinal analysis of major macroeconomic and R&D indicators.

Starting from analysis of wages and employment indicators as input parameters for the model the volume of funding needed for budget R&D financing is forecasted. The forecast of salary is calculated on the basis of several scenarios dependent on external factors (such as inflation rate).

Variants of salary forecasts are calculated with regression or factor models on the basis of inflation rate forecasts. The employment forecast is obtained from traditional extrapolation (trends, decomposition) models. Taking into account that share of salary in total intramural R&D expenditure is more or less stable (34 – 40%) the total R&D expenditure is forecasted. Varying input parameters, it is possible to calculate a set of output forecast estimations.

Key words: Macroeconomic Indicators, Budget Expenditure on R&D, Wages and Employment Indicators, Forecast Models.

1. Approaches to a Long-term Forecasting of Major R&D Indicators in Russia

The main strategic goal for the forthcoming decade for Russia is to keep its position among the great nations with the national economy providing high living standards. The efficiency of economic activities, defence potential, national culture are to a great extent defined by the level of scientific development in the country. As it is declared in the Doctrine of the Development of Russian Science (see Ministry of Science and Technological Policy 1995), an improvement of the financial mechanisms becomes a key point in the process of reforming S&T management in Russia. The fields of S&T, that have a vital importance for the country under condition of transition to a market economy and economic crisis, should receive an assistance from the state. The main sources of demand for research and development (R&D) could be distinguished as follows:

- demand from the state;
- demand from R&D-intensive industrial production;
- internal demand for adjustment of technologies purchased abroad;
- demand for Russian R&D personnel from foreign countries.

The distribution of demand for R&D will be changed depending on the stage of economic reforms in Russia. It is connected with both volume of budget R&D allocations and predominant sources of demand for R&D at each of the stages.

At the first stage, the state demand will be the predominant one. It is caused by the necessity of adjusting national S&T system to the market environment. Besides, under condition of the lack of financial resources, it is impossible to provide sufficient budget funding for R&D in all fields of science. So, the governmental support is to be concentrated on the priority fields of S&T. The main goal to be achieved at that stage is to keep the most important elements of the national S&T potential. That is why the share of civil budget R&D expenditure is to be increased to 3.6–4.0 per cent in 1997 (whereas it was only 1.76 per cent in 1995).[1]

The second stage of reforms (1998–2003) will be the period of completing restructuring of the national economy and transition to the rapid development of the national industrial production. At that stage, the R&D aimed at resource saving and modernisation of industrial production will be in a great demand, both from the state and from industrial enterprises and commercial companies.

At the same time, the state is responsible for the stable budget R&D funding and promotion of investments to R&D from industry, financial institutes, international organisations, and individuals. It will also support competition for budget R&D allocations through governmental R&D programmes, projects, budget foundations.

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1 Source: Ministry of Science and Technology Policy, Centre for Science Research and Statistics.

The third stage of reforms (since 2004–2005) should become a period of the large-scale implementation of post-industrial technologies into the national economy and creation of developed internal market meeting the best world standards. At that stage, the role of state regulation and support to the R&D will be focused on the priority fields of S&T and on the promotion of foreign investments. One of the crucial problems for R&D-performing institutions is financing. Currently, the main source of R&D financing is the government budget. Its share in the gross expenditure on R&D (GERD) accounted for more than 90 per cent in 1991–1993. Since then, it decreased but the budget still remains the main source of funding for the most R&D units.

During the last years, budget R&D allocations on civil R&D have been permanently decreasing. Their volume measured in constant prices decreased 4 fold in 1991–1995. The decline in GERD as a per cent of gross domestic product (GDP) is also very sharp – from 1.03 per cent in 1991 to 0.3 per cent in 1995 (see CSRS (1996)).

While developing long-term research plans, it is useful to estimate probable volumes of R&D funding. They, in their turn, depend on main macroeconomic indicators, such as GDP, that is, on the one hand, one of the principal parameters reflecting the state of the national economy, and, on the other hand, a basis for forming the state budget. Governmental economic and statistical bodies pay large attention to short- and long-term forecasting of GDP. Many estimates are regularly published by them. The present study focuses on the calculation of forecasts for GERD on the basis of above mentioned estimates of GDP and ratio of GDP to the state budget.

Under conditions of unstable economic situation, there arises a problem of estimating of the share of the state budget in GDP and distribution of budget allocations by sector of economy. Besides, the forecasts of budget R&D expenditure are based not on the fixed GDP volume, but on the spectrum of its estimates.

In the above described case, it is useful to apply an imitation model. It gives a possibility to obtain a set of forecast estimates of output parameter (in our case – volume of budget R&D expenditures) by varying values of input parameters.

The scenario approach is widely used for economic forecasting. There are usually presented three variants of economic development – optimistic, pessimistic and compromised ones. The degree of supplying financial demand of the state budget funded institutions could be estimated on the basis of those forecasts. Such approach is called "top-to-bottom" forecast – from macroeconomic indicators to budget R&D allocations. Let us apply this approach to forecasting of budget R&D allocations for 1996. Time series of GDP, volume of state budget expenditure and budget R&D allocations for 1991–1995 (Table 1) are used as a basis for calculations of estimates.

Table 1. **Time series for GDP, state budget, and budget R&D allocations.**

	GDP*	State budget expenditure*	Budget R&D allocations		
			total*	as a % of GDP	as a % of state budget expenditure
1991	1,300	348	13.4	1.03	3.87
1992	15,000	3,873	87.5	0.69	2.66
1993	162,300	34,070	848.9	0.52	2.49
1994	630,000	146,400	2,791.5	0.44	1.91
1995	1,659,000	286,600	5,030.0	0.30	1.76

* Billion rubles, in current prices.

The forecast model of the budget R&D allocations for 1996 is as follows. Let this indicator be a dependent variable, whereas GDP and state budget expenditure – the independent ones.

We assume that for each of independent variables, to more or less degree of proximity, there exist the regression equation that gives its relation with dependent variable. The independent variable can be modelled on the basis of different growth curves (parabola, exponent, etc.).

Thus, we obtain several forecast models of the same indicator. The models complement each other because they are based on different assumptions. It is possible to build integrated (combined) forecasts.

$$X_f = \sum_{i=1}^{m} V_i X_i ,$$

where

m = number of individual models

X_i = individual forecasts

X_f = integrated forecast

V_i = weights

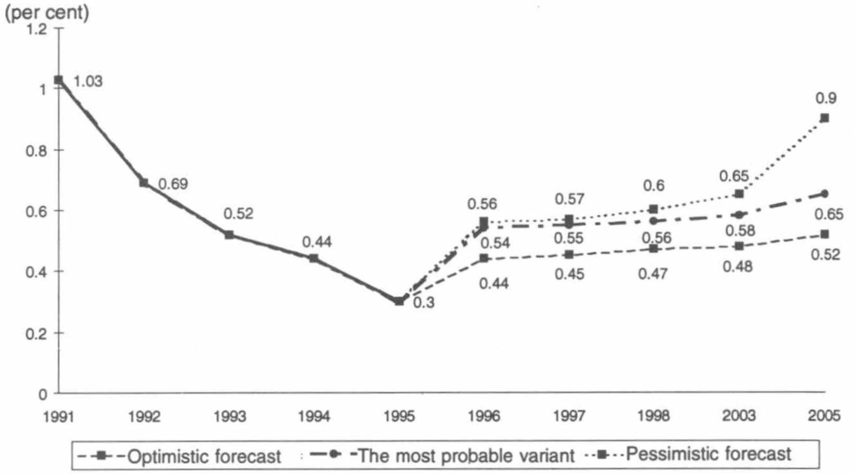
The problem consists in finding such a set of weights $V_i, i=\overline{1,m}$, that minimises error of the combined forecast. To exclude systematic bias, it is required that

$$\sum_{i=1}^{m} V_i = 1\ ,\ \ 0 \le V_i \le 1.$$

The coefficients are chosen under condition of minimisation of the norm (variance) of the error vector of the combined forecast.

The problem comes to the least squares problem with limitations in the form of equations and inequations. In the case of non-correlated errors of individual forecasts, the solution could be find by iteration procedure (in order to avoid using methods of non-linear programming). The forecasts of civil budget R&D allocations depending on different basic variants obtained with the application of above mentioned procedures are shown in the Figure 1.

Figure 1. **Budget R&D allocations as a per cent of GDP. Variants of forecasts for 1996 – 2005.**



To estimate volume of budget R&D allocations needed for R&D institutions, it is also necessary to forecast average salary and employment in the sector "Science and Scientific Services".

The salary forecast should be calculated for different variants depending on external factors, such as inflation rate et al. There is a spectrum of forecasts for inflation index calculated by government bodies. Variants of salary forecasts are calculate on their basis (with application of factor or regression models). If there are additional data, it is also possible to use traditional extrapolation models (trend, decomposition, etc.).

The forecast for employment in the sector is also calculated by extrapolation or regression. In that case, the total employment in the national economy is used as an independent variable.

Taking into account that expenditures on salary give more or less constant share (34–40 per cent) of total intramural R&D expenditure, the gross expenditure could be forecasted on the basis of the extra-mural expenditure.

Let us illustrate this approach on the forecast for 1996.

It is evident that at the first stage of forecasting some methods or groups of methods have to be chosen. "The choice of forecasting technique is obviously dependent on the characteristics of the indicator to be forecasted. The special characteristics of individual countries, and indeed sectors, each with its own determinants and pace of change, militated against the adoption of standard procedures" (see OECD 1994, Annex 9). In our case it means that, before choosing method of the forecast calculation, it is necessary to clarify the following points:

- availability of statistical data for the indicator;
- period between the data collection in time series;
- length of time series;
- relations with other indicators.

According to the above mentioned points, there could be used various procedures of the forecast calculation.

Let us begin with the forecast of average salary. Rather long time series for this indicator are available. That gives the following possibilities:

- to build a process model and to perform necessary calculations;
- to get some retrospective forecast errors;
- to assess the accuracy of the model on the basis of the retrospective errors.

The long time series allow to apply a wide range of forecast models. The model that gives rather accurate forecasts (average annual forecast error is 5.0–5.5 per cent) have been developed.

The model is built on the basic assumption that there is a stable dependence of one indicator from another within a given interval of its values. In our case we assume that the average salary Z depends on the inflation rate I according to the following equation:

$$\frac{Z_t}{\sum_{k=0}^{m} Z_{t-k}} = P_t \frac{I_t}{\sum_{k=0}^{m} I_{t-k}} , \tag{1}$$

where P is a proportionality coefficient.

Let us assume that the inflation rate I varies from $I_{\min}$ to $I_{\max}$. The border values $I_{\min}$ and $I_{\max}$ are related with optimistic and pessimistic variants of the economic strategies. Let us express I as follows:

$$I = I_{\min} + \alpha(I_{\max} - I_{\min}) , \quad 0 \le \alpha \le 1 .$$

The procedure of forecast calculation is performed in several steps:

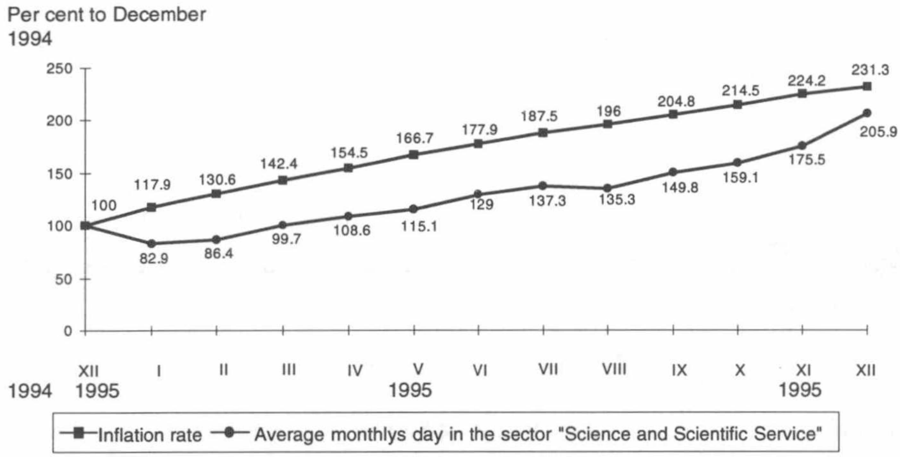
- choice of the augment for the parameter α (usually 0.1–0.2)
- calculation of I values for each value of α
- for each I, the system of equations similar to (1) is built up
- the optimal forecast is chosen by minimising retrospective errors
- in case of necessity, the border values (minimal and maximal) of forecasts are taken as variants of forecast.

This approach allows to obtain forecasts for one month after the last point of the time series.

In the model described it is assumed that an indicator is used as an independent variable which values are known (or given) for the forecast period. If it is necessary to obtain several variants of forecast, a model of dependence between the value of average salary and inflation rate is to be built up. That interdependence is shown on the Figure 2.

In different sources, different variants of possible inflation rate are given depending on the probable development of the economic situation in the country. The most optimistic variant is some 1 – 2 per cent growth a month. That variant is related to the policy of macroeconomic stabilisation, liquidation of the industrial decline and transition of the Russian economy to a growth trajectory. However, there is a possibility of the situation, when the Government, under pressure of different economic and political factors, will try to support industrial production through the financial injections. That pol-

Figure 2. **Change of the inflation rate* and average salary** in the sector "Science and Scientific Services"**



* Data source for the estimation of the inflation rate – Centre for Economic Conjuncture and Forecasting (1996).
** Data source – Centre for Science Research and Statistics.

icy, by estimates of some economists, could lead to the inflation rate of 7 to 8 per cent a month.

So, we can simulate both above mentioned situations by iterations of the procedure described below:

- to calculate the forecast for the next month and to use it as the last point of time series;
- to correct the forecast at each step to avoid a systematic error.

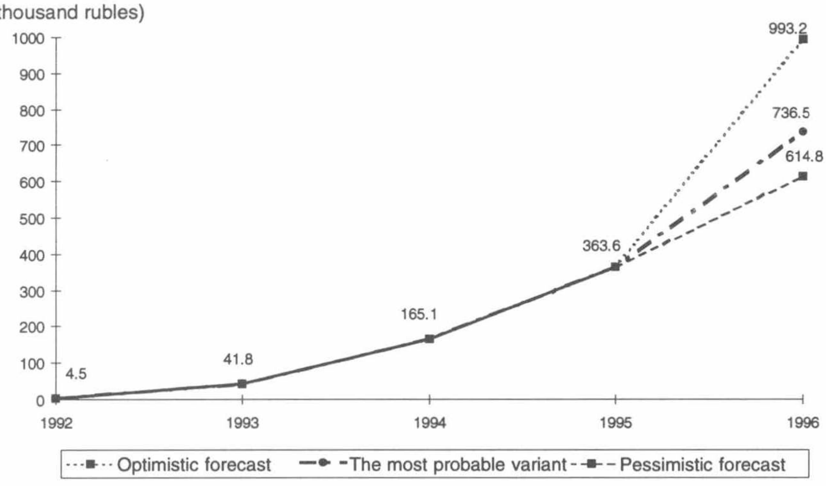
The following additional data can be used in order to correct the estimates:

- relation of the average salary in science to the average salary in the national economy (this ratio is more or less stable);
- dynamics of the forecasted indicator within a quarter (3 month period).

The time series for the average salary with variants of forecasts are shown on the Figure 3.

On the one hand, the maximal variant could be assumed as the optimal one. At the same time, it is related with the maximal inflation rate. The practice shows that real income usually grows slower than the consumer prices.

Figure 3. **Average salary in the sector "Science and Scientific Services", in current prices.**



Income of employees in a sector of economy to more or less degree defines time series of employment in the sector. The total employment in Russia decreased in 1993–1995 for 13 per cent. At the same time, the employment in some sectors (first of all in those involved in the creation of market infrastructure, housing, services) is growing.

Compared to the other sectors, the sector "Science and Scientific Services" is in much worse position. The total employment in the sector declined 32 per cent in January 1993 – December 1995. The decline in 1993 (15 per cent) was the largest for all the sectors of the national economy. In 1994-1995 the decline was some 9 per cent. If the tendencies will be kept then the total decline in employment in the Russian science according to our forecasts will give more than 40 per cent compared to the 1993 level.

The total decline of employment in science has a strong impact on the national economy. To perform deeper analysis of the problem it is necessary to track the dynamics of employment in individual R&D-performing units. Such an analysis was performed for R&D indicators for more than 4000 R&D institutions for five years (data bases of the Centre for Science Research and Statistics). The data allow to give long-term forecasts of employment in different types of R&D institutions (research institutes, designing bureaux, etc.) and in different sectors of science (government sector, business enterprise sector, higher education, private non-profit sector).

Under general decline of employment in science, the distribution of employment by individual R&D-performing institutions, has drastically changed. The most important changes from 1991 to 1994 were in the group of organisations with the number of employees more than 100 persons. The quantity of organisations with the number of employees from 100 to 500 persons increased by 28 per cent; with the number of employees more than 500 persons – by 81 per cent, at the same time the quantity of smaller organisations decreased insignificantly.

The decline in number of R&D-performing units is also very heterogeneous. Thus, the number of design organisations reduced for 33 per cent in 1991-1995. The number of research institutes grew, whereas their average personnel declined.

This analysis gives a possibility to highlight the main reasons of changes and principal trends in the transformation of the institutional infrastructure of science. It complements the results obtained with the help of scenario forecasts and gives, not very detailed, but real picture of forthcoming changes in the national S&T system.

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Part F

Wages, Technology, Exports

Bellmann and Köller

As already noted technological change may increase the demand for high-skilled and decrease for low-skilled labour. The amount of churning then depends on the number of qualified already employed.

The effect of the firm size is also significant in the churning equation. Firms reporting a high profitability are displacing and replacing their workforce at a significantly higher rate only in 1993. The other variables are again insignificant. Thus, we conclude, our theoretical considerations are not supported empirically, since the technology level is not significant in the wage gap and the churning equation. For France Entorf and Kramarz studied the impact of both use of and experience with computer-based technology on wages with matched worker-firm data. After carefully controlling for observed and unobserved worker quality the significance of the technology effect disappears.

Boon

The results show that firms that have the highest R&D intensity or that have the highest labour productivity pay their workers the highest wages, when controls for worker quality are included. Finally we find that the use of manufacturing technology has no significant influence on the wages of workers. Firm characteristics play a less important role at the wage formation than employee and job characteristics like age, education and job level.

Laaksonen and Vainiomäki

The results do not appear to show a straightforward connection between the average wages of manufacturing establishments and the technology level of their industries among the high, medium-high or medium-low technology levels. However, the establishments in industries with the lowest technology have paid lower wages during the whole period. We also found that relative non-manual to manual wage ratio increased over time in the highest technology levels.

Eriksson

The larger the number of managers considered to have significant responsibilities in the firm, the larger is the wage spread. Thus, the prediction of tournament models of a positive relationship between the number of participants in and the prize of the tournament is supported. Another prediction gaining support is a larger pay dispersion in firms characterised by more variable business conditions.

I conclude that the findings do provide some positive evidence of tournament models. This is important in view of the weak link observed between firm performance and individual managers' pay.

Bernard, Jensen and Wagner

This paper presents directly comparable results on the differences between exporters and non-exporters for two major industrialised countries -- Germany and the U.S. In both countries, exporters have significantly higher employment, sales, capital intensity, and productivity compared to non-exporters. In the U.S., but not in Germany, wages are also significantly higher at exporters. Importantly, in both countries, future exporters have these good characteristics several years prior to entry into export markets. The results suggest that in both countries, success leads to exporting.

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TECHNOLOGY, WAGES AND CHURNING IN WESTERN GERMANY: Estimates from the IAB-Establishment Panel

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Most theories of the impact of the implementation of new technology on employment predict that technological change involves the reshuffling of workers between firms implementing new technology and those business units located further away from the technological frontier. However, based on data from the first and third wave of the German Establishment Survey (using the information of about 4000 establishments interviewed 1993 and 1995), we estimated a structural model for the technology level, wage drift and churning, i.e. the same firms experienced both hirings and firings, and tested the hypothesis that firms located on the technological frontier experience larger turnover rates than other units.

Thereby technological change, churning and wages are ultimately endogenous to firms: they can either change their workforce in response to changes in the technology they use or upgrade existing jobs, i.e., via the retraining of workers and a more gradual introduction of new machinery. This choice between internal and external adjustment is also likely to be affected by conditions external to firms, such as the availability of workers matching the skills required by new technologies, the costs of dismissals associated to employment protection regulations and collective bargaining, constraints placed on the hiring process, etc..

Key words: Wages, Technology, Churning, Endogeneity.

JEL classification: J31.

1. Introduction

The increasing dispersion of wages in the 1980s and early 1990s and the dominant role of technology therefore as an explanatory factor was shown empirically for the USA (cf. Bound and Johnson 1992) and recently for Western Germany by Bellmann and Möller (1995a&b, 1996) and Möller (1996). However, technological change was measured rather indirectly on the industry level. In contrast to that, in the German Establishment Survey (using the information of about 4000 establishments interviewed 1993 and 1995) firms' representatives were asked to rank the technology used in their firm on a five-item scale. Using information of this variable we were able to estimate a structural model with the technology level, wage gap and churning as endogenous variables. In our theoretical model of the impact of the implementation of new technology on labour demand technological change involves the displacement and replacement of workers at the level of each business unit.

Thus, in contrast to other theories of the impact of the implementation of new technology on employment we do not consider the reshuffling of workers between firms implementing new technology and those business units located further away from the technological frontier. In our model creative destruction of jobs occurs at the establishment level. This means that creative destruction is ultimately endogenous to firms: they can either change their workforce in response to changes in the technology they use or upgrade existing jobs, i.e., via the retraining of workers and a more gradual introduction of new machinery. This choice between internal and external adjustment is also likely to be affected by conditions external to firms, such as the availability of workers matching the skills required by new technologies, the costs of dismissals associated to employment protection regulations and collective bargaining, constraints placed on the hiring process, etc..

The paper is organised as follows. In the second section the determinants of the technological level, churning and the wage gap are discussed and a theoretical model of the adjustment in labour demand induced by technological change is outlined. Then the empirical concept and the estimation method are explained in Section 3. The establishment panel data are described in Section 4 and the empirical results are presented in Section 5. In Section 6 the results are compared with those of studies obtained for Great Britain, Finland, France, the Netherlands and the U.S.. The last Section provides a conclusion.

2. Theory

Determinants of the technology level

Mortensen and Pissarides (1995) have developed an equilibrium model, where the implementation cost of a new technology determines its introduction. In their model the implementation cost is an internal adjustment costs, not unlike the internal adjustment costs assumed in the literature on investment, plus the cost of training the worker to use the new machine. If the cost of implementing new technology is high compared with job creation costs, the firm may keep the job open for as long as it yields some positive profit and then destroy it. Firms with smaller implementation costs may update their technology on the job, without job destruction. Furthermore, Mortensen and Pissarides (1995) assume that wages in new jobs grow with productivity, so that wages in existing jobs must also grow with even if productivity is constant, to reflect the fact that the worker's outside option grows.

Bartel and Lichtenberg (1987) have argued on the basis of the learning curve hypothesis that highly educated workers have a comparative advantage with respect to the adjustment to and implementation of new technologies. Thus, the larger the proportion of qualified in the establishment is, the more likely the advanced technologies are used.

Key organizational features of large firms are their diverse capabilities, the normalization of tasks and procedure. They create a specialised technology department, which can implement new technologies more effective (cf. Majumdar 1995). Larger firms have a greater amount of capital to experiment with and can invest in risky projects. However, efficiency diminish because of loss of control by top managers. Furthermore, smaller firms are more flexible. Schumpeter (1942) has pointed out that entry threat by potential rivals spurs innovative behaviour regardless of firm size. If the production of firms is profitable it is easier to finance the modernisation of the capital stock. We now want to show in a more rigorous way that churning may be an optimal strategy of firms which face technological changes.

Adjustment in labour demand induced by technological changes

The model explains how changes in the production technology are reflected by changes in the demand for different kinds of labour. Although, alterations in labour demand are considered, there is no need to look at the dynamic behaviour of adjustment. As soon as there are incentives to change the demand for factors of production, the employers are willing to do so. Their actual behaviour is ruled by the costs of adjustment and the direction of the adjustment process is specified by the new optimum. So the focus is on changes in the long-run equilibrium of labour demand. However, if one assumes that changes in the production technology are subject to technological progress and that for this reason there is a higher demand for high-skilled instead of low-skilled labour, churning will be an optimal strategy for employers.

This result is due to the implicit assumption, that all employees are paid equally. This assumption is justified, because following Akerlof and Yellen (1990) workers may regard fairness as an important part of their utility function. When they do not receive the same remuneration, the result would be a loss in efficiency of production. A wider formulation of this point without changing of the qualitative results is given, if the difference between the wages of the different groups of labour is relatively fixed and these difference is not allowed to change substantially. Technological progress changes the relative productivity of the factors of production. Therefore, the adoption of new technologies involves a process of dis- and replacement of workers. If high-skilled employees have a higher productivity than low-skilled while working with the new machines, then low-skilled will be replaced by high-skilled. A churning process takes place, when the firms does not already employ only high-skilled workers.

Although disregarding the dynamics or at the goods markets and with some very restrictive assumptions, it is possible to identify churning as an important reason for changes in the workforce of a firm (cf. Bellmann and Boeri 1995). Churning is not regarded as a process, but as an optimal strategy for employers to react to technological changes, if the workforce is not highly qualified. Otherwise, only internal solutions like re-training or further education can be used to face new technologies.

Determinants of the wage gap

In Germany wages are determined in a centralised bargaining process. Trade unions and employers' associations negotiate contracts regulating a complex range of issues like wages, working hours or working conditions. Most of the agreements are negotiated at sector level, but there are contracts at company level, as well. The company-level agreements are usually modelled on those of the respective sector with only slight modifications. The majority of agreements are made about wages for a period of 1215 months. Contracts on other issues are generally made for longer periods. Many companies are obliged to apply the regulations of the collective agreements, even if they do not belong to a employers' association. The regulations therefore have the character of minimum wages and of minimum conditions.

Because negotiations are rather centralised in Germany the collective agreements tend to disregard the problems, special situation and interests of a particular company or a region. The collective agreements of different sectors and regions are closely related. Thus the individual sectors and regions do not sufficiently differentiate as would be required by the different labour demand and supply conditions applying to them. Many firms pay higher wages than are institutionally negotiated. The difference between the negotiated and the actually paid wages is called the wage gap. The wage gap is a very important instrument for the firms. It guarantees the economy as a whole that the wage structure fulfils its information and allocation function and therefore supports the functioning of the labour market.

The greater the value of the number of vacancies per employee, the more pronounced the shortage of labour for the firm and the higher the wage level should be. But, the labour-turnover version of the efficiency wage theory (cf. Schlicht 1978) modifies the firms' strategies to attract labour with the instrument of efficiency wages. This suggests that firms may pay higher wages in order to reduce staff turnover.

To reduce the implementation cost of new technologies firms may hire highly educated workers, because they have a comparative advantage with respect to the adjustment to and implementation of new technologies. Thus, technological change could involve the displacement and replacement or churning of workers at the level of each business unit. If the negotiated wages are not flexible enough therefore, firms may be forced to pay higher wages than institutionally negotiated.

Oi (1993) notes that larger firms tend to operate productions processes to provide mass-produced goods, a practice that exhibits highly formalised production methods and a rigid division of labour. In comparison, smaller firms tend to fill market demands for more specialised products, affording greater variety of jobs. Therefore, large establishments try to select employees with both greater general human capital endowments and a willingness to fit into a highly interdependent production process (cf. Idson and Feaster 1990). Thus, the resulting firm-size wage differential compensates the employees for a disadvantage of their jobs.

Determinants of churning

As already noted technological change may increase the demand for high-skilled and decrease for low-skilled labour. The amount of churning then depends on the number of qualified already employed. Bartel and Lichtenberg (1987) argued that the learning-curve hypothesis implies that industries characterised by high rates of innovation are *continuously* implementing new technologies and tend to employ a larger proportion of qualified labour compared to less innovative industries. The same holds true for firms and establishments. Furthermore, qualified employees should not be regarded as a homogenous group. Ideally it would be necessary to account for the vintage of the human capital embodied. Since this is not possible, variables affecting the technology level may determine the amount of churning. It was argued in Section 2.1 of this paper that this is the case for the firm size and the profitability variables.

3. Empirical Approach

The structure of the outlined theoretical model and the variables in the IAB-Establishment Panel require a simultaneous analysis of metric and non-metric data. The program system MECOSA (Mean and COvariance Structure Analysis, cf. Schepers and Arminger 1992) allows for the interdependent regression models with metric and non-metric endogenous variables. The technology level, churning and wage gap are the endogenous variables in our empirical model. Whereas the variable churning is a metric, the technology level (1 = very new, ..., 5 = very old) is an ordered categorical and the wage gap a left-sided censored variable, since a negative wage gap does not exist. For the variance-covariance matrix of the error variables we assumed zero off-diagonal elements. The system is exactly identified, which can be verified by the rank and the order condition. The restrictions can be justified as follows: New technologies are associated with lower adjustment costs if qualified employees are kept in the firm and/or are hired. Thus, churning and a high-wage policy should be regarded as consequences rather as prerequisites of technological change.

Churning may change the firms' employment structure towards the highly qualified, who are scarce relative to less qualified workers, so that the wage gap should be higher. Since the same wage gap is paid for all employees within the same establishment, the variables proportion of women and proportion of part-time employees are not included in the wage gap regression. This contrasts to the estimation of wage level regressions (cf. Bellmann and Kohaut 1995).

4. Data and Variables

The IAB-Establishment Panel (cf. Bellmann, Kohaut and Kühl 1995) is based on the employment statistics register of the Federal Employment Services (cf. Cramer 1986, Rudolph 1986). The data for these statistics are collected by the social insurance institutions for their own purposes according to a procedure introduced in 1973 and finally made available to the Federal Employment Services. Every year all employers have to report all changes in the number of their employees subject to a compulsory social security scheme. Misreporting is legally sanctioned.

As a comparison with the labour force sample survey data shows the register covers all dependently employed persons in the private and public sector, i.e. almost 80 % of total employment in West Germany. The remaining 20 % are civil servants, unpaid family worker, self-employed and workers not eligible for social security because their earnings and/or working-time are too low (cf. Bellmann, Reinberg and Tessaring 1994). Individual plants are assigned separate identification numbers, even though they belong to the same company.

A stratified sample of the establishments included in the employment statistics register is taken using selection probabilities depending on the variation in the number of employees in the respective stratum. In total 16 industries and 10 firm sizes are considered. The establishments are classified according to size which results in greater differences between establishments with respect to the size of their workforces, i.e. the difference is more pronounced, the larger the establishments are. Therefore the selection probabilities have to increase with the size of establishments (cf. Pfanzagl 1978, 162 ff.).

The overall and size-specific response rates are over 70 % (with exception of the first two classes), which is quite a high rate. The field work was done by Infratest Sozialforschung, Munich, whose highly qualified interviewers were given sufficient addresses from the employment statistics register to interview 4356 establishment representatives during the summer of 1993. In the second wave 3900 of them were re-interviewed and 3404 in the third wave. Furthermore, in the second wave 238 newly-founded establishments were included, too. 182 of these also answered in the third wave together with 511 newly-founded establishments.

Three questions in the IABEstablishment Panel related to the wages paid by various firms in excess of statutory wages established in collective bargaining at the level of the industry and the region (socalled wage gap). The first question was whether a collective bargaining agreement at industry and regional level applies to the respective establishment. Then the firm should state whether wages are paid in excess to those established by collective bargaining. When both answers were affirmative, the wage gap should be estimated.

Concerning the effect of technologies adopted the question asked was the following: "How would you assess the modernity of your technical equipment compared to other firms in the branch?" Respondents were asked to rank the technology used in their firm on a five-item scale ranging from 1 (very new), to 5 (very old) technology. We used this subjective ranking of the owners and managers to define a taxonomy of technologies in this study.

Churning is measured as one minus the relation between the growth of firms (net employment change) and the gross flows of workers. With H and S denoting total hirings and separations in each establishment, the churning rate is given as

$$\mathrm{CHR} = \begin{cases} 1 - \dfrac{|H-S|}{H+S} & \text{if } H+S>0 \\ 0 & \text{if } H+S=0 \end{cases}$$

The churning rate is the larger, the more separations are accompanied by hirings within the same establishment. The churning rate is zero if only hirings or separations occur. For establishments without hirings and separations the churning rate is assumed as zero.

Since the technology level was only asked for in the first and third wave of the IABEstablishment Panel, the analysis is performed only for 1993 and 1995. The other exogenous variables used are the number of vacancies per employee (vacancy rate), the proportion of women, parttime and qualified employees, the log of the number of employees indicating the firm size and the profit rate (ranging from 1 = very high to 5 = very poor). The analysis is restricted to the manufacturing sector of the West German economy, so that the sample size was 1411 for 1993 and 1018 for 1995.

5. Econometric Results

The estimation results of the simultaneous equation systems are presented in table 1 for the year 1993 and in table 2 for the year 1995. The systems are identically specified. It is estimated using MECOSA's three step procedure, which means that the estimates can be regarded as structural parameters estimates.

The churning rate and the firm size exhibit a positive and at the 5 % level significant effect on the wage gap. In contrast the other variables are insignificant.

The effect of the firm size is also significant in the churning equation. Firms reporting a high profitability are displacing and replacing their workforce at a significantly higher rate only in 1993. The other variables are again insignificant. Thus, we conclude, our theoretical considerations are not supported empirically, since the technology level is not significant in the wage gap and the churning equation. In the equation with the technology level as the dependent variable the proportion of qualified employees exhibits a

Table 1. **Simultaneous – Equation – Model Estimates (manufacturing, 1993).**

Endogenous variables (measurement level)	**Wage gap** (one side censored)	**Churning** (metrically scaled)	**Technology level** (ordered categorical
Exogenous variables			
Wage gap	1	0	0
churning	0.042*	1	0
	(2.32)		
Technology level (1 = very	–0.091	0.082	1
new, ..., 5 = very old)	(1.84)	(1.13)	
Proportion of qualified	0.113	0.276	–0.419**
workers	(0.71)	(1.06)	(2.73)
ln (firm size)	0.048*	0.317**	–0.036
	(2.15)	(6.86)	(1.86)
Proportion of part-time	0	–0.917	0.720*
employees		(1.20)	(2.02)
Proportion of women	0	0	–0.195
			(1.03)
Vacancy rate	–0.111	0.718	–0.897
	(0.22)	(0.57)	(1.60)
Profitability (1 = very high, 0,058	–0.387**	0.165**	
..., 5 = very poor)	(1.44)	(6.21)	(5.03)
Constant	–2.438**	–2.503**	0.448**
	(13.23)	(7.51)	(2.61)
σ^2	2.171	5.129	
Threshold			2.749**
			(29.08)

Remarks:
Absolute t-values are given in parenthesis.
** (*) means significance at the 1% (5%) level for a two-sided test.
N of cases 1411.
Source:
IAB-Establishment Panel 1993.

highly significant and negative effect for the year 1993. This means, establishments with a qualified workforce use advanced technologies, so that Bartel and Lichtenberg's hypothesis is corroborated. In both years the firms reporting a high profitability are technological leading. The significant estimates for the proportion of parttime employees with altering signs may be due to multicollinearity of this variable with the proportion of women.

Table 2. Simultaneous – Equation – Model Estimates (manufacturing, 1995).

Endogenous variables (measurement level)	**Wage gap** (one side censored)	**Churning** (metrically scaled)	**Technology level** (ordered categorical
Exogenous variables			
Wage gap	1	0	0
churning	0.077*	1	0
	(3.62)		
Technology level (1 = very	0.001	–0.055	1
new, ..., 5 = very old)	(0.02)	(0.62)	
Proportion of qualified	0.190	–0.222	0.150
workers	(0.98)	(0.73)	(0.83)
ln (firm size)	0.095**	0.293**	0.032
	(3.15)	(5.89)	(1.25)
Proportion of part-time	0	–1.165	–0.911*
employees		(1.80)	(2.08)
Proportion of women	0	0	0.204
			(0.87)
Vacancy rate	1.423	0.642	2.037
	(0.90)	(0.24)	(0.70)
Profitability (1 = very high,	0,039	–0.080**	0.242**
..., 5 = very poor)	(0.86)	(1.19)	(6.35)
Constant	–2.960**	–2.242**	–0.255
	(11.93)	(5.85)	(1.04)
σ^2	2.207	4.869	
Threshold			2.869**
			(28.91)

Remarks:
Absolute t-values are given in parenthesis.
** (*) means significance at the 1% (5%) level for a two-sided test.
N of cases 1018.
Source:
IAB-Establishment Panel 1995.

6. Discussion

Thus, in contrast to the results obtained with rather indirect proxies for the technology adopted we are not able to corroborate the dominant role of advanced technologies for the increasing wage dispersion. However, these technological wage differentials are estimated on the basis of establishment data in quite a few new studies. According to our best knowledge only the analysis performed by Chenells and van Reenen (1995) has *not* assumed that all the explanatory variables in the wage equation are strictly exogenous. Using the 1984 and 1994 Workplace Industrial Relation Survey they found that the technology-wage relationship is *not* driven by the effects of new technologies on wages, but that high wages signal a higher ability mix so that the firm can adopt advanced technologies at a lower cost.

From matched worker-firm data Doms, Dunne and Troske (1995) for the U. S. and Laaksonen and Vainiomäki (1995) for Finland have estimated significant effects of modern technologies on wages. In contrast, for the Netherlands Boon (1996) did not find significant influence of computer aided manufacturing technology on wages. For France Entorf and Kramarz (1995) also studied the impact of both use of and experience with computer-based technology on wages with matched worker-firm data. After carefully controlling for observed and unobserved worker quality the significance of the technology effect disappears.

7. Conclusion

We have estimated a model that takes into account the interdependencies between structural technological choice, wage determination and the recruitment of employees at the firm level. Furthermore, we considered some of the conditions at the firm level for the choice between internal and external adjustment, such as the structure of the work force (i.e. the proportion of qualified, women and part-time employees), the establishment size, profitability and the availability of workers matching the skill required (i.e. the vacancy rate). However, in contrast to the empirical results of other studies we were not able to corroborate the dominant role of advanced technology for the increasing wage dispersion. The same results holds true for the effect of technology on churning. Among the determinants of the wage gap, the technology level and churning the variables proportion of qualified employees, the establishment size and the rate of profits exhibit significant and theoretically expected results.

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EFFECTS OF FIRM PERFORMANCE AND TECHNOLOGY ON WAGES: EVIDENCE FROM CROSS-SECTIONAL MATCHED WORKER-FIRM DATA

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Recent empirical studies on wage determination stress the existence of inter-industry wage differentials for employees with comparable qualifications and performing similar tasks. This paper investigates the impact of firm performance and technology use on worker wages in the Netherlands manufacturing industry for the years 1979, 1985 and 1989. Our empirical analysis uses cross-sectional worker-firm data which are created by joining the Netherlands Wage Survey, the Production Survey, the R&D Survey and the Survey of Manufacturing Technology. The results show that firms that have the highest R&D intensity or that have the highest labour productivity pay their workers the highest wages, when controls for worker quality are included. Finally we find that the use of manufacturing technology has no significant influence on the wages of workers.

Key words: Wage Differences, Productivity, Technology, Matched Worker-Firm Data.

1. Introduction

According to neo-classical competitive theory there are no wage differentials between employees with comparable skills and working under similar conditions. In fact, however, there are systematic differences in wages across industries or firms (enterprises and establishments) which cannot be explained on the basis of observed worker and job characteristics (such as age, education and shift

1 The views expressed in this paper are those of the author and do not necessarily reflect the policies of Statistics Netherlands.

work). Empirical evidence for the above is established by several studies, like Krueger and Summers (1988) for the US and Hartog et al. (1994) for the Netherlands. Obviously, the market does not equalise all wage differences.

Alternative theories, among which the efficiency wage theory and the insider-outsider theory, have proposed possible explanations for the persistent wage differentials between industries or firms. In view of the important role of trade unions in the Netherlands at wage formation, we consider the insider-outsider theory. This theory emphasises that workers (insiders) have more bargaining power in wage bargaining than the unemployed (outsiders). This difference in bargaining power is due to different levels of knowledge and skills. In particular workers of technologically advanced firms possess strategically important knowledge, such as know-how gained at an R&D department or by experience with computer-based production processes. Because of the constant threat for the firm that employees run over with their knowledge to the competitor, they have much bargaining power. Given their bargaining power, insiders are able to obtain a share of the revenue of a firm in addition to the reservation wage of outsiders. If this bargaining model is correct, the wage rate at firm-level depends on the performance, the technology-intensity and the number of insiders of the firm.

Determining the empirical relevance of alternative models of wage determination is quite important since the non-competitive models generate implications with respect to issues such as unemployment and industrial policy. An increase in the wage above the competitive wage by insider power of unions, could under certain circumstances lead to a reduction of the employment of the outsiders. One may consider the research on persistent wage differences across firms as an attempt to test indirectly the validity of the competitive model of wage determination against the insider-outsider theory.

In trying to explain why non-competitive wage differentials exist, various studies have examined the effect of an employee's industry or firm on wages. Most empirical work relies either on worker surveys with little information about employers or on firm surveys with little information about workers. Only a few studies used detailed information at micro-level on both employer and worker characteristics to analyse the effect of technology use and profitability on wages. In this paper we examine the wage differences across firms in the Netherlands manufacturing sector. To study the effect of technology and performance on wages, we will use a cross-sectional database that matches data on individual workers and on their employers from three years. This data set contains information on earnings, personal and job characteristics, firm-level productivity, R&D expenditures and manufacturing technology use for individual workers.

The remainder of this paper is organised as follows. Section 2 reviews previous studies of the impact of firm performance and technology on wages. Before the estimation results of the wage regressions are described in section 4, section 3 describes the data used in the study. Section 5 concludes and suggests topics for further research.

2. Previous Studies

Previous studies examining the relationship between wages and firm (or industry) characteristics fall into three categories. The first group consists of studies attempting to relate firm attributes and average worker characteristics to a measure of firm average wages. Adopting a log-linear wage function derived from human capital theory:

$$In\ w_j = \Sigma_m \beta_m x_{jm} + \Sigma_n \gamma_n z_{jn} + \varepsilon_j , \tag{1}$$

where $\ln w_j$ is the (log) average hourly wage paid to workers in firm j, x_{jm} is a set of average characteristics $(m=1,...,M)$ of workers in firm j, z_{jn} is a set of firm characteristics $(n=1,...,N)$, β_m and γ_n are parameters and ε_j is a normally distributed error term.

Another group of studies uses individual data on wages and personal characteristics, and augments the set of explanatory variables of (log) wage functions with average firm attributes. The specification is thus:

$$In\ w_{ij} = \Sigma_m \beta_m x_{im} + \Sigma_n \gamma_n z_{jn} + \varepsilon_{ij} , \tag{2}$$

where $\ln w_{ij}$ is the (log) hourly wage of worker i in firm j, x_{im} is a set of worker i characteristics and ε_{ij} is a normally distributed error term. The problem with this approach is that the inclusion of aggregate data in a micro specification can lead to some bias in the estimated parameters.

A third group proceeds in two steps and offers a possible solution to the aggregation problem. In the first step an individual wage equation is estimated with firm characteristics z_{jn} replaced by firm dummies α_j. In the second step these firm dummies α_j are regressed on firm characteristics z_{jn}. This two-step regression has the following form:

$$In\ w_{ij} = \Sigma_m \beta_m x_{im} + \alpha_j + \mu_{ij}, \tag{3a}$$

$$\alpha_j = \Sigma_n \gamma_n z_{jn} + \mu_j, \tag{3b}$$

where μ_{ij} and μ_j are normally distributed error terms.

A large part of the research on the relationship between wages and firm characteristics is concerned with the effect of firm performance (that is profitability and productivity). Dickens and Katz (1987) give a review of early studies. Recent studies that adopted a bargaining or insider-outsider model are Nickell and Wadhwani (1990), Holmlund and Zetterberg (1991), Nickell and Kong (1992), Nickell et al. (1994), Lever and Van Werkhoven (1995) and Johansen (1996). These studies were based on industry-level or firm-level data for different countries and used a wage equation including value added per employee (the inside factor) and the aggregated wage rate (the outside factor) as explanatory variables. The overall conclusion was that inside factors, measured by labour productivity, have a significant positive effect on wages. Hildreth (1995) has investigated not only whether employers share rents with their workers but also which shocks create rent-sharing. Using British matched worker-firm data he found large rent-sharing effects for workers whose employers have invested in new process technology.

There is a growing body of empirical evidence on the role of technological change in influencing wage inequality. Brouwer and Kleinknecht (1994) have tested the prediction that technology-intensive firms try to prevent their workers from quitting by paying higher wages. After controlling for the influence of worker education, age and sex they found that high-technology firms pay high wages. This study used Netherlands firm-level data on R&D activities (measured by the percentage of R&D personnel in total employment). Other empirical studies which used R&D activities as a proxy for technological change are Tan and Batra (1995) and Laaksonen and Vainiomäki (1995). Tan and Batra showed by using data for individual firms in Taiwan, Mexico and Colombia that employer investments in R&D and training lead to large wage premia for skilled workers but not for unskilled workers (after controlling for firm characteristics). Laaksonen and Vainiomaki found no straightforward connection between the (average) wages of Finnish manufacturing firms and the technological level (measured by R&D expenditures) of their industries. The wage equations estimated in the last two studies did not include controls for characteristics of the workforce in the firms.

Another measure of the technological position of a firm is the use of computer-based machines such as CNC (computer numerical control), DNC (distributed numerical control), robots, (personal) computers and computer aided design. The following two studies applied this technology measure. Dunne and Schmitz (1995) found that firms that use the most advanced technology pay the highest wages. They used linked firm-level US data. No controls for worker quality were included in this study. Using matched worker-firm data Doms et al. (1995) found similar correlations between advanced technological use by employers and wages, though the size of the wage premium was substantially diminished after controlling for worker characteristics (such as education, occupation, age and sex). Their results were based on two approaches: one-step regression (1) using firm data and two-step regression (3a,b) using matched worker-firm data. Krueger (1993) explored the impact of the 'computer revolution' on the wage structure using worker-level data. He showed that US employees are rewarded more highly if they use computers at work. Computer-use included programming, word processing, computer-aided design etc. In this study controls for the effect of worker education, age, sex, race and occupation were included.

A problem with cross-sectional estimates is that they could be biased because of unobservable worker or firm fixed effects (such as inborn worker skills). Panel data offer the opportunity to control for the biasing effects of unobservable time invariant variables. Entorf and Kramarz (1995) studied the impact of both use of and experience with computer-based technology on wages. This analysis was based on cross-sections as well as panels, which matched French data on individuals and on their firms. The range of technology covered was larger than the computer-based technology investigated in Doms et al. (1995) and Krueger (1993). The French data also included advanced office technologies. In the wage regressions there was controlled for worker education, experience, occupation, sex, full-time/part-time, firm size and profits. Results based on individual panel data differ from what emerged from the cross-sectional estimates. After the elimination of the individual effects the technology use by workers had no longer a significant influence on wages. This could be explained by the fact that higher average wages at the firm level for technologically advanced firms are related to higher unobserved quality of the workers.

Most studies assume that all explanatory variables in the wage regressions are strictly exogenous. This may be questionable with firm-level variables like technology. Chenells and Van Reenen (1995) have implemented a two-stage least squares (2SLS) model to deal with the simultaneous determination of technology (with R&D intensity and number of patents as instruments) and wages. They used UK firm-level data and defined technology as a dummy variable for whether there has been an advanced technical change in the firm. The human capital controls were relatively crude. Controlling for the endogeneity bias led to the conclusion that the introduction of new technologies does not cause higher wages and that high wages appear to give firms greater incentives to introduce new technologies.

3. Data Description and Summary Statistics

The data used in this study concern cross-sectional information on individual workers and their firms in the Netherlands manufacturing sector for the years 1979, 1985 and 1989[1]. The worker-firm data are created at Statistics Netherlands (CBS) by joining micro data of the Wage Survey (WS), the Production Survey (PS), the R&D Survey (RDS) and the Survey of Manufacturing Technology (SMT).

The annual Wage Survey provides data on the structure of earnings in firms which have employees. Data from the Wage Survey is broken down by employee characteristics like age, education and sex, and job characteristics like the working hours arrangement (regular, irregular or shift work). The survey has a two-stage sample design. First the CBS takes a stratified sample of firms and then each sampled firm takes a simple random sample of its employees. For each sampled employee, his employer provides data on, amongst others, gross weekly wages (excluding overtime and vacation pay). The gross weekly wages are transformed into gross hourly wages using information on hours worked per week. Only in the years 1979, 1985 and 1989 the firms have been asked about the level of education of their workers.

In the annual Production Survey firms in the manufacturing sector are asked for detailed information on inputs and outputs. This information contains, amongst others, sales, gross output, value added, wage bill, number of employees, materials and electricity usage. From these survey data we have calculated a measure for labour productivity as gross value added (at factor costs) per employee. The measure for profitability equals gross value added (at factor costs) minus wage bill divided by number of employees. Till 1987 all firms with 10 or more employees were observed and smaller firms were

1 We could not create a panel of individual workers, because in our data set there were no variables available which uniquely identify each worker in the course of time.

excluded. Since 1987 all firms with 20 or more employees are surveyed and from the firms with less than 20 employees a sample is drawn.

The yearly R&D Survey provides insight into the size and the structure of R&D activities in the Netherlands. In the years 1985 and 1989 an extended R&D Survey was held among all firms with 50 or more employees. From these surveys data is available on R&D full-time equivalents and other personnel and expenditures on in-house (or own) R&D and outsourced R&D. The R&D expenditures are further disaggregated by type of cost (personnel costs, costs of materials used and R&D equipment investments), by type of research (basic and applied) and by object of research (process and product innovation). We have used (total) own R&D expenditures per employee (henceforth called 'R&D intensity') as a measure of the technological position of a firm.

The four-yearly Survey of Manufacturing Technology asks firms to indicate whether they used any of a list of computer aided manufacturing (CAM), design (CAD) and production planning (CAPP). However, we focus in this paper on the information pertaining to CAM equipment, because this technology leads in general to labour productivity improvements. The CAM technologies include CNC, DNC and robots. The SMT was conducted in 1985 and 1989 among firms with 5 or more employees. Only in 1989 firms were requested to state how many pieces of each type of CAM technology were in operation. That is why we have created a measure of technology by summing the positive responses to binary questions on usage of 3 different types of CAM technologies. This measure is henceforth denoted by 'use of CAM equipment'.

We have analysed the effects of firm performance and technology on individual wages by means of a log-linear regression model which relates the logarithm of gross hourly wages to employee, job and firm characteristics (see equation (2)). In appendix A a description is given of the regressors used in the analysis. We have refrained from the use of profitability in the wage model, because this variable is highly correlated with labour productivity. Further we have added as regressor the sector of economic activity (according to the 2-digit level of the CBS Standard Industrial Classification) to capture the influence of other firm-specific variables like capital intensity. For most regressors a set of dummy variables is created by treating each category of the regressor in question as a separate variable. To avoid multicollinearity it is necessary to exclude one of the dummies (marked with a star in appendix A) for each explanatory variable. We have taken no account of the interaction effects between the regressors in the wage equation. Addition of interaction terms would lead to a large increase in the number of dummies and with that to inaccurate estimates of regression parameters. Further it is assumed that all explanatory variables in the wage regression are strictly exogenous, so that the model can be estimated unbiasedly by ordinary least squares (OLS).

Our cross-sectional data set is the result of joining micro data of a number of surveys. To examine how representative the linked data are, Appendix B and C give some summary statistics for the original and the linked data sets. Appendix B presents the average labour productivity, the average R&D intensity and some frequency distributions of observed manufacturing firms for both the original data sets (PS, RDS and SMT respectively) and the linked data sets (WS-PS, WS-PS-RDS and WS-PS-SMT respectively). It appears that firms in the linked data sets are larger than in the original samples. Appendix B also indicates that a larger portion (smaller portion respectively) of firms in the linked data sets are in the chemical and petroleum industry (other manufacturing industries). Appendix C reports the average hourly wage and a number of frequency distributions of observed manufacturing workers for both the original WS sample and the above-mentioned linked data sets. This appendix shows that workers in the original sample and in the linked samples are fairly similar. One exception is the mean hourly wage: workers in the linked data set earn higher wages than the workers in the original WS data set. There is much empirical evidence that large employers pay their workers more than small employers (see for instance Brown and Medoff, 1989). The fact that our linked samples contain larger firms implies that our linked samples will also contain higher wage workers. Therefore, we have to take into account that the regression estimates based on linked data may be subject to some sample selectivity bias.

4. Empirical Results

Appendix D, E, F and G show the estimation results from the log-linear wage regressions with various sets of explanatory variables and based on different data sets for the years 1979, 1985 and 1989. In these appendices the OLS estimates of the regression parameters along with their statistical significance levels are given. These parameters represent approximately the proportional change in the hourly wage resulting from a change in one of the explanatory variables (given the effect of the other included variables).

First, we consider the estimation results based on the WS sample data (see appendix D). The included employee characteristics have a statistically significant effect (at the 95% level) on (log) wages. The regression model excluding firm characteristics based on the WS 1989 results in an adjusted multiple correlation coefficient (R^2) of 56%, that means that 56% of the variation in the log hourly wages is explained by the model. For the standard human capital variables as age, sex and education we find the usual theoretical effects in the (log) wage regressions. The wage which a worker earns, increases as he or she gets older. The estimated regression parameter based on 1989 WS data for the category woman equals –0.1299, which means that a woman earns ceteris paribus 13% less than a man. Higher educated workers receive higher wages than workers with a lower education. Further, full-time workers are better rewarded per hour than part-timers or flexible labour forces, irregular or shift work earns better than regular work, and higher jobs are better paid than lower jobs. The variable indicating whether or not a worker is covered by a collective labour agreement has also an influence on wages: wages at covered firms are lower than at uncovered firms.

Next, we look at the impact of firm performance on worker wages. In appendix E the wage effect of labour productivity, sector of economic activity and size of the firm is determined upon the matched WS-PS data, controlling for the influence of the above-mentioned employee and job characteristics. The addition of the firm characteristics to the wage equation increases in 1989 R^2 by 3.9% (compare column (1) with (2)). In other years the increase in R^2 is lower (0.9% in 1979 and 2.3% in 1985). Comparing the coefficient estimates of column (1) with those of (2) we find that including the firm variables reduces the effect of education and working hours arrangement on wages. The main cause is the correlation between education, working hours arrangement and firm size.

The firm-specific variables have less sizable effects on the wages than the employee and job variables. From the coefficient estimates in column (2) it can be inferred that firm labour productivity has a statistically significant (at the 95% level), but in size limited, effect on worker reward. This effect is quite stable across time. Increasing the value added per employee with 1000 Dutch guilders results in a hourly wage rise by 0.06–0.08% in the considered years. It appears from our data set that there exists a correlation between labour productivity on the one hand and working hours arrangement, firm size and sector of activity on the other. Excluding the last three variables from the wage regression leads to a minor increase in the productivity effect from 0.06–0.08% to 0.09–0.14% (see column (3) in appendix E). It can be concluded from the empirical estimates based on our matched worker-firm data that the wage rate in the Netherlands manufacturing industries is to a small extent determined by firm performance.

With respect to firm size we see in appendix A the result that workers in large firms are rewarded with higher wages. The effect of the sector of economic activity is harder to determine because of the relative high standard errors (here not shown) of the coefficient estimates. The average worker wage in 1989 is in the textile, apparel and leather industry and the other manufacturing industry relatively low and in the paper and printing industry relatively high. From the comparison of appendix D with column (1) of appendix E it can be seen that the coefficient estimates of the employee characteristics from the original WS data do not differ much from those estimated from matched WS-PS data. This implies that the sample selectivity bias in the estimates, caused by the drop out of firms when linking data, is rather limited.

Finally, we examine how worker wages vary with technology usage of their firm. As already mentioned we employ in this study two measures of the technological position of a firm: internal R&D expenditures per employee of a firm and number of CAM technologies utilised at the firm. The OLS estimates based on linked WS-PS-RDS data in appendix F (column (3)) show that the size of internal R&D activities of a firm has a statistically significant (at the 95% level) but limited effect on the hourly wage. Including R&D intensity in the wage regression increases R^2 only by 0.5% and 0.1% in 1985 and 1989 respectively (compare column (2) with (3)). Increasing the own R&D expenditure per employee with 1000 Dutch guilders results in a wage rise by 0.01-0.07%. Thus, R&D intensive firms pay higher wages. In our data set we do not find a strong correlation between R&D intensity and other included variables (such as education). This means that the R&D effect on wages does not increase after excluding other variables in the model (compare column (3) with (4) in appendix F). From the comparison of appendix D with column (1) of appendix F for the years 1985 and 1989 it can be inferred that the sample selectivity bias in the regression coefficients based on linked WS-PS-RDS data is higher than the bias in the coefficients based on WS-PS data.

Appendix G presents the influence of firm use of CAM technologies on worker rewards. The regression results based on matched WS-PS-SMT data show that there does not exist a statistically significant CAM technology effect on wage rates (see column (3)). Addition of the CAM variable in the wage model even results in a drop of the adjusted R^2 (compare column (2) with (3)). It is possible that the insignificant CAM coefficient is caused by correlation between CAM use and other included variables. Evidence of multicollinearity can be found by deleting some variables like labour productivity, firm size and sector of economic activity from the wage equation. From the estimation of this restricted equation it can be derived that this does not lead to a large improvement of the significance of the CAM effect (see column (4) in appendix G). From our results we can conclude that there does not exist a clear relation between worker wages and firm use of CAM equipment.

Another way of assessing the relative importance of the included employee, job and firm variables in explaining wages is to consider the decrease in R^2 when a variable (or the set of dummy variables for all categories of a variable) is removed from the wage equation that contains all explanatory variables. The result is given in appendix H. A large change in R^2 indicates that a variable provides unique information about the wages that is not available from the other explanatory variables. The variable use of CAM equipment is excluded because of insignificance. The omission of age from the wage equation results in a decrease in R^2 by 10.9–22.1%. Similar effects for education are 2.7–21.8%, for job level 5.8%, for labour productivity 0.2–1.2% and for R&D intensity 0.1–0.6%. These numbers indicate that employee and job characteristics like age, education and job level are the most important explanatory variables. The firm variables play a less important role at the wage determination.

5. Conclusions and Further Research

This paper investigates the impact of firm performance and technology use on worker wages in the Netherlands manufacturing industry for the years 1979, 1985 and 1989. Our empirical analysis uses cross-sectional worker-firm data which are created by joining the Netherlands Wage Survey, the Production Survey, the R&D Survey and the Survey of Manufacturing Technology.

The estimation results show that firms that have a higher R&D intensity or that have a higher labour productivity pay their workers significantly higher wages. We have adequately controlled for the influence of worker quality. Further we found that the use of manufacturing technology has no significant influence on the wages of workers. Firm characteristics play a less important role at the wage formation than employee and job characteristics like age, education and job level. The omission of firm R&D intensity and labour productivity from the wage regression equation that contains all characteristics results in a decrease in the explained variation in the log hourly wages by 0.1–0.6% and 0.2–1.2% respectively. The results presented here for the Netherlands can be seen as providing weak support for the insider-outsider model of wage determination and not as a structural test of this model. This means that wages differences caused by insider power do not play a substantially large role in Netherlands manufacturing firms. In other words, the Netherlands labour market behaves itself reasonably in accordance with competitive theory.

Finally, we want to point at some limitations of the results presented. In the wage model we included aggregate data (firm-level) as well as micro data (worker-level). OLS estimates of the wage regression parameters can be biased because of this aggregation problem.

There are more larger firms in the linked data set than in the original sample. Thus, the estimated regression coefficients of the wage equations may be subject to some sample selectivity bias.

It is assumed that all explanatory variables in the wage regressions are strictly exogenous. This may be questionable with firm-level variables such as technology and productivity. Unfortunately we lack instruments to take endogeneity into account by econometric methods.

The wage regression estimates are based on cross-sectional data and can be biased by neglecting unobservable worker or firm effects. However, in defense of our analysis, there are a number of variables used here that are often subsumed into the fixed effects component.

Only panel data of workers and their firms would enable us to deal more satisfactorily with the problems of fixed effects. The Netherlands Socio-Economic Panel Survey can offer good possibilities for further research, because in this annual survey a panel of individuals are asked for their demographic, geographic, labour and income data. By linking this panel worker survey with cross-sectional (worker-)firm surveys such as the Wage Survey and the Production Survey we can create a promising research database.

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Appendix A.
Description of variables used in the analysis

Variable	*Definition*
Employee characteristics	
age	≤ 19 years
	20–24 years
	25–29 years*
	30–34 years
	35–49 years
	≥ 50 years
sex	man*
	woman
level of education	primary education
	advanced primary education
	intermediate education*
	higher vocational education
	university education
	unknown
Job characteristics	
employment contract	full-time*
	part-time/flexible
working hours arrangement	regular*
	irregular/shift work
job level	lower personnel*
	supervisors, foremen
	intermediate executive personnel
	higher personnel
collective labour agreement	yes*
	no
Firm characteristics	
sector of economic activity	food, beverages, tobacco*
	textile, apparel, leather
	paper, printing
	chemical and petroleum
	metal, electrical engineering
	other manufacturing
firm size	≤ 99 employees
	100–499 employees*
	≤ 500 employees
labour productivity	gross value added per employee
R&D intensity	own R&D-expenditures per employee
use of CAM equipment	none*
	1 type
	2 types
	3 types

* Included in the constant term of the wage regression

Appendix B.
Sample statistics for firms[1]

		PS			RDS		SMT		WS-PS			WS-PS-RDS		WS-PS-SMT	
		1979	1985	1989	1985	1989	1985	1989	1979	1985	1989	1985	1989	1985	1989
								% firms							
sector of economic activity	food, beverages, tobacco	17	17	15	17	15	18	17	18	18	17	20	17	19	16
	textile, apparel, leather	9	7	8	3	5	7	7	11	7	7	3	5	6	7
	paper, printing	13	14	13	6	6	14	12	13	13	14	6	5	12	11
	chemical and petroleum	7	8	8	22	22	9	10	9	13	12	26	23	13	13
	metal, electrical engineering	37	39	40	45	47	39	42	34	39	40	40	44	40	44
	other manufacturing	16	16	18	7	7	13	12	15	11	11	6	6	10	10
firm size	99 employees	84	85	88	22	22	71	69	62	43	45	5	10	31	31
	100-499 employees	14	13	10	55	58	24	27	32	42	44	51	62	52	59
	500 employees	3	2	1	22	19	5	4	6	16	10	44	29	17	10
use of CAM equipment	none	.	.	.	.	.	79	83	.	.	.	.	.	68	73
	1 type	.	.	.	.	.	18	13	.	.	.	.	.	26	20
	2 types	.	.	.	.	.	3	3	.	.	.	.	.	5	6
	3 types	.	.	.	.	.	0	1	.	.	.	.	.	1	2
mean labour productivity		50.8	70.4	82.3	.	.	.	.	53.0	80.4	88.9	92.9	102.5	83.0	92.9
mean R&D intensity		.	.	.	19.4	25.9	.	.	.	.	.	16.3	35.8	.	.
number of firms		8843	8785	12563	430	511	3577	2756	3492	924	1653	190	332	552	682

1 WS = Wage Survey,
PS = Production Survey,
RDS = R&D Survey,
SMT = Survey of Manufacturing Technology.

Appendix C.
Sample statistics for employees[1]

		WS			WS-PS			WS-PS-RDS		WS-PS-SMT	
		1979	1985	1989	1979	1985	1989	1985	1989	1985	1989
						% employees					
age	≤19 years	6	3	3	6	2	2	1	1	2	2
	20–24 years	13	15	13	13	14	12	12	8	13	11
	25–29 years	13	15	17	13	15	17	16	17	16	18
	30–34 years	15	13	15	15	13	15	12	15	13	15
	35–49 years	34	37	37	34	38	38	40	40	39	39
	≥50 years	19	18	16	19	19	17	19	19	18	16
sex	man	85	85	85	85	85	86	85	88	88	87
	woman	15	15	16	15	15	15	15	12	12	13
level of education	primary education	26	19	15	27	20	15	19	18	18	15
	advanced primary education	43	40	35	43	40	35	35	31	39	39
	intermediate education	14	24	26	13	24	26	27	26	26	28
	higher vocational education	4	7	7	4	7	8	10	12	8	7
	university education	6	2	2	6	2	3	4	5	2	2
	unknown	8	8	15	8	7	14	4	9	7	9
employment contract	full-time	94	94	94	95	95	95	94	96	96	97
	part-time/flexible	6	6	6	6	5	5	6	4	4	3
working hours arrangement	regular	82	80	80	82	79	78	73	72	76	75
	irregular/shift work	18	20	20	18	21	22	27	28	24	25
job level	lower personnel	77	.	.	77	.	.	.	.	.	.
	supervisors, foremen	6	.	.	6	.	.	.	.	.	.
	intermediate executive personnel	6	.	.	6	.	.	.	.	.	.
	higher personnel	11	.	.	10	.	.	.	.	.	.
collective labour agreement	yes	84	.	.	85	.	.	.	.	.	.
	no	16	.	.	15	.	.	.	.	.	.
mean hourly wage		15.5	19.9	21.9	15.4	20.2	22.3	21.7	24.3	20.6	22.4
number of employees		155232	1874	5334	139550	1702	4886	675	1992	982	1749

1 WS = Wage Survey,
PS = Production Survey,
RDS = R&D Survey,
SMT = Survey of Manufacturing Technology.

Appendix D.
OLS regression estimates of the effect of employee and job characteristics on (log) hourly wages using WS data.

Variable		1979	1985	1989
intercept		2.5966*	2.9082*	2.9662*
age	≤19 years	–0.4972*	–0.7562*	–0.7314*
	20–24 years	–0.1150*	–0.1950*	–0.1870*
	25–29 years	0	0	0
	30–34 years	0.0583*	0.1133*	0.1162*
	35–49 years	0.1222*	0.2352*	0.2567*
	≥ 50 years	0.1372*	0.2803*	0.2948*
sex	man	0	0	0
	woman	–0.1042*	–0.1285*	–0.1299*
level of education	primary education	–0.1962*	–0.2862*	–0.2451*
	advanced primary education	–0.0989*	–0.1521*	–0.1421*
	intermediate education	0	0	0
	higher vocational education	0.1015*	0.2706*	0.2668*
	university edcuation	0.3090*	0.4309*	0.4525*
	unknown	–0.0920*	–0.1132*	–0.1011*
employment contract	full-time	0	0	0
	part-time/flexible	–0.0559*	–0.0720*	–0.1075*
working hours arrangement	regular	0	0	0
	irregular/shift work	0.1354*	0.1388*	0.1280*
job level	lower personnel	0		
	supervisors, foremen	0.1969*		
	intermediate executive personnel	0.2765*		
	higher personnel	0.4997*		
collective labour agreement	yes	0		
	no	0.0564*		
adjusted R^2		0.682	0.593	0.557
sample size (employees)		155232	1874	5334

* significantly different from zero at the 95% level.
# significantly different from zero at the 90% level.

Appendix E.
OLS regression estimates of the effect of firm performance on (log) hourly wages using WS-PS data

Variable		1979			1985			1989		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
intercept		2.5948*	2.5363*	2.5337*	2.9176*	2.8873*	2.8463*	2.9662*	2.9117*	2.9022*
age	≤19 years	–0.4918*	–0.4799*	–0.4945*	–0.7099*	–0.6831*	–0.7075*	–0.7298*	–0.6885*	–0.7327*
	20–24 years	–0.1108*	–0.1076*	–0.1100*	–0.1722*	–0.1642*	–0.1719*	–0.1778*	–0.1631*	–0.1727*
	25–29 years	0	0	0	0	0	0	0	0	0
	30–34 years	0.0587*	0.0583*	0.0621*	0.1151*	0.1180*	0.1173*	0.1234*	0.1165*	0.1148*
	35–49 years	0.1204*	0.1212*	0.1255*	0.2365*	0.2350*	0.2323*	0.2622*	0.2540*	0.2519*
	≥50 years	0.1335*	0.1331*	0.1328*	0.2896*	0.2853*	0.2798*	0.2998*	0.2871*	0.2830*
sex	man	0	0	0	0	0	0	0	0	0
	woman	–0.1054*	–0.1018*	–0.1245*	–0.1325*	–0.1420*	–0.1519*	–0.1216*	–0.1312*	–0.1389*
level of education	primary education	–0.1982*	–0.1793*	–0.1651*	–0.2961*	–0.2771*	–0.2675*	–0.2517*	–0.2294*	–0.2241*
	advanced primary education	–0.0989*	–0.0859*	–0.0865*	–0.1602*	–0.1419*	–0.1491*	–0.1423*	–0.1192*	–0.1270*
	intermediate education	0	0	0	0	0	0	0	0	0
	higher vocational education	0.0919*	0.0811*	0.0833*	0.2519*	0.2259*	0.2212*	0.2685*	0.2436*	0.2418*
	university education	0.2967*	0.2703*	0.2826*	0.4081*	0.3737*	0.3710*	0.4498*	0.3903*	0.3927*
	unknown	–0.0848*	–0.0874*	–0.0733*	–0.1254*	–0.0905*	–0.1095*	–0.1006*	–0.0746*	–0.0881*
employment contract	full-time	0	0	0	0	0	0	0	0	0
	part-time/flexible	–0.0510*	–0.0460*	–0.0543*	–0.0456	–0.0492#	–0.0518#	–0.0844*	–0.0722*	–0.0817*
working hours arrangement	regular	0	0		0	0		0	0	
	irregular/shift work	0.1363*	0.1109*		0.1298*	0.0775*		0.1256*	0.0676*	

Variable		1979			1985			1989		
		(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
job level	lower personnel	0	0	0						
	supervisors, foremen	0.1976*	0.1953*	0.1894*						
	intermediate executive personnel	0.2794*	0.2752*	0.2612*						
	higher personnel	0.5164*	0.5214*	0.5014*						
collective labour agreement	yes	0	0	0						
	no	0.0566*	0.0566*	0.0415*						
firm size	≤99 employees		–0.0109*			–0.0456*			–0.0491*	
	100–499 employees		0			0			0	
	≥500 employees		0.0312*			0.0324*			0.0459*	
sector of economic activity	food, beverages, tobacco		0			0			0	
	textile, apparel, leather		–0.0547*			–0.0541#			–0.0585*	
	paper, printing		0.0577*			0.0232			0.0603*	
	chemical and petroleum		0.0084*			0.0058			0.0081	
	metal, electrical engineering		–0.0104*			–0.0456*			–0.0161	
	other manufacturing		–0.0092*			–0.0591*			–0.0726*	
labour productivity			0.0008*	0.0014*		0.0006*	0.0011*		0.0006*	0.0009*
adjusted R^2		0.681	0.690	0.674	0.564	0.587	0.565	0.539	0.578	0.550
sample size (employees)		139550	139550	139550	1702	1702	1702	4886	4886	4886

* significantly different from zero at the 95% level.
# significantly different from zero at the 90% level.

Appendix F.
OLS regression estimates of the effect of firm R&D intensity on (log) hourly wages using WS-PS-RDS data

Variable		1985				1989			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
intercept		2.8491*	2.7696*	2.7643*	2.8789*	2.9474*	2.9035*	2.8999*	3.0099*
age	≤19 years	–0.4458*	–0.4351*	–0.4317*	–0.4687*	–0.5419*	–0.5224*	–0.5254*	–0.6438*
	20–24 years	–0.1127*	–0.1069*	–0.1076*	–0.1419*	–0.1127*	–0.1110*	–0.1091*	–0.1626*
	25–29 years	0	0	0	0	0	0	0	0
	30–34 years	0.1489*	0.1577*	0.1595*	0.1371*	0.1535*	0.1495*	0.1511*	0.1281*
	35–49 years	0.3048*	0.2980*	0.3004*	0.2344*	0.3061*	0.3024*	0.3030*	0.2260*
	≥50 years	0.3902*	0.3829*	0.3789*	0.3011*	0.3600*	0.3527*	0.3540*	0.2489*
sex	man	0	0	0	0	0	0	0	0
	woman	–0.0723*	–0.0880*	–0.0895*	–0.1498*	–0.1064*	–0.1071*	–0.1077*	–0.1831*
level of education	primary education	–0.2870*	–0.2661*	–0.2665*		–0.2611*	–0.2436*	–0.2444*	
	advanced primary education	–0.1099*	–0.1015*	–0.1030*		–0.1170*	–0.1015*	–0.1023*	
	intermediate education	0	0	0		0	0	0	
	higher vocational education	0.2534*	0.2338*	0.2301*		0.2710*	0.2696*	0.2693*	
	university education	0.4572*	0.4482*	0.4441*		0.4476*	0.4279*	0.4280*	
	unknown	–0.0956#	–0.0719	–0.0722		–0.0533*	–0.0522*	–0.0520*	
employment contract	full-time	0	0	0	0	0	0	0	0
	part-time/flexible	–0.1429*	–0.1360*	–0.1401*	–0.2301*	–0.0244	–0.0253	–0.0255	–0.0662#

Variable		1985				1989			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
working hours arrangement	regular	0	0	0		0	0	0	
	irregular/shift work	0.1462*	0.1058*	0.1113*		0.1068*	0.0816*	0.0819*	
firm size	≤99 employees		–0.0347	–0.0307			–0.0568	–0.0529	
	100–499 employees		0	0			0	0	
	≥500 employees		0.0206	0.0150			0.0299*	0.0310*	
sector of economic activity	food, beverages, tobacco		0	0			0	0	
	textile, apparel, leather		–0.1098	–0.1052			–0.0880*	–0.0868*	
	paper, printing		0.0437	0.0453			0.0386	0.0396	
	chemical and petroleum		–0.0061	–0.0194			–0.0049	–0.0119	
	metal, electrical engineering		–0.0398	–0.0431			–0.0382*	–0.0394*	
	other manufacturing		–0.0467	–0.0407			–0.0432	–0.0426	
labour productivity			0.0010*	0.0010*			0.0005*	0.0005*	
R&D intensity				0.0007*	0.0012*			0.0001*	0.0001*
adjusted R^2		0.524	0.545	0.550	0.315	0.505	0.522	0.523	0.258
sample size (employees)		675	675	675	675	1992	1992	1992	1992

* significantly different from zero at the 95% level.
# significantly different from zero at the 90% level.

Appendix G.
OLS regression estimates of the effect of firm use of CAM equipment on (log) hourly wages using WS-PS-SMT data

Variable		1985				1989			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
intercept		2.9085*	2.8702*	2.8645*	2.8861*	2.9645*	2.9108*	2.9116*	2.9664*
age	≤19 years	–0.6841*	–0.6453*	–0.6437*	–0.7697*	–0.7389*	–0.6911*	–0.6898*	–0.8195*
	20–24 years	–0.1343*	–0.1259*	–0.1262*	–0.2079*	–0.1535*	–0.1362*	–0.1356*	–0.1858*
	25–29 years	0	0	0	0	0	0	0	0
	30–34 years	0.1319*	0.1375*	0.1380*	0.0912*	0.0847*	0.0865*	0.0863*	0.0700*
	35–49 years	0.2396*	0.2388*	0.2381*	0.1834*	0.2565*	0.2562*	0.2561*	0.2290*
	≥50 years	0.2745*	0.2797*	0.2793*	0.2186*	0.2705*	0.2640*	0.2638*	0.2012*
sex	man	0	0	0	0	0	0	0	0
	woman	–0.1343*	–0.1393*	–0.1390*	–0.1741*	–0.1355*	–0.1354*	–0.1358*	–0.1870*
level of education	primary education	–0.2971*	–0.2760*	–0.2747*		–0.2396*	–0.2131*	–0.2132*	
	advanced primary education	–0.1598*	–0.1421*	–0.1421*		–0.1295*	–0.1099*	–0.1097*	
	intermediate education	0	0	0		0	0	0	
	higher vocational education	0.2836*	0.2448*	0.2454*		0.3280*	0.2976*	0.2972*	
	university education	0.3648*	0.3129*	0.3142*		0.4442*	0.3232*	0.3231*	
	unknown	–0.0577	–0.0235	–0.0212		–0.0722*	–0.0468*	–0.0480*	
employment contract	full-time	0	0	0	0	0	0	0	0
	part-time/flexible	–0.0233	–0.0196	–0.0190	–0.0824	–0.0563	–0.0619#	–0.0616#	–0.0954*
working hours agreement	regular	0	0	0		0	0	0	
	irregular/shift work	0.1238*	0.0693*	0.0688*		0.1368*	0.0753*	0.0747*	

Variable		1985				1989			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
firm size	≤99 employees		–0.0663*	–0.0650*			–0.0560*	–0.0571*	
	100–499 employees		0	0			0	0	
	≥500 employees		0.0249	0.0238			0.0498*	0.0526*	
sector of economic activity	food, beverages, tobacco		0	0			0	0	
	textile, apparel, leather		–0.1036*	–0.1013*			–0.0544*	–0.0548*	
	paper, printing		0.0244	0.0232			0.0524*	0.0526*	
	chemical and petroleum		–0.0370	0.0376			–0.0062	–0.0066	
	metal, electrical engineering		–0.0449*	–0.0431#			–0.0222	–0.0202	
	other manufacturing		–0.0484	–0.0486			–0.0615*	–0.0610*	
labour productivity			0.0007*	0.0007*			0.0006*	0.0006*	
use of CAM equipment	none			0	0			0	0
	1 type			0.0121	0.0402#			–0.0003	0.0146
	2 types			–0.0033	0.0554#			–0.0119	0.0576*
	3 types			0.0783	0.1525			–0.0263	0.0021
adjusted R^2		0.521	0.553	0.552	0.325	0.536	0.585	0.584	0.366
sample size (employees)		982	982	982	982	1749	1749	1749	1749

* significantly different from zero at the 95% level.
\# significantly different from zero at the 90% level.

Appendix H. Decrease of R^2 when a variable is removed from the wage equation[1]

Removed variable	Number of dummies	Decrease of R^2		
		1979	1985	1989
age	5	0.1090	0.2211	0.2044
sex	1	0.0049	0.0050	0.0072
level of education	5	0.0266	0.1907	0.2176
employment contract	1	0.0005	0.0058	0.0002
working hours arrangement	1	0.0082	0.0144	0.0091
job level	3	0.0581	.	.
collective labour agreement	1	0.0019	.	.
firm size	2	0.0014	0.0005	0.0024
sector of economic activity	5	0.0035	0.0036	0.0034
labour productivity	.	0.0023	0.0124	0.0084
R&D intensity	.	.	0.0056	0.0013

1 Based on respectively the linked WS-PS data set for 1979 and the linked WS-PS-RDS data set for 1985 en 1989.

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THE EFFECTS OF TECHNOLOGY ON WAGES IN FINNISH MANUFACTURING, 1974–93

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We study the effects of technology on establishment level wages using a classification of the technology levels of manufacturing industries. We have analysed technology effects on wages and changes in it over the time period 1974–1993, but paying more attention to the latest years, when more control variables were available. The technology wage premiums have been estimated separately for non-manual and manual workers using wage equations with available establishment control variables for plant and work force characteristics (human capital). The results do not appear to show a straightforward connection between the average wages of manufacturing establishments and the technology level of their industries among the high, medium-high or medium-low technology levels. However, the establishments in industries with the lowest technology have paid lower wages during the whole period. We also found that relative non-manual to manual wage ratio increased over time in the highest technology levels. These findings are fairly consistent with technology wage premiums and skill-biased technological change found in other studies.

Key words: Manual and Non-Manual Workers, Manufacturing Industries, Random Effects Model, Technology Intensity, Wage Equations, Worker-Employer Data.

1. Introduction

In this paper we report results on the effects of the level of technology on wages in Finland. For some other countries recent studies have found that firms with more advanced technology pay higher wages and use more skilled work force than those with conventional technology, see e.g. Bartel and Lichtenberger (1987) and Dunne and Schmitz (1992). In a parallel study we have analysed job creation and job destruction for the period 1986–93 using the same database, see Vainiomäki and Laaksonen, this volume.

We study this question using plant/establishment level data for average wages and work force characteristics. The plant level data come from two micro data sets constructed at Statistics Finland: (i) a panel data file of industrial establishments (DIE) for 1974–93, and (ii) a longitudinal worker/establishment database (WEDB) for 1988–1992. The DIE includes wages, hours and number of employees separately for manual (blue-collar) and non-manual (white-collar) workers. From the second file we obtain measures for the average (human capital) characteristics of workers of plants, which are matched to the DIE information. To get a long term perspective we perform some analyses without the additional variables from WEDB.

We use wage equations to estimate the effect of technology level on average establishment wages, with available establishment variables to control for their effects. The technology level of plants is determined according to their main industry. Our technology indicator is based on the relative R&D expenditure of the whole industry, using a Finnish survey from 1989. This is not ideal. A better way would be to use a technology indicator at the establishment level, but this information was not available for this work.

In Section 2 we briefly review some relevant literature. Section 3 informs about Finnish labour markets trends, Section 4 includes our empirical results on wage equations, and Section 5 concludes. The appendix gives some details on the data sets and variables used.

2. Previous Studies and Some Theoretical Considerations

The theoretical discussion of the possible effects of technological change on wages are often conducted using the competitive labour market analysis. Within this setting the important factors determining how technology effects divide between wage and employment effects are the labour demand and supply elasticities, the complementarity and substitutability of different factors of production, and the bias of technological change. On purely theoretical grounds the effects of technological change on *relative* wages of different worker groups is ambiguous (see e.g. Bartel and Lichtenberger (1987), Blackburn and Bloom (1988), Bound and Johnson (1992) and Mincer (1989) for more detailed discussions). If technological change is biased towards skilled labour and supply is not infinitely elastic, then skilled relative wage would rise. If there are no obstacles to labour 'migration' between groups in the long run (supply infinitely elastic), technology induced relative wage premiums would be abolished. On the other hand, wage *levels* for both groups may rise due to any type of technological change as long as marginal productivity of the group rises and supply is not fully elastic.

More generally insider factors (like union power) or efficiency wages have been argued to shape wage determination in addition to external labour market conditions. Van Reenen (1993) suggests rent-sharing as an alternative explanation of technological wage differentials. He argues that innovations may be a potential source of the surplus to be bargained over, if either the unit that adopts the new technology is also the first producer of it, or if there are organisation specific features in the adoption of new technology that are potential objects of bargaining ('organisational rents'). However, in addition to technology there are many other potential sources of rents like product market power or large irreversible capital investments, which may be interrelated with technology. It may be difficult to control all these factors and interactions to obtain independent effects of technology.

Union bargaining power, and consequently union wage premium, is related to the elasticity of demand for labour. Betcherman (1991) discusses the possible effects of technological change on labour demand elasticity to provide a link between technology and wages. Theoretically the direction of these effects are however indeterminate. For example, labour cost shares may increase or reduce depending on the bias of technological change. Or the direction of change in demand elasticity and wages depend on how new technologies affect job design, skill requirements, and location of control over the production process. As an empirical matter these factors are likely to be difficult to control for (with the exception of labour cost share and proxies for work force skill).

Still another type of relation between technology, wages and work force composition is proposed in Dunne and Schmitz (1992). Troske (1994) uses their model in relation to the size-wage premium. The essential predictions of the model are that the probability of a firm adopting advanced technology and the skill of the firm's work force are both increasing functions of firm size. These predictions are based on the assumptions that advanced technology capital is more costly to adopt and it is skill-biased. In empirical terms this means that wages (size premiums) include components that reflect worker skill and advanced technology, if these factors are not adequately controlled. It also means that the work force skill composition and the technology level are correlated.

It is clear that there are many difficulties related in detecting technology wage premiums. Even if one finds wage differences according to level of technology, they may simply reflect the higher skill composition or higher quality of work force that is rewarded a normal return. Controlling measured characteristics may still leave returns for unobservable skill or quality components in wage premiums ('within skill group upgrading'). Furthermore, the causality between technology and skill and the related wage premium is an issue. It is possible that more skill leads to more adoption of new technology. For example the findings of Doms, Dunne and Troske (1996) indicate that causality may be reverse. They find that plants which use a large number of new technologies employ more educated workers and pay higher wages, but the plants which adopt new technologies have more skilled work force both pre- and post adoption.

As mentioned above, it is possible that technology affects the 'skill requirement' within skill groups. For example, it seems appropriate to believe that the creation of new technology or supervision of its use in production requires a firm to hire higher-quality experts and to pay higher wages correspondingly. On the other hand, it may not be as clear that the usage of the new technology in production by production workers requires necessarily any higher skill level. Therefore the effects of technology level on skill requirements and wages may be different for different worker groups, like production and non-production workers. It is also possible that the usage of older technology can be more demanding in other respects, e.g. working conditions may be worse, and a firm must pay higher wages as a compensation. It would therefore be important to control for both work force characteristics and job characteristics in any analysis of technology wage premiums.

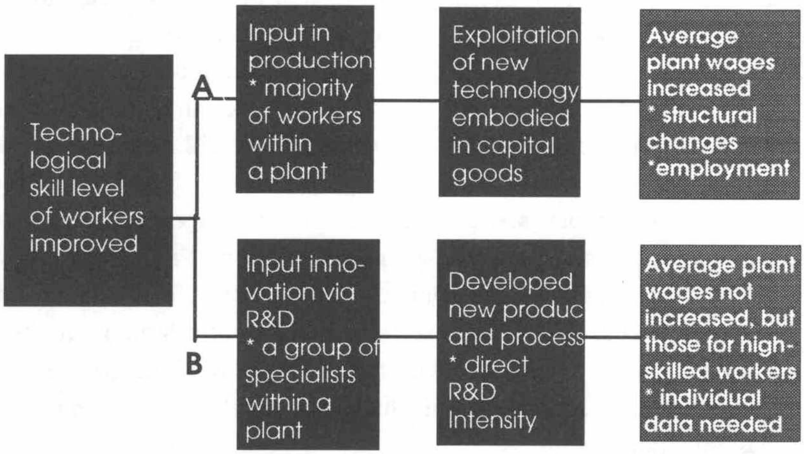
Scheme 1 describes some possible differences across worker groups in the technology effects.

3. Finnish Labour Markets and Economic Trends

Before reporting our results we briefly characterise Finnish labour market institutions and outline the general economic trends of the Finnish economy, in order to give perspective to the results.

A centralised system of wage bargaining has been in effect since 1968 in Finland. It is often called a tri-partite system, as three parties, the govern-

Scheme 1. **Two possible channels to wages from technological development.**



ment, the central organisations of employers (2) and those of employees (3–4) take part in the negotiations. Over time the government's role has varied from more to less active, and the degree of centralisation from weak (resulting in industry level bargaining rounds) to strong (central frame agreements implemented in most industries). In last few years there have been more pressures to displace the centralised system with local (firm/plant level) bargaining. However, during the whole period there has been also local bargaining in addition to the centralised levels (national, industry), which gives rise to the wage drift and is a potential source of firm/plant level wage differences. Despite of these less centralised components, this system has probably contributed to the fact that wage structures in Finland have been fairly rigid, for example industry wage differences have been fairly persistent over time (see e.g. Vainiomäki and Laaksonen 1995).

Turning to the general economic development, the second part of the 1970s was a period of slow growth, increasing unemployment, and decreasing inflation as an aftermath of the oil crisis. This was followed by a period of fairly stable growth and unemployment until the end of 80's. In the end of 80's Finnish economy experienced strong growth and rising inflation (overheating) due to e.g. liberalisation of the capital markets. This was followed by the worst recession in the Finnish economy after the second world war. In the beginning of 90's unemployment exploded from about 5 % to almost 20 %, and the GDP declined over some years. This development reached a turning point after our data period in 1994.

4. Technology and Wages: Results from Wage Equations

Specifications of estimated equations

As discussed in Section 2, it is possible that new (advanced) technology increases wages and the required skill of workers, at least in the short run. It is also obvious that the success in analysing technology wage premiums crucially depends on the ability to control for other important determinants of wages. We attempt here to accomplish this by analysing the connection between plant average wages and its technology level using simple static wage equations of the following form (i indicates plant, j technology group and t year of observation)

$$\log(W_{ijt}) = a + D_t' b + X_{ijt}' c + H_{ijt}' d + TECH_{jt}' f + u_{ijt}$$

where W_{ijt} is the average plant wage for manual workers or non-manual workers, X includes control variables for plant characteristics, H the human capital characteristics of workers, TECH indicators for the technology level of plants, and D the time dummies (see the appendix for details of variables).

We attempt to control for work force human capital effects in two ways. First, we estimate wage equations separately for manual and non-manual wages. This amounts to allowing unrestricted coefficients of control variables across this basic skill-classification. Second, we include work force characteristics available from WEDB for the 1988–92 period. These variables include education shares, age shares, female share and technical (science) educated share. These variables are not available for the longer period 1974–93, and hence omitted from the equation. The plant level control variables available from DIE were included in all equations and are fairly standard, like size class, region, export share, foreign ownership, type of plant (single/multiple) etc. (see Tables below).

In estimations we have used three different estimation methods corresponding with different specifications for the error term uijt. Treating data as a pooled cross-section and assuming a zero mean and constant variance error term we use GLM-OLS. It is well known that if there are plant-specific effects correlated with explanatory variables, OLS is biased. To allow for unobservable plant-specific effect we use standard random and fixed effects panel estimators. However, our fixed effects estimations are plagued by the small time-variations in several explanatory variables, especially the technology indicator, which is our main interest here. Therefore, we do not present any results for these models.

Most models are estimated using unbalanced panels but some using 1988–92 data also using balanced panels. A balanced panel includes a more homogeneous group of plants as entering and exiting plants are omitted. We study possible differences in technology effects between these groups also using entry/exit dummies.

Technology wage effects and changes over time

Panel A of Table 1 gives our estimates of technology wage premiums for both groups of workers for the whole period 1974–93 and five-year sub-periods to indicate possible changes over time. The figures are differences (log percent) in wage *levels* by technology group (reference group is the low technology) separately for manuals and non-manuals, and are based on pooled OLS estimates.

Comparing the wage effects across technology levels, it is notable that the 'low' technology group always pays the lowest wages, which is consistent with a positive technology wage premium obtained in other studies. However, among the higher technology levels the relationship appears to be reversed or flat, that is the 'medium' groups tend to have higher wages than the 'high' group. This pattern is clear for manual workers but is flatter for non-manuals. It is hard to explain this patterns in terms of bias of technology. The most likely explanation is that there are important factors influencing wages missing from our equations that intervene with the technology effect.

However, there are other features in these results that are consistent with skill-biased technical change. First, looking at the development over time, it is observed that for manual workers the relative wage in 'high' technology has declined, and less so for the 'medium' groups, from the 70s to the 90s. There is no such clear trend for non-manual workers. Second, when the human capital characteristics of plant's work force are included (for period 1988–92), the technology wage premiums decline. This means that compared to the 'low' group the work force in higher technology groups tends to be more skilled in term of measured education, experience (age) and technical

Table 1. **Estimated wage premiums in four technology groups based on multi-year regression models separately for manual and non-manual workers and for various periods.**

	Technology Level of the industry				
Populations, and model	**High**	**Medium-High**	**Medium-Low**	**Low**	**R-square**
A. Pooled cross-section data					
1974–93					
– Manual workers	0.067	0.155	0.167	0.000	0.86
– Non-manual workers	0.086	0.111	0.133	0.000	0.74
1974–78					
– Manual workers	0.138	0.200	0.194	0.000	0.51
– Non-manual workers	0.138	0.134	0.149	0.000	0.41
1979–83					
– Manual workers	0.114	0.164	0.180	0.000	0.47
– Non-manual workers	0.064	0.107	0.180	0.000	0.34
1984–88					
– Manual workers	0.046	0.147	0.160	0.000	0.39
– Non-manual workers	0.101	0.116	0.136	0.000	0.28
1989–93					
– Manual workers	0.021	0.136	0.151	0.000	0.32
– Non-manual workers	0.089	0.111	0.151	0.000	0.20
1988–92, incl. Human Capital variables					
– Manual workers	0.001	0.075	0.104	0.000	0.42
– Non-manual workers	0.067	0.085	0.115	0.000	0.25
B. Pooled data 1986/87–1992/93					
Excl. variable SURV:					
– Manual workers	0.025	0.139	0.153	0.000	0.49
– Non-manual workers	0.097	0.111	0.135	0.000	0.31
Incl. variable SURV:					
– Manual workers	0.026	0.140	0.153	0.000	0.49
– Non-manual workers	0.092	0.111	0.135	0.000	0.33

(science) education, which is consistent with skill-biased technology. Third, Table 2 shows the non-manual to manual *relative* wage premiums by technology level compared to the relative wage in 'low' group. These are calculated as differences between the wage level estimates for manuals and non-manuals in Table 1, and since 'low' is the reference group it becomes the reference group for relative wages (and is assigned a value 0).

Table 2. **Non-manual to Manual Relative wage by technology level.**

	1974–78	1979–83	1984–88	1989–93	1988–92 (Inc. HR)
High	0.000	–0.050	0.055	0.068	0.066
Medium-High	–0.064	–0.057	–0.031	–0.025	0.010
Medium-Low	–0.045	0.000	–0.024	0.000	0.011

These figures indicate that the relative wages of non-manual workers have increased especially after mid 80's compared to manual wages in high-tech and medium-high establishments. These results imply that in recent years plants in high technology group developing and adopting more new technology have hired more skilled or qualified non-manual workers and paid them higher wages than plants in lower groups. The negative numbers indicate lower relative non-manual wages compared to low group, and probably result from the problems in estimates of wage level premiums mentioned above. However, the positive effects in high group and the rising trend in relative wages provide some support for skill-biased technical change, if either the speed of technological change has increased or it has become more biased than previously. Note also that the premium in relative wages turns positive in medium groups when human capital controls are included in 1988–92.

Tables 3a and 3b present full estimation results including the human capital variables for the 5 year period 1988–92. These tables also show differences due to estimation method (GLM-OLS and random effects) and between balanced and unbalanced panels.

Table 3a. **Estimates from wage models, including human capital variables, data 1988–92. Manual workers, (t-values in parentheses).**

Variable	GLM-OLS				Random Effects			
	Balanced		Unbalanced		Balanced		Unbalanced	
Technology								
High	−0.021	(−2.8)	0.001	(0.2)	−0.024	(−1.9)	0.012	(1.2)
Medium-High	0.060	(12.0)	0.075	(17.7)	0.065	(7.7)	0.087	(13.8)
Medium-Low	0.095	(23.2)	0.104	(30.0)	0.096	(13.4)	0.112	(20.3)
Low	0.000		0.000		0.000		0.000	
Level of Education								
2	−0.028	(−2.1)	−0.002	(−0.2)	0.015	(1.1)	0.012	(1.2)
3	0.020	(0.8)	0.000	(0.0)	0.003	(0.1)	−0.016	(−0.8)
4	0.024	(0.8)	0.056	(2.5)	0.020	(0.7)	0.038	(1.8)
5	0.512	(1.9)	0.448	(2.4)	0.592	(2.2)	0.398	(2.0)
Technological Educ.	0.002	(0.2)	0.064	(0.8)	0.034	(3.0)	0.020	(2.3)
Size 1	−0.180	(−30.2)	−0.180	(−15.5)	−0.101	(−6.0)	−0.099	(−6.7)
2	−0.167	(−14.1)	−0.173	(−15.3)	−0.106	(−6.5)	−0.108	(−7.1)
3	−0.154	(−13.1)	−0.157	(−14.1)	−0.094	(−5.9)	−0.099	(−6.6)
4	−0.128	(−10.8)	−0.133	(−11.9)	−0.073	(−4.7)	−0.081	(−5.4)
5	−0.075	(−6.6)	−0.078	(−7.1)	−0.033	(−2.2)	−0.039	(−2.7)
Export%	−0.031	(−4.1)	−0.030	(−4.6)	−0.000	(−0.0)	0.001	(0.1))
Rent	0.014	(11.5)	0.013	(14.2)	0.007	(6.4)	0.007	(8.1)
Manual%	−0.066	(−5.1)	−0.049	(−4.7)	−0.154	(−8.7)	−0.123	(−9.4)
Wage%	0.221	(3.3)	0.133	(1.4)	0.189	(2.3)	0.015	(0.8)
Female%	−0.247	(−30.2)	−0.242	(−37.1)	−0.167	(−13.7)	−0.174	(−19.3)
Age 2	0.164	(9.9)	0.140	(11.3)	0.098	(6.9)	0.081	(6.8)
3	0.214	(13.8)	0.199	(17.0)	0.092	(5.5)	0.097	(7.8)
4	0.156	(9.0)	0.115	(8.5)	0.073	(3.6)	0.058	(3.8)
Non-Foreign	−0.001	(−0.1)	−0.020	(−2.6)	0.003	(0.3)	−0.025	(−2.4)
Single/Multi	−0.052	(−13.0)	−0.050	(−14.7)	−0.033	(−6.7)	−0.040	(−9.4)
Region	significant							
Year	significant							
R^2	0.422		0.418					
RMSE	0.193		0.205					
var – cross-section					0.023		0.028	
var – error					0.015		0.017	
N Total	14935		23835		14935		23835	
N panel	2986				2986			

Table 3b. **Estimates from wage models, including human capital variables, data 1988–92. Non-manual workers, (t-values in parentheses).**

Variable	GLM-OLS				Random Effects			
	Balanced		Unbalanced		Balanced		Unbalanced	
Technology								
High	0.069	(6.6)	0.067	(7.8)	0.077	(4.4)	0.092	(7.0)
Medium-High	0.070	(10.1)	0.085	(14.4)	0.076	(6.5)	0.077	(10.0)
Medium-Low	0.113	(20.1)	0.115	(24.0)	0.112	(11.5)	0.120	(15.7)
Low	.							
Level of Education								
2	0.089	(5.0)	0.094	(7.1)	0.049	(2.7)	0.077	(5.7)
3	0.032	(1.0)	0.094	(3.8)	0.083	(2.5)	0.093	(3.5)
4	0.238	(7.0)	0.244	(9.2)	0.171	(4.8)	0.228	(8.3)
5	0.220	(0.7)	0.421	(2.1)	0.300	(1.0)	0.224	(1.1)
Technological Educ.	0.046	(3.4)	0.052	(4.9)	0.039	(2.5)	0.043	(3.6)
Size 1	–0.240	(–13.7)	–0.223	(–13.7)	–0.136	(–5.8)	–0.153	(–7.1)
2	–0.131	(–7.9)	–0.116	(–7.3)	–0.061	(–2.8)	–0.080	(–3.8)
3	–0.056	(–3.4)	–0.030	(–1.9)	–0.029	(–1.4)	–0.022	(–1.0)
4	–0.019	(–1.2)	–0.000	(–0.0)	0.003	(0.2)	0.009	(1.0)
5	–0.002	(–0.1)	–0.012	(–0.8)	0.015	(0.8)	0.020	(1.0)
Export%	0.033	(3.2)	0.032	(3.6)	0.032	(2.2)	0.034	(2.9)
Rent	0.006	(4.1)	0.006	(5.0)	0.002	(1.4)	0.003	(2.1)
Manual%	–0.071	(–5.6)	–0.111	(–10.6)	0.053	(0.0)	–0.063	(–4.5)
Wage%	–0.168	(–1.7)	–0.124	(2.6)	0.009	(0.2)	–0.143	(–2.8)
Female%	–0.072	(–6.5)	–0.065	(–7.2)	–0.056	(–3.5)	–0.062	(–3.7)
Age 2	0.174	(7.7)	0.172	(10.2)	0.050	(2.4)	0.083	(5.2)
3	0.192	(9.2)	0.231	(14.4)	0.069	(3.2)	0.132	(17.9)
4	0.128	(5.4)	0.120	(6.4)	0.080	(3.0)	0.107	(5.2)
Non-Foreign	–0.017	(–1.4)	–0.028	(–2.8)	–0.041	(–2.3)	–0.051	(–3.6)
Single/Multi	0.012	(2.3)	–0.003	(–0.7)	–0.011	(–1.6)	–0.017	(–3.0)
Region	significant							
Year	significant							
R^2	0.234		0.250					
RMSE	0.272		0.292					
var – cross-section					0.047		0.058	
var – error					0.028		0.032	
N Total	16090		25295		16090		25295	
N panel	3218				3218			

There are no dramatic differences in technology estimates between random effects and OLS models, although the previous ones yield slightly higher wage premiums for both manual and non-manual workers. Thus even when controlling for random establishment-specific effects technology effects remain significant. The estimates from fixed effects models are quite different: technology effects disappear, but this is probably an artefact related to our technology indicator, which has hardly any variation over time.

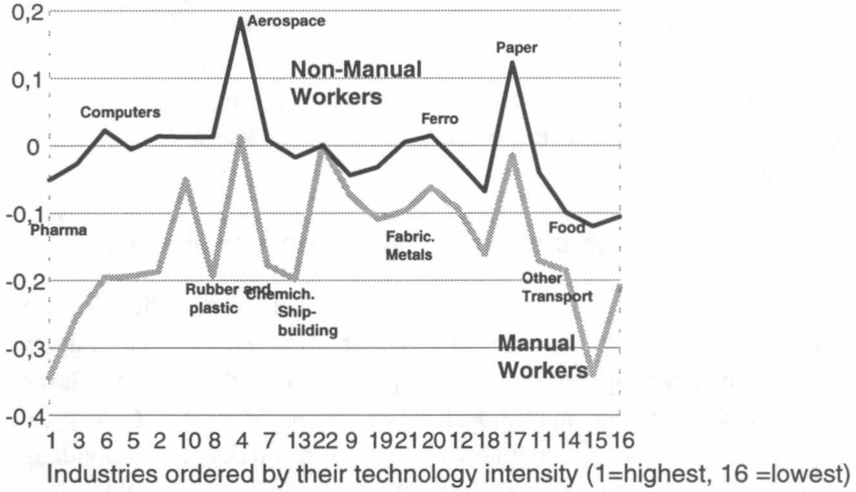
The balanced panels include only establishments which have survived over the period, whereas unbalanced panels cover also entering and exiting establishments. The most notable difference in technology effects is that wages for the low-tech group are relatively higher in case of balanced panels than using unbalanced panels. Therefore technology wage effects may be different by entry/exit status of plants. We examine this question below (see Figures 2a and 2b). Also the estimates for control variables are discussed briefly below.

Industry wage premiums and technology intensities

In this section we look at the technology wage effects from a slightly different perspective. A large literature has analysed whether 'unexplained' industry or firm/establishment wage differences exist or not (e.g. Krueger and Summers (1988), Groshen (1991), and Abowd, Kramarz and Margolis (1994)). In our previous work we used longitudinal census information for individuals to examine this question for Finland, finding that industry premiums exist although smaller than in USA but larger than in Sweden (Vainiomäki and Laaksonen 1995). Here we examine if technological wage premiums could explain industry wage differences. That is we take the estimated industry wage premiums from the wage equation and a measure of the technology intensity of industries, and look for any correlation between the two.

Figure 1 presents the estimated wage premiums by 22 industries for both manual and non-manual workers. The industries are ordered by their technology intensities as measured by total Research and Development expenditures per total production (Virtaharju and Åkerblom 1993). There does not appear to be any clear connection between technology intensity and industry wage premiums for manual workers. For non-manual workers there is some tendency for wages to increase with R&D intensity, but this positive relation breaks at the highest R&D levels. There are also notable outlier industries such as pharmaceuticals where wage premiums are 'too low,' in particular for manual workers. Correspondingly, wage premiums are 'too high' for paper and pulp industry for both worker groups. These results conform with observations in our earlier study using individual data. Note also that the *relative* non-manual wage is to some extent positively correlated with R&D intensity, since the gap between non-manual and manual wage premiums tend to increase with higher R&D intensity (being fairly stable at low levels of R&D).

Figure 1. **Wage premiums by industries for manual workers and non-manual workers from the GLM-OLS model for the years 1988–92.**



Note: the profiles of both curves are comparable, not the levels

We also used partial correlations to analyse technology-industry wage connections in more detail with respect to components of total R&D intensity. In Table 4 there are correlations between five technology intensity variables and four wage premiums. The technology variables decompose the total intensity to the direct (own) intensity and to component 'embodied' in domestic and imported intermediate inputs and capital inputs. The industry wage premiums are for two periods for manual and non-manual workers. This table shows that the correlations between wage premiums for different periods are fairly high (over 0.9) and thus imply a fairly rigid wage structure in Finland during the last 20 years. The correlations between manual and non-manual premiums are lower, but still fairly high (about 0.6–0.7), indicating that the structure of industry wage premiums do not deviate essentially between manual and non-manual workers.

Table 4. **Pearson correlation coefficients between technology intensities and wage premiums.**

Variables	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. DIRECT	1.00								
2. DOMINT	0.37	1.00							
3. IMPINT	0.23	0.32	1.00						
4. DOMCAP	–0.06	–0.30	–0.28	1.00					
5. IMPCAP	–0.04	–0.44	–0.22	0.86	1.00				
6. WMA7493	–0.42	0.16	0.12	0.26	0.06	1.00			
7. WMA8892	–0.51	0.02	–0.17	0.26	0.12	0.95	1.00		
8. WNM7493	–0.01	0.06	–0.08	**0.63**	**0.48**	0.63	0.63	1.00	
9. WNM8892	–0.00	0.16	–0.07	**0.56**	**0.39**	0.67	0.64	0.98	1.00

Technology intensity is decomposed to following sources:
DIRECT (Own), DOMINT (= Domestic Intermediate), IMPINT (=Imported Intermediate), DOMCAP (=Domestic Capital), IMPCAP (= Imported Capital). The wage premiums are from four models, two for the years 1974 93 and two for the years 1988 92. WMA means Manual Workers and WNM Non Manual Workers. The 5% significance level is about +0.35 (n = 22 manufacturing industry groups).

The correlations with technology variables are examined to see if wage premiums are related to some specific components of technology intensity. Note that different technology components are *not* very highly correlated However, the correlations between wage premiums and technology intensities are mostly quite low, except in two cases. Non-manual wages premiums and the two capital related intensities (domestic and imported) are significantly positively correlated. This correlation arises partly because certain extreme industries in terms of wage premiums conform better with the general intensity pattern, such as paper products where the values of both capital related intensities were among the highest. This finding indicates that important omitted variables in our wage equations may relate to the capital input and its interaction with technology. It is possible that there are complex interrelations between technology, capital and worker skill that are not included in our wage equations and therefore obscure the estimated wage premiums. The second significant relation is the *negative* correlation between manual wages and direct technology intensity. Since non-manual wages are not correlated with this intensity, the *relative* non-manual wage is *positively* related to direct technology intensity, which is consistent with skill biased technology.

Finally, we examine the overall significance of technology as a source of wage variation. Table 5 presents the effects (increases in the sum of squares explained) of technology and industry when the other variables were already in the model. In general, these effects are not very high but are significant. It is interesting that these are higher for manual workers. Decomposing the explanatory power into the effect of technology and that of industry within technology, it appears that technology does have an independent effect (of industry) on wages, about 2/3 of joint effect. This decomposition is based on

Table 5. Analysis of Technology and Industry as Sources of Wage Variation.

Panel A. 1974 93, Base line, the whole period

Source of Variation	Percent Explained of Total Sum of Squares	Degrees of Freedom	F-statistic
Technology and Industry			
• Manual workers	3.0	21	464.2
• Non Manual workers	1.5	21	16.1
Technology			
• Manual workers	1.9	3	1872.4
• Non Manual workers	1.0	3	518.3
Industry within Technology			
• Manual workers	1.1	18	202.9
• Non Manual workers	0.5	18	47.3

Numbers of observations are 42 637 for Manual workers and 41 122 for Non Manual.

Panel B. 1988 92, Including human capital variables

Source of Variation	Percent Explained of Total Sum of Squares	Degrees of Freedom	F -statistic
Technology and Industry			
• Manual workers	7.1	21	161.5
• Non Manual workers	3.8	21	58.6
Technology			
• Manual workers	2.5	3	114.2
• Non Manual workers	1.8	3	183.5
Industry within Technology			
• Manual workers	4.6	18	167.1
• Non Manual workers	2.0	18	37.1

Numbers of observations are 25 295 for Manual workers and 2 4401 for Non Manual.

Figure 2a. **Wage premiums for manual workers by technology group and different 'survival' and growth categories. Data 1986/87 to 1992/93**

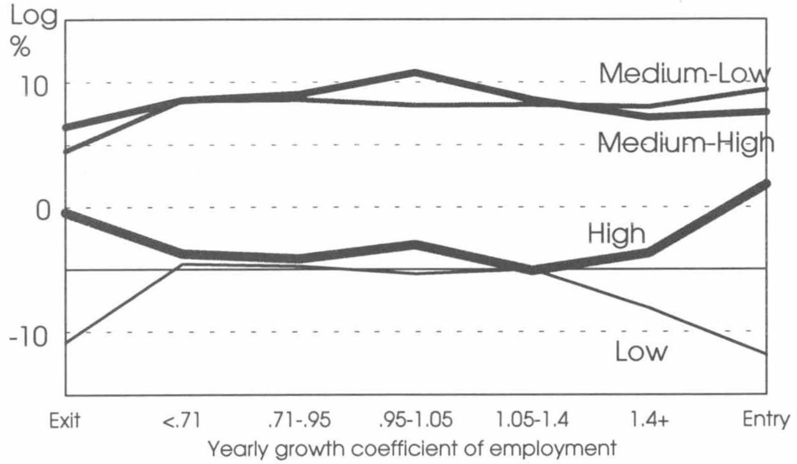
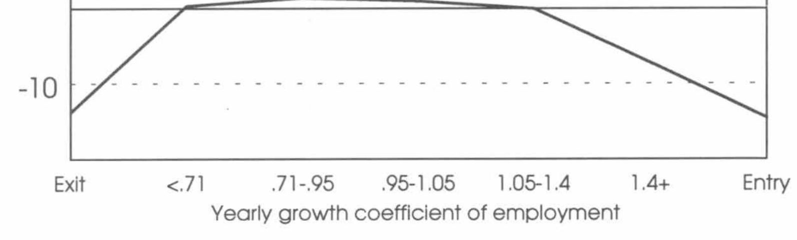


Figure 2b. **Wage premiums for non-manual workers by technology group and different 'survival' and growth categories. Data 1986/87 to 1992/93**



the fact that industry is nested within technology, so technology is allotted a share of the wage variation that is common to all industries in a technology group. When work force human capital variables are included (in panel B) the relative importance of technology decreases, and more so for manual workers (to 1/3 for manuals and to 1/2 for non-manuals). This implies that these new variables are positively correlated with technology, but more so for manuals (as implied also by estimates in Table 4.1), which is puzzling. Note that one cannot compare the levels of explained shares across panels A and B, because the data periods are so different.

Effects of plant entry/exit and growth/decline

Panel B of Table 1 and Figures 2 are based on data from 1986/87 to 1992/93, not including human capital variables. When a variable indicating the 'survival' status of plant (entry/exit/continuing) was entered linearly, there were hardly any change in the estimated technology wage premiums. However, when the 'survival' variable was interacted with technology some interesting effects emerged. It should be noted that demographic dynamics was fairly strong during this period (1987–93). The most notable difference is between high and low technology groups' profiles for manual workers. In low-tech wages were lower in both entry and exit categories, whereas the opposite is true in high-tech group. In low-tech, and to some extent in medium-low, also non-manual wages were lower in entry and exit categories. In general there is some tendency for exiting plants to pay lower wages for both worker groups in all technology levels, except high-tech. A possible explanation for this pattern may be that exiting plants have already experienced problems for some time and attempted to remain in business by cost cutting wages. In the entry category, it is possible that new low-tech firms were able to pay relatively low wages, because high unemployment made suitable low-skilled workers abundant. On the other hand, new high-tech firms must have offered relatively higher wages to attract more qualified manual workers from existing jobs. There is also some indication that fast growing high-tech plants paid higher non-manual wages. This and low wages in exiting plants could mean that high wages and success of the plant go hand in hand (without proposing any direction of causality here).

Effects of control variables

Mostly the estimates were as expected, although they are not always robust across estimation methods or type of data (balanced vs. unbalanced) used. We do not go into details here rather point only the main tendency of the effects.

Starting with the work force human capital variables, education effects are larger and significant for non-manuals and often insignificant for manual workers. However, the estimates obtained for the highest level of education are puzzling for both worker groups, which may be due to small group size for this class (research education). It is also notable, that even after controlling general level of education, the technical (science) education obtains a positive and significant wage premium. The age (experience) and gender effects are as usual, with highest premium usually for the age group 45–54 years, and higher female share decreasing wages especially for manuals. The difference in female effects between manual and non-manual workers is notable. However, all these effects often turn out insignificant in fixed effects.

Turning to the plant level controls, in all models (except fixed effects) wages are significantly increasing in size of establishments, in particular for manual workers. For non-manual workers the differences are fairly small among the medium-sized and large size classes. This is an interesting finding, since separate estimates for manual and non-manual workers are not often possible. If we estimate one model for both worker groups, wage premiums are increasing in size. For the other variables we find that when the establishment is majority foreign owned, the wage tends to be significantly higher for non-manuals in particular, and multi-establishment firms pay more than single establishments for manuals in particular. The share of exports has a positive effect on wages for non-manuals, but insignificant or negative for manuals (cf. Bernard, Jensen and Wagner in this volume, who find that exporters in the U.S. pay higher wages for both production and non-production workers, but in Germany only for production workers; however causality may be from good performance to exporting rather than reverse).

The rent measure usually obtains a significant positive effect for both worker groups, and the share of manual workers a significant negative effect. For manuals this may reflect the Marshallian rules of labour demand, whereby lower demand elasticity leads to higher wages ('importance of being unimportant'). For non-manuals it could be related to skill requirements of production (more manuals means less skill intensive production and hence lower non-manual wages). The share of wages in total cost usually has a positive effect on manual wages and negative or insignificant for non-manuals. The positive effect (for manuals) could be reverse causality.

6. Conclusions

Using average establishment wages and the technology level of establishment's industry we found that establishments in lowest technology level paid lowest wages during the whole period 1974 to 1993. This technology wage premium

We may, in summary, conclude that the findings do provide some positive evidence of tournament models. This is important in view of the weak link observed between firm performance and individual managers' pay.

***Table 1.* Fixed effects estimation results.**

Responsibility levels		**Positions**	
Tactic, higher	0.174 (0.009)	Lower level manager board/top member	0.101 (0.010)
Strategic, lower	0.464 (0.010)	Higher level manager no membership	0.375 (0.025)
Strategic, higher	0.721 (0.017)	Higher level manager top-level group	0.327 (0.015)
Policy level	1.210 (0.090)	Higher level manager board member	0.472 (0.020)
		Vice president	0.607 (0.030)
		CEO	0.923 (0.020)
R^2 (adj.)	0.824		0.865
N. of obs.	9150		9150

***Table 2.* Test of the effect of the number of contestants.**

Dependent variable: log CEO pay – average log managerial pay in 1994

Constant	0.187 (0.052)	0.122 (0.034)	0.111 (0.033)
Number of contestants	0.017 (0.005)	0.015 (0.008)	0.012 (0.004)
Firm size (log sales)	0.0002 (0.0001)	0.0002 (0.0001)	0.0002 (0.0001)
CV of firm sales		0.014 (0.008)	
CV of industry output			0.016 (0.004)
R^2 (adj.)	0.097	0.121	0.134

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Appendix: Data bases used in this study

1) A longitudinal/cross-sectional data file of industrial establishments for 1974–93 (DIE)

The original files are based on the yearly censuses of manufacturing industries. The census is mandatory for establishments with 5 or more employees. There is a large range of variables in the DIE, of which only the following ones have been used in this work:

- permanent establishment codes and permanent firm/enterprise codes
- number of employees used to define SIZE classes for the current point of time:
  6 categories in models: 5–9, 10–19, 20–49, 50–99, 100–499, 500+
- number of working hours separately for manual and non-manual workers
- total wages paid separately for manual and non-manual workers
- average wage per hour separately for manual and non-manual workers,
  used as log(W) in models
- total numbers of manual and non-manual workers
- share of manual workers, MANUAL%
- industry classification of 1979
  aggregated to the 22 groups used in the OECD technology classification (Englander and Gurney 1994), INDUSTRY
  industries were further aggregated to the four technology groups, TECH (HIGH, MEDIUM-HIGH, MEDIUM-LOW, LOW) based on Finnish technology intensity, see Virtaharju and Åkerblom 1993, 66
- location of establishment (county and municipality),
- reclassified to seven REGIONs
- share of exports from production, EXPORT%
- dummy for mainly domestic or foreign ownership, NON-FOREIGN
  1 = the foreigners own at least 50 percent, 0 = otherwise
- dummy for multi-establishment mother enterprise, SINGLE/MULTI
  1 = yes, 0 = no
- share of wages from total cost, WAGE%
- value added
  in models log((value added minus total wages)/total hours), RENT
- year (to create time dummies)

In addition to use entry/exit/growth information for the period *1986/87–1992/93*, we constructed a separate file where the variables are measured as follows:

- for metric variables, say y:
  if both values $y(t)$ and $y(t+1)$ are available, we use their average value:
  - $y(t, t+1) = (y(t)*k+y(t+1))/2$
  - for exiting plants only $y(t)$ is available, so $y(t, t+1) = y(t)*k$
  - for entering plants only $y(t+1)$ is available, so $y(t, t+1) = y(t+1)$
  - where k is an inflation factor to make monetary values comparable

  for categorical variables we used the latest available value
  for this data we constructed a variable reflecting entry, exit or employment growth rate of the plant, SURV

2) The Worker-Employer Data Base (WEDB)

This data base is constructed from two sources: (a) The business register consisting of all the enterprises and establishments (local units, local kind of activity units, plants), although there is some undercoverage for service sector businesses, (b) The register information on all employees working for at least one business unit each year.

From this data base we aggregated worker characteristics information at the enterprise level and matched them to plant data from DIE using enterprise codes. These are our HUMAN CAPITAL variables.

- number and share of employees in the enterprise by four age groups:
  less than 35, 35–44, 45–54, and 55+
- number and share of employees in the enterprise by five education levels:
  1 = less than any official professional education, 2 = lower secondary,
  3 = upper secondary and lower university, 4 = university degree,
  5 = post-graduate university degree
- number and share of workers having technical (science) education
- number and share of female workers

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THE MANAGERIAL PAY STRUCTURE – SOME TESTS ON A DANISH DATA SET[1]

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The purpose of this paper is to add to the small empirical literature on managerial pay structures. I test several propositions of tournament models on a fairly rich data set. The data set is an unbalanced panel containing information about 2600 executives in 260 Danish firms (per year) during a fouryear period. In addition to individual and firm characteristics, the data provide detailed information about the jobs and positions held be the executives. Thus, the dallow me not only to analyse pay differentials (and changes therein) between individuals and job levels, but also to study the consequences of differences in pay spread on company performance.

Key words: Managerial Pay, Tournament Theory, Firm Performance.
JEL Classifications: J33, J41, M12

1. Introduction

In this paper I test some predictions concerning the managerial pay structure which emerge from the theory of tournaments. The data base for the analysis comes from a major Danish consulting firm and contains fairly detailed information about managers, their jobs, their compensation and the firms in which they are employed.

There is only a very small empirical literature on this subject. This is due to the fact that most available data sets on managerial pay contain information about one individual per firm only (usually the CEO or the highest paid

1 The type of data set used in this paper is not likely to be nor become available in many countries. However, tournament theory, and tests thereof, seem highly relevant also for other groups of employees than managers.

member of the management team). There are, however, also some case studies of a single firm. Another characteristic of the literature is that almost all investigations of managerial pay structures have been carried out on data from the US.

The basis of the analysis in this paper is more general than the bulk of the literature as the data are from over 260 companies. Moreover, I try to test for several aspects of tournament theory on the *same* data set, whereas most previous studies, save Main et al. (1993), have examined whether facts square with only one or two predictions for each data set. It should be noted, however, that individually the tests are rather coarse as the alternative hypothesis is not always exactly identified.

I focus on the following aspects of tournaments. Are pay differentials between job levels, controlling for individual and firm characteristics, consistent with relative compensation? Is the prize in the tournament affected by the number of participants? Is the pay dispersion between job levels greater in noisy business environments? Does a wider spread in pay enhance firm performance? Are there differences between firms in this respect? Is the average pay lower in firms with more compressed pay structures?

The paper proceeds as follows. In the next section some basic theoretical notions and earlier work is briefly discussed. The data to be used in the empirical analysis is described in the third section. Two sections of tests follow next. The first is concerned with shape of the pay and job level relationship and the other reports some tests of other aspects of tournaments. In the final section some concluding remarks are offered.

2. Theory and Existing Work

The theoretical framework of the analysis in this paper is the tournament theory of pay structures, promotions and raises. Due to space limitations, the theory will not be described in any detail here.[1] In stead we focus on the implications of the theory. The point of departure in tournament models is the notion that company pay structures are set up in the same way as sports tournaments. Sports and promotion tournaments have three important characteristics in common. The first is that prizes (raises) are set in advance and are independent of the absolute performance of players. Second, the basis of the compensation scheme is relative performance, that is, the players are rewarded for being better than other

1 An excellent review and discussion of tournament theory is found in Lazear (1995).

players. Third, the effort put forth depends on the increase in the prize from advancing to higher positions.[1]

The four implications of tournament models which are examined in this paper are:

1 In case there are several positions within the firm, will there be a *convex pay – job level relationship* within firms (see Rosen 1986). This follows directly from that the equilibrium level of effort is increasing in the spread between the winning and the loosing prize. At the final level, we expect to find an extra prize. This is because each prize in fact consists of two parts: the current prize *and* the possibility to compete for further larger prizes at higher levels. At the top the CEOs have to be compensated for the absence of the second component. Thus, tournament models predict *an extraordinarily large pay differential* between the CEO and the managers at the level next below.

2 *The more contestants there are, the higher is the winning prize.* This arises from individuals in the tournament forfeiting part of their expected compensation which goes into the prize pool. Of course, there more players there are, the larger the pool and hence, the higher the pay if promoted.

3 The greater the importance of the random components (like varying demand and cost conditions) in company performance which are beyond the control of management, the lower is the optimum level of effort for a given pay spread. Thus, in order to induce managers to put forth more effort, they have to be paid more. Empirically you would, therefore, expect to find *a positive relationship between pay spread and the amount of noise or risk in the business environment.*

4 The larger the spread in pay, the better the performance of the firm and *the higher the average pay in the firm.* This follows directly from the effort inducing effect of bigger raises in case of promotion. It should be noted, however, that this abstracts from the fact that senior management of a firm often acts as a team performing highly interdependent work and so, compensation based on individual performance may be inappropriate because it leads to too fierce competition among the members in the management team. As shown by Lazear (1989), pay compression may dominate tournament aspects in so called "hawkish" firms in which the managers are especially good at uncooperative behaviour.

1 The prize differential cannot too big, however, As this would induce too few players.

As noted above, the empirical literature on managerial pay structures, and tournament models in particular, is quite small. Strong evidence of tournament notions has above all been obtained from studies of sports (see e.g. Ehrenberg and Bognanno 1990) and in controlled experiments (see Bull et al 1987). Studies based on data on actual executives are thin on the ground, simply because data sets containing information about several mangers per firm are rare.

Most previous studies have focused on the convexity of the pay structure. O'Reilly et al (1988), Leonard (1990) and Main et al (1993) all using the same data set have shown that differences in compensation between hierarchical levels are consistent with tournament theory. Similar results are obtained by Lambert et al (1993) and in two detailed studies of the personnel records of a single firm, Lazear (1992) and Baker et al (1994). In a recent study, Conyon (1995), using a large sample of UK firms also isolates a convex pay and job level relationship. Additional evidence is somewhat more mixed, however. O'Reilly et al (1988) find a negative and Main et al (1993) a positive relationship between the number of tournament participants and pay differentials. Main et al (1993) also consider the effects of the pay structure on firm performance finding evidence in support of tournaments. Knoeber and Thurman (1994) study the performance of broiler producers facing a tournament compensation structure. Their tests of predictions concerning the effects of prize level and prize differentials, the effects of ability and the existence of handicap systems, all provide strong evidence in favour of tournament theory.

3. Data Description

The bulk of the data used in this paper comes from an unbalanced panel containing information about approximately 2.600 managers in about 210 Danish firms (per year) during the four-year period 1992–95. The data have been obtained from confidential files of a major Danish consulting firm and provide in addition to annual compensation data, fairly detailed information about the individual characteristics of managers, their jobs and the firms in which they are employed.

The compensation variable includes salary and bonus components as well as the employers' contributions to pension funds. A relatively small proportion – 20 to 25 per cent of all managers and a third of the CEOs – are paid bonuses and/or tantiemes and their average share of total compensation varies between 10 and 12 per cent during the four-year period. Stock options, deferred compensation (except contributions to pensions) and stock awards are not included. This omission is not likely to affect our results much as all three forms of compensation are rare among Danish managers.

The renumeration data set has been augmented with further information on the firms regarding their performance (accounting profits, sales) in the eight-year period 1987–94. This information has been derived from an annual handbook of all Danish firms with an annual turnover exceeding 40 million Danish kroner in 1994 prices or more than 50 employees, called *Greens - Børsens håndbog om dansk erhvervsliv.*

The majority of the firms in our data set are medium-sized or large firms (in the Danish sense) and the data are, therefore, not representative of all Danish firms. However, the sample at our disposal is fairly representative of the medium-sized and large firms with respect to distribution across industries and geographical location.

4. Pay and Job Levels

The first of the tests I carry out concerns the shape of the pay and organisational level relationship. I test for whether differentials in pay between levels (defined in alternative ways) in corporate hierarchies are consistent with tournament models. To obtain estimates of the pay differences between adjacent organisational levels, I estimate compensation equations from a short panel of the following form:

$$W_{ijt} = \alpha_i + \beta X_{ijt} + \gamma Z_{ijt} + \varepsilon_{ijt} \tag{1}$$

where W is the logarithm of annual compensation, α_i individual fixed effects, X is a vector of individual and firm characteristics, and Z is a vector of job level dummies. X includes age, tenure in current position, educational level, industry, number of employees, number of subordinates and (log of) sales and year dummies. Z will be defined in three alternative ways; see below. Thus, the -estimates are derived from a model which controls for individual traits, individual specific fixed effects as well as some firm characteristics. This may be important as some part of the inter-level pay differences may reflect differences in these characteristics.

It is not self-evident how to define job levels in hierarchies. The data set contains information about jobs according to their function (production, sales, logistics, personnel etc.), formal position (CEO, VP, higher level manager ("fagdirektør") and lower level manager ("fagchef")) as reported by the firm, membership in the board or the top-management group, and responsibility level (see below). In none of these descriptions are job levels identified according to the pay connected to them.

In order to check the sensitivity of the results to the job level definition adopted, I have used three alternative sets of levels (or positions) in the corporate hierarchy variables. The most detailed description, which however is available only for a portion of the whole sample, is a classification of positions into nine levels according to a job authorities evaluation system created by the consulting firm. The classification is based on grades (1 to 6) given to six factors: complexity of the problems to be solved, independence in decision making, reporting, responsibility, experience and training requirements. To save space the results using this definition are not reported here (but are available from the author upon request), suffice it to say that they are quite similar to the ones shown below.

The second classification is a cruder version of the first one[1] and classifies the positions held into five different responsibility levels.[2] All jobs in the sample are covered by this classification. The third set of level dummies has been constructed from two pieces of information: the titles of positions as reported by the firms and board or top-management group membership. This gives me six levels: CEO, VP, a board member higher level manager, a non-board member higher level manager, a board or top-level group member lower level manager and a non-member lower level manager. This classification is also available for all observations in the sample.

In Table 1 the estimates from equation (1) are shown. The coefficients are those of level dummies in estimations in which the dependent variable, total pay, is in logs and the (omitted) reference category is always the lowest job level in the data set. As in some previous studies (see e.g. Leonard 1990, Lazear 1992 and Baker et al 1994), job levels turn out be a very important determinant of pay. Adding the job level dummies to a specification with standard human capital variables, industry dummies and firm characteristics significantly improves the explanatory power of the model.[3]

1 The two lowest levels in the cruder classification correspond largely to levels 1 to 4 in the more detailed classification, levels 3 and 4 to 5 and 6, and level 5 to levels 7 to 9.

2 The jobs are classified into three main responsibility levels: the tactical level, the strategic level and the policy level, which is the highest one. For the two lowest responsibility levels a further distinction is made on the basis of whether the position involves making propositions or decisions. Thus, for instance a position at the lower strategic level involves making propositions regarding principal strategies and plans for the firm whereas a person in the position at the higher strategic level has the authority to make those decisions.

3 Estimations for single years show that the pay differences are relatively stable across years. Catering for heterogeneities by an individual fixed effects specification does not change the estimated coefficients much. Nor is the picture obtained from simply looking at mean pay for different job levels change much when individual and firm characteristics are controlled for.

The key result of the econometric exercises is that the pay difference increases as one moves up in the hierarchy. This increase in spread at higher levels in the hierarchies is consistent with tournament theory. However, the analysis fails to isolate an extraordinarily large increase in the reward at the very top of the hierarchy as suggested by rank-order tournament models.

The convexity of the relationship between pay and levels in hierarchy documented above also fits well in with the results of an earlier study using the same data, Eriksson and Lausten (1996), which found only a very weak pay for performance relationship. It may well be that executive pay has little to do with the absolute performance of the CEO or other senior managers and that instead the increasing pay differences act as an incentive to provide greater effort.

Although a widening pay gap through the corporate hierarchy is a key prediction of tournament models, the pattern observed does not per se imply tournament theory as other, economic (see Rosen 1992) as well as sociological theories (see O'Reilly et al 1988) also predict a convex pay and job level relation-ship. Thus, for example, provided superiors' decisions affect directly the productivity of lower-level employee, sorting of more able persons into higher level positions will lead to higher marginal productivity of people at higher levels.

Of course, the data description gives no evidence regarding the other key prediction of tournament models, the efficiency of the pay structure. We do not know whether the pay differences are large enough to give rise to incentive effects as suggested by tournament theory.

5. The Pay Structure: Does It Work?

The aim in this section is to try to test some other aspects of tournament theory than the shape of pay-job level relationship. I consider two types of aspects. First, I investigate whether inter-firm differences in pay dispersion are affected by the factors suggested by tournament models. Are reward differences affected by the number of tournament participants? Are pay differences between job levels higher in noisy or risky environments? Is average pay lower in firm with more compressed pay structures? Second, I carry out a simple test of the key prediction of tournament models, namely that a wider pay dispersion enhances the economic performance of firms.

In investigating these aspects of tournament models, the units of analysis become *firms*. The sample examined below consists of those firms for which there are observations on minimum five employees (one of which is the CEO), complete records on firm performance for the period 1987–94 and on managerial compensation for all four years 1992–95. These restrictions reduces the sample to 111 firms.

McLaughlin (1988) suggests as a test of the presence of tournaments testing for the existence of a positive relationship between CEO pay and (given the average pay of the tournament participants) the number of contestants. Of course, in order to carry such a test, the participants in the tournament have to be identified. One obvious candidate group is the vice presidents. However, as many of the companies in the data set do not have formal VP positions, I have, following O'Reilly et al. (1988), used the number of managers reported by the firms to have significant responsibilities, that is, the managers whose jobs are classified as being at the policy level, as the group of contestants. The dependent variable is the log difference between the CEO pay and the average pay of the other tournament participants.

The results from estimations on data for 1994 are presented in Table 2. The estimates do suggest that a greater number of contestants increases the winning prize, as predicted by tournament models.

As was shown in Section 2, a prediction emanating from tournament models is a larger spread in pay in firms operating in noisy or risky environments to compensate for the relatively greater importance of random factors. Consequently, we expect firms in industries where demand or cost conditions vary a lot to have a steeper pay-job level hierarchy.

The main problem with attempting to test this hypothesis is, of course, to find a variable that accurately captures differences in firms' (industries') demand or cost conditions. I have used two alternative pieces of information. The data set provides information about the sales of the firms in the period 1987 to 1994. From these series I have for each firm calculated the coefficient of variation of (deflated) sales.[1] These coefficients of variation is the first proxy measure of a noisy environment. The other measure is derived in a similar fashion, but now I make use of industry level information. Coefficients of variation were calculated from the Industrial Statistics for the 1987-1993 period for volume of production for each of the two-digit level industries the firms in the sample are operating in.[2] The dependent variable is the CEO-contestants differential constructed for the test above.

1 The firms which have had changes in sales due to acquisitions of other firms or sales of the parts of the firm had to be discarded

2 Some firms operate in several industries. I have assigned them to the industries re-ported by themselves As their main industry.

According to the estimation results set out in Table 2, there is indeed a positive and statistically significant relationship between the variability of the sales (production) of the firm (industry) and the intra-firm pay dispersion. Naturally, in interpreting the results it should be kept in mind that the coefficient of variance measure can at best only be crude proxy for a noisy or risky business environment. In particular, they may not capture intra-firm differences in the internal risk of the firms.

The results of the two tests carried out so far clearly provide some additional support for the notion of rank-order tournaments. The reward differences are larger the more important are random factors for the development of the performance of the firm and the more competitors are participating in the tournament. It should be noted, however, that the above analysis has been concerned with what things look like, and not whether they work. The latter is presumably the most critical feature of tournament theory. So, let us now turn to consider the consequences of the pay structure on firm performance.

As is plain from most tournament models, the wider the pay dispersion, the higher the level of effort put forth. However, as discussed by Lazear (1989), (1995), there may also be incentive motives for firms to adopt a more compressed pay structure. In order to attract (the right) people to participate in a tournament, the spread cannot be "too big". Moreover, if the co-operation of the managers is essential for the success of the firm, rewarding them according to their individual achievements may not be a good idea. Not all firms benefit from their top managers acting as a team, however.[1] For those firms, for which co-operation is less important – "hawkish" firms in Lazear's terminology – wider pay gaps may enhance performance, whereas this is not the case in "dovish" firms. Clearly, the main difficulty in testing the hypothesis of the performance enhancing effects of pay dispersion is finding a variable or indicator which enables us to distinguish between "hawkish" and "dovish" firms. We follow Main et al (1993) in using an executive team interdependency indicator, constructed as the proportion of profit center heads of the total number of managers, which is interacted with our measures of pay dispersion.

As was pointed out earlier, most of the firms in the data set are not publicly held. Hence I cannot rely on stock market indicators as measures of firm performance but use accounting profits information instead. The perfor-

1 As pointed out by Lazear (1995), an alternative to pay compression as a means of reducing anti-co-operative behaviour of managers is to set up the structure of the firm in such a way that the consequences of competitive behaviour to the firm are minimised.

mance of the firms is measured as a three year average of profits divided by sales.

What do I find? First of all I find a weak positive relationship between firm performance and average pay; see Table 3. As for the pay dispersion variables, these also attach positive coefficients; a significant one for the CEO-contestants difference and an almost significant one for the coefficient of variation variable. The team inter-dependency variable as well as the interaction terms never differed significantly from zero. Thus, the industrial politics argument for pay compression in managerial teams is not supported by the analysis.

Regressions of the average log of pay on pay dispersion controlling for firm size and industry, show, consistent with tournament theory, a lower average pay in firms with less pay dispersion; see Table 2. But again, I failed to find a significant coefficient for the interdependency variable and the interaction term. It should be noted, that although I have drawn two blanks on these variables, there is considerable scope for improving the analysis, in particular by accounting for differences in the organisational structure of the firms.

6. Concluding Remarks

In this paper I have investigated some aspects of tournament theory using a data set on Danish executives. I find that there is a stable convex relation between pay and job levels and that this is relatively robust with respect to differences in how job levels are defined. The larger the number of managers considered to have significant responsibilities in the firm, the larger is the wage spread. Thus, the prediction of tournament models of a positive relationship between the number of participants in and the prize of the tournament is supported. Another prediction gaining support is a larger pay dispersion in firms characterised by more variable business conditions.

As for the consequences of the pay structure, some evidence of a larger spread being associated with better performance of firms has been found. There does not seem to be any differences with regard to the effects of pay dispersion on firm performance between firms the managerial teams of which are more interdependent and those in which they are not. However, it must be noted, that these results are tentative as they may be affected by the problems of measuring accurately the interdependency of managers and/or firm performance.

We may, in summary, conclude that the findings do provide some positive evidence of tournament models. This is important in view of the weak link observed between firm performance and individual managers' pay.

Table 1. **Fixed effects estimation results.**

Responsibility levels		**Positions**	
Tactic, higher	0.174 (0.009)	Lower level manager board/top member	0.101 (0.010)
Strategic, lower	0.464 (0.010)	Higher level manager no membership	0.375 (0.025)
Strategic, higher	0.721 (0.017)	Higher level manager top-level group	0.327 (0.015)
Policy level	1.210 (0.090)	Higher level manager board member	0.472 (0.020)
		Vice president	0.607 (0.030)
		CEO	0.923 (0.020)
R^2 (adj.)	0.824		0.865
N. of obs.	9150		9150

Table 2. **Test of the effect of the number of contestants.**

Dependent variable: log CEO pay – average log managerial pay in 1994

Constant	0.187 (0.052)	0.122 (0.034)	0.111 (0.033)
Number of contestants	0.017 (0.005)	0.015 (0.008)	0.012 (0.004)
Firm size (log sales)	0.0002 (0.0001)	0.0002 (0.0001)	0.0002 (0.0001)
CV of firm sales		0.014 (0.008)	
CV of industry output			0.016 (0.004)
R^2 (adj.)	0.097	0.121	0.134

Table 3. **Tests of effects of pay spread on firm performance and average pay.**

Dependent variable:	**Profits/sales**		**Log of average pay**	
Constant	0.010 (0.003)	0.011 (0.003)	6.420 (0.391)	6.398 (0.362)
Number of employees			0.0004 (0.0002)	0.0004 (0.0003)
Log average pay	0.011 (0.004)	0.012 (0.003)		
CV of pay	0.050 (0.026)		0.392 (0.200)	
CEO-contestants difference		0.004 (0.002)		0.204 (0.096)
Interdependency indicator	0.004 (0.005)	0.005 (0.005)	0.111 (0.407)	0.125 (0.750)
Interaction (interdependency and pay spread)	-0.008 (0.016)	-0.007 (0.013)	0.113 (0.222)	0.179 (0.451)
R^2(adj.)	0.247	0.280	0.648	0.662

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THE GOOD GO ABROAD EVIDENCE FROM LONGITUDINAL MICRO DATA ON GERMAN AND U.S. EXPORTERS[1]

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Traditional trade models focus on industries as the appropriate unit of analysis for the study of trade among countries. A growing body of empirical work demonstrates the benefits of using plant-level data to examine the role of exporters in the world economy. This paper presents directly comparable results on the differences between exporters and non-exporters for two major industrialised countries – Germany and the U.S. In both countries, exporters have significantly higher employment, sales, capital intensity, and productivity compared to non-exporters. In the U.S., but not in Germany, wages are also significantly higher at exporters. Importantly, in both countries, future exporters have these good characteristics several years prior to entry into export markets. The results suggest that in both countries, success leads to exporting.

Key words: Trade, Productivity, Export-Led Growth, Germany, United States of America.

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1. Introduction

Traditionally trade theory has thought of industries as the appropriate unit of analysis for the study of the flows of goods and services among countries. In such a world, differences in technologies and factor endowments are reflected in composition of imports and exports across industries. In recent years, a series of papers have begun to ask what is being missed by analysing exports at the level of the industry and has documented the extraordinary and important heterogeneity of firms within industries. This body of research uses longitudinal surveys of establishments to underscore the importance of firm attributes in exporting. We extend this body of research by presenting directly comparable results from studies of establishments in Germany and the U.S. to highlight the similarities and differences found in potentially very different economic environments.

By far the most striking finding in this new micro literature on trade is the dramatic difference in size between plants that export and those that produce solely for the domestic market. Bernard and Jensen (1995c) report that exporting plants in the U.S. are 88% larger in terms of employment and 113% in terms of shipments than non-exporters in the same state and industry. Bernard and Wagner (1996) find that German exporters are 71% larger in terms of employment and 96% larger in terms of shipments that non-exporters in the same industry (see also Wagner 1995a & 1996). These differences are not limited to exporters in developed economies. Bernard (1995) reports that exporters in Mexico employ twice as many people and have shipments 135% higher than non-exporters. These systematic, large differences between exporters and non-exporters are not as readily apparent at the industry level.

Work in the area of the empirical microeconomics of trade is still largely in its infancy, but already we see important questions and answers arising from this research agenda. The recent round of activity using micro panel data at the establishment level (Bernard and Jensen 1995a,c; Bernard and Wagner 1996) raises the question of why exporters are so different from non-exporters and whether the sources of these differences are important for understanding the dynamics of international trade and associated policy. A paper by Bernard and Jensen (1996) documents the importance of exporting plants in the recent rise in wage inequality in the U.S. and suggests that export demand may be associated with increasing wage premia for white collar workers. In other areas Roberts and Tybout (1995) and Bernard and Jensen (1995b) have examined the decision to export and the magnitude of sunk costs in exporting for various countries. Aitken, Hanson, and Harrison (1996) use panel data on Mexican plants to consider the importance of spillovers from multinational activity for the entry of domestic firms in the export market.

In this paper we focus on the question of why good characteristics are positively associated with exporting. We draw on similar work that has been conducted on German and U.S. plant level data to examine whether good performance predates exporting or whether exporting enhances the performance of firms.

The rest of the paper proceeds as follows: in Section 2, we describe the two micro longitudinal data sets. Then we proceed to document the differences in numerous characteristics between exporters and non-exporters at a point in time using large cross-sections of plants. Section 4 outlines potential explanations for the observed superiority of exporting plants and presents evidence on the ex-ante differentials. In Section 5 we conclude and discuss the potential benefits of increased use of cross-national comparisons in exploring the relationships between exporting and firm characteristics.

2. Longitudinal Establishment Data for the U.S. and Germany

US Data

We use detailed plant-level data from the Census Bureau's Annual Survey of Manufactures (ASM) to investigate the relationship between exporting and plant performance. The ASM surveys U.S. manufacturing establishments and collects information on production and non-production employment, production hours, salaries and wages, shipments, value-added, capital measures, ownership structure, and direct exports.[1]

For exports, the ASM asks establishments to "Report the value of products shipped for export. Include direct exports and products shipped to exporters or other wholesalers for export. Also include the value of products sold to the United States Government to be shipped to foreign governments. Do not include products shipped for further manufacture, assembly, or fabrication in the United States." To the extent that plants do not know the ultimate destination of products they ship, these directly reported exports understate the true value of exports from establishments. In 1992, every plant in

1 For more information on the LRD, see McGuckin and Pascoe (1988).

the Census of Manufactures was asked to report direct exports. We use this Census to construct detailed cross-section comparisons and the ASMs to examine the performance of exporters and non-exporters over time.

While we are able to link plants' information across time, the ASM is not designed as a long-term panel. Instead, the ASM is a series of 5-year panels of U.S. manufacturing establishments. Each five years the sample is partially redrawn. Questionnaires are sent to about 56,000 of the 220,000 establishments that are surveyed in the Census of Manufactures (which occurs every five years). Some of the 56,000 establishments are included in the sample with certainty. These 'certainty' cases include establishments with large total employment (greater than 250 employees), establishments with large value of shipments, and establishments owned by large enterprises. Other establishments are sampled with probabilities ranging from 0.99 to 0.005, based on the size and industry of the establishment. The sample is designed to be representative of the population of manufacturing establishments in terms of industry and plant size but does not necessarily capture aggregate exports.

The plant level data, while limited by the nature of the panel and sampling issues, give us the ability to identify and control for differences between plants in the same industry. This is important because of the considerable heterogeneity that exists within industries, even at the 4-digit SIC level. Size, production techniques, output, and propensity to export all vary considerably across plants within the same 4-digit SIC category.

Total employment represents the total number of employees at the plant, which is broken into two components, production workers and non-production workers. Salaries and wages represent the total gross earnings paid in the calendar year to employees at the establishment. Benefits are supplemental labour costs, both those required by State and Federal laws and those incurred voluntarily or as part of collective bargaining agreements. Salaries and wages and benefits are deflated by the Bureau of Labor Statistics (BLS) regional consumer price index (1987=100). Total value of shipments represents the output of the plant. We use the machinery assets at the end of the year as our capital measure. It represents the original cost of all production machinery, transportation equipment, and office equipment and any costs incurred in making the assets usable.[1] Value-added is derived by subtracting the cost of materials, containers, fuel, purchased electricity, and contract work from the value of shipments. The result of this calculation is adjusted

1 Other research suggests that this measure of capital performs comparably to more detailed measures such as perpetual inventory methods. See Bailey, Hulten, and Campbell (1992).

by the net change in finished goods and work-in-process between the beginning and end-of-year inventories. Shipments, capital, and value-added are deflated by 4-digit sectoral deflators.

German Data

The data employed in this study are establishment level data from manufacturing industries in the one of the 'old' German Federal States (Laender), Lower Saxony (Niedersachsen). They were collected in the regular surveys by the Statistical Office (Niedersaechsisches Landesamt fuer Statistik – NLS). The coverage of the surveys is all establishments from manufacturing industries that employ at least 20 persons in the local production unit or in the company that owns the unit. For details on coverage in specific industries see Methner (1992).

Due to the strict data protection legislation in Germany, as a rule researchers from outside the Statistical Office cannot use these micro data. An exception is a joint project that allows one of us to have programs run inside the NLS and to receive the output if the results do not violate any data protection rules (see Wagner 1995b for a description of this project.)

Using the establishment identification code, we matched surveys from 1978 through 1992 to form an unbalanced panel. Annual data is available on: industry, blue collar hours, blue collar workers, sum of annual gross wages, sum of annual gross salaries, total employment (average from monthly reports), blue collar employment (average from monthly reports), sales in Germany, sales outside of Germany, investment (in machinery, in land with/without buildings), payments for rents and leasing, value of production.

All monetary values are reported in current prices. To compute real values, wages and salaries were deflated using the consumer price index (Preisindex für die Lebenshaltung, Früheres Bundesgebiet, Gesamtlebenshaltung). Sales and value of production were deflated using the price index of production at the two digit SYPRO industry level (Index der Erzeugerpreise gewerblicher Produkte) and investments in machinery were deflated using the price index for machinery goods (Preisentwicklung nach den Volkswirtschaftlichen Gesamtrechnungen, Früheres Bundesgebiet, Anlageinvestitionen / Ausrüstungen).

Capital stocks for establishments were calculated from real investment in machinery using a perpetual inventory method with an 18% depreciation rate. After construction of the capital stocks we are left with data for 1983–1992.

3. Exporters and Non-Exporters – How Different Are They?

We noted in the introduction that exporters consistently show up as larger than non-exporters in terms of both employment and shipments across numerous countries, time periods and industries. However, the differences between exporters and non-exporters within an industry are not limited to size. Table 1 reports the export premia for various characteristics from establishments in the U.S. and Germany.

Comparison of exporter premia in the U.S. and in Germany show both striking similarities and differences. The similarity of the export premia for most performance characteristics in the two countries is remarkable. Value-added per worker, a measure of labour productivity, is 18.9% higher at U.S. exporters and 21.6% higher at German exporters. Exporters are also more capital intensive in both countries, 20.2% in the U.S. and 12.2% in Germany. After controlling for plant size, Bernard and Jensen (1995a) estimate an exporter capital intensity difference of 9.3%, very similar to the German estimate. Even the division of the workforce between non-production (white collar) and production (blue collar) workers shows a comparable pattern. In both countries, exporters have 3–4% more non-production workers than non-exporters.

The overall picture painted by these export premia is one of substantially "better" plants engaged in exporting. Good performance characteristics, in particular size and productivity, go hand in hand with exporting, although the source of the positive relationship is not revealed by the cross-section estimates.

The biggest difference between German and U.S. export premia comes in the area of wages. U.S. exporters pay a significant wage premium to both production and non-production workers while in Germany within-industry wage differentials are significant only for non-production workers. Note that this disparity cannot be explained by the inclusion of the plant size variable in the regressions for Germany – see Bernard and Jensen (1995a) where wage premia are reported for pooled data from 1976 – 1987 controlling for plant size.

While we have not formally investigated the source of the disparity in the wage premia, one possible explanation is the difference in wage determination practices in the two countries. In the U.S., for most industries, wages are determined by the firm, while in Germany, contract wages are usually bar-

Table 1. **Exporter Premia in the U.S. and in Germany***

	U.S.	Germany
Total employment	88.1%	71.7%
Shipments	112.6%	95.7%
Value-added per worker	18.9%	21.6%
Non-production/total workers	3.3%	4.0%
Average wage	11.9%	1.7%
Production wage	9.0%	–1.8%
Non-production wage	11.4%	2.3%
Capital per worker	20.2%	12.2%

* Results for the U.S. are coefficients on an export dummy in a regression of the form

lnX(i) = a + b*EXPORT(i) + c*INDUSTRY + d*STATE + e(i)

where i indicates the plant, EXPORT(i) = 1 if the plant is an exporter, INDUSTRY is a vector of 4-digit (SIC) industry dummies, and STATE is a vector of US state dummies. Data are for 1992. All differences are significant at the 1% level.
Source: Bernard and Jensen (1995), Table 1.
Results for Germany are coefficients on an export dummy in a regression of the form

lnX(it) = a + b*EXPORT(it) + c*lnSIZE(it) + d*INDUSTRY + f*YEAR + e(i)

where i indicates the plant, t is the year, EXPORT(it) = 1 if the plant is an exporter, SIZE(it) is the number of employees, INDUSTRY is a vector of 185 4-digit (SYPRO) industry dummies, and YEAR is a vector of dummies for the years 1983 to 1992. SIZE is not included in the regressions for total employment and shipments. The differences for wage per employee and production wage are not significant at the 5% level, the difference for non-production wage is. Other differences are significant at the 1% level.
Source: Bernard and Wagner (1996), Table 5.

gained at the industry level with smaller firm specific deviations from the industry average.

The results in Table 1 present a clear question for empirical research on the microeconomic relationship between exports and firm characteristics: why is good performance associated with exporting. In the following section, we report some evidence on this question from the German and U.S. data.

4. Exporting and Success: Cause, Effect, or Both?

The previous section documented emphatically that exporters have better performance characteristics than non-exporters in both Germany and the U.S.. In particular, productivity at exporters is substantially higher than at non-exporters. However, the exact relationship between exporting and good firm outcomes is not revealed by the cross-section analysis. In this section, we discuss some potential explanations for the cross-section results and present results on the characteristics and performance of firms before they begin exporting.

The Good Go Abroad (Success Leads to Exporting)

The idea that "good", or low average cost, firms are more easily able to export is relatively uncontroversial. If there are additional expenses associated with selling goods in foreign markets, then only firms that can still make a reasonable return after incurring those costs will enter the export market. Examples of extra costs might include transport costs, expenses related to establishing a distribution channel, or production costs to modify domestic models for foreign tastes. Although many of these extra costs have declined over time, and particularly rapidly in recent years, they still exist to a greater or lesser extent and provide an entry barrier that less successful firms cannot overcome. The end result is that in a sample of non-exporting firms within the same industry, the larger, more productive firms should be more likely to become exporters.

Going Abroad is Good (Exporting leads to success)

There are several theoretical reasons why exporting might improve firm performance. First, exporting provides a natural expansion of the market. Serving a larger market might allow a firm to take advantage of any economies of scale in production or to provide some reduction in domestic variations in demand. In either case we would expect to see higher output levels at exporting firms as well as a lower probability of failure.

Another link running from exporting to success stems from the more nebulous notion of international competition. The typical argument is that firms participating in international markets are exposed to more intense competition and must improve faster than firms who sell their products domestically and face no international markets. We would expect that, on average, exporting firms should outperform non-exporters in terms of sales and productivity growth

Yet another route for exporting to lead to success focuses on product variety. If firms are not differentiated by cost of production, but rather by product attributes, then those products that are desirable to foreign consumers will be exported. Exporting firms will sell more goods and hire more inputs but might have no relative gain in productivity. Empirical implications of this model include relative employment and output increases when firms begin exporting but no growth advantages in the long run for any characteristic.

Getting Good to Go Abroad (Succeeding in order to export)

There is yet another version of the argument that exporting causes better firm performance. In this scenario, the focus is on the forward looking nature of firms. Some firms realise that a potential avenue of continued growth for their products is through foreign sales. However, to begin exporting these same firms must first improve their performance to cover the additional costs and increased competition. This line of reasoning implies that there may not be large initial differences between firms, i.e., before they consider exporting, but that after the decision is reached to try to enter the foreign market, the firms undergo substantial performance improvements. The empirical implications of this story are difficult to extract. There is no implication that after beginning to export that exporters will outperform non-exporters, largely because their improvements will occur before exporting begins. Similarly, several years before exporting there may be no differences between future exporters and future non-exporters. During the time leading up to the first foreign sale, however, future exporters should be improving their performance relative to firms that will not export.

The Evidence

To provide some evidence on the various possible relationships between exporting and success, we focus on one part of the story and ask whether firms that start to export are already good. We leave the question of whether exporting benefits the firm to the conclusion and future research.

To address our question, we select a sample of plants that do not export for several years in a row but may or may export in the last year. We then look at two measures of success before exporting reported in Table 2. In the first two columns, we test if future exporters already had desirable performance several years before they began to export. In the last two columns of Table 2 we calculate how much better the future exporters performed in the years immediately prior to entry in the export market.

Table 2. **Levels and Growth Rates Advantages for Future Exporters in the U.S. and Germany***

	Ex-ante Advantage		Growth Rates before Exporting	
	U.S.	**Germany**	**U.S.**	**Germany**
Total employment	45.1%	9.7%	0.04%	1.3%
	(10.78)	(1.57)	(0.05)	(2.74)
Shipments	54.6%	11.2%	2.9%	2.7%
	(11.51)	(1.62)	(3.00)	(2.55)
Value-added per worker	8.7%	5.0%	2.4%	1.0%
	(3.55)	(1.07)	(2.03)	(0.78)
Non-production/total workers	0.7%	0.1%	0.3%	0.1%
	(1.34)	(0.12)	(1.29)	(0.56)
Average wage	4.4%	0.2%	0.9%	–0.03%
	(4.10)	(0.14)	(1.92)	(0.09)
Production wage	2.8%	–1.5%	0.6%	–0.3%
	(2.43)	(1.14)	(1.11)	(0.89)
Non-production wage	2.1%	2.5%	1.1%	0.2%
	(3.36)	(0.95)	(1.36)	(0.31)

* Numbers in parentheses are t-statistics.
Results for the U.S.: (a) Ex-ante Advantage – Plants are included if they did not export in any of the initial years (1989 – 1991). Plants may or may not have exported in the final year. The numbers represent the premia for future exporters (1992) in the initial year, controlling for 4 digit (SIC) industry and state. (b) Growth Rates Before Exporting – Same plants as in (a). The numbers represent the extra annual growth rates in plant characteristics for future exporters (1992) over future non-exporters, controlling for 4 digit (SIC) industry and state.
Source: Bernard and Jensen (1995), Table 2 and Table 3.
Results for Germany: (a) Ex-ante Advantage – Plants are included if they did not export for three years in a row; plants may or may not have exported in the final year. The numbers represent the premia for future exporters in the initial year, controlling for 4-digit (SYPRO) industry and initial year. (b) Growth Rates Before Exporting – Same plants as in (a). The numbers represent the extra annual growth rates in plant characteristics for future exporters (1992) over future non-exporters, controlling for 4 digit (SIC) industry and initial year.
Source: Bernard and Wagner (1996), Table 7 and Table 8.

As with the export premia, the broad picture is similar for the U.S. and Germany. Plants who enter export markets are better than their non-exporting counterparts from the same industry in the years before entry. Future exporters are larger and more productive several years before they begin to export and they grow faster in the years just before they start to ship abroad.

These ex-ante differences are much more pronounced in the U.S. than in Germany – they tend to be both larger and statistically more significant for U.S. plants. The differences in p-values might be caused by the small number of future exporters relative to future non-exporters in Germany. This could reflect the nature of the German manufacturing sector which is traditionally more export oriented or it could reflect smaller costs of entry into exporting in Germany due to geography and transport cost. The differences between the U.S. and Germany in the results for the wage variables may again be related to the industry level bargained contract wages. The conclusion from the results in Table 2 is quite clear. Whatever the benefits of exporting to the firm, it is good firms that select into the export market.

5. Conclusion

For many countries the importance of exports and exporters continues to rise. Only recently, however, have researchers begun to ask questions about the firms involved in international trade using detailed microeconomic data. This paper represents a first step in an important effort to learn from research done in different countries. By comparing and contrasting the results across countries, we hope to learn more about what is common and uncommon in the decision of firms to export and prosper in the export market.

A growing body of research is documenting the dramatic differences between exporters and non-exporters in the same industry. For all samples and time periods, we find that exporters have sizeable advantages in desirable performance characteristics such as employment, sales and productivity. In this paper, we attempt to provide some evidence on the source of these differentials. Evidence from both the U.S. and Germany suggests that good firms enter the export market, thus explaining some, if not all, of the differences at any point in time.

Research is progressing on answering the other half of the question: does exporting provide any benefits to the firms. Preliminary results suggest that productivity growth is not higher at exporters than at non-exporters in both Germany and the U.S. This is at least partly due to the substantial entry into and exit out of exporting. However, at the same time, there does appear to be evidence that exporting firms are less likely to fail than non-exporters, suggesting that there might indeed be benefits to the firm from exporting.

The research agenda on the empirical microeconomics of trade is just getting underway and stands to benefit greatly from the analysis of comparable data sets from a wide variety of countries.

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