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Micro level dynamics of productivity growth

An empirical analysis of the great leap in Finnish manufacturing productivity in 1975-2000

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To my parents

ABSTRACT: This study analyses the dynamics of productivity growth at the micro level in Finnish manufacturing industries. It is shown that productivity-enhancing restructuring (so-called "creative destruction") has played a crucial role especially since the mid-1980s. Empirical evidence is provided that R&D efforts and exposure to global competition through imports and exports have affected positively with a few years' lag.

The results for R&D are in accordance with the views that innovations and technological progress entail experimentation, selection and reallocation of resources at the micro level that are important for economic development. An increase in productivity divergence seems to precede increases in creative destruction, which also fits the picture. However, at the same time creative destruction also compresses productivity dispersion by cleansing low productivity units. No empirical evidence is found that wage dispersion between plants has a positive effect. The positive effect of international trade, in turn, points to the importance of product market competition which is emphasised in the recent theoretical literature. Finally, the main part of productivity-enhancing restructuring can be attributed to newly established plants, which indicates the importance of entrants to creative destruction.

Various aspects of identifying and measuring the components of aggregate productivity growth by means of productivity decomposition methods are discussed in detail. It is demonstrated that there is a great variation between the results obtained by different methods. Some new variants of the methods are proposed. These tools have two main advantages. Firstly, they yield components that are useful when evaluating the usefulness of the representative firm model. Secondly, the results are not very sensitive to the usual measurement problems inherent in micro data.

The usual caveat of ignoring labour quality in productivity decompositions is tackled by using linked employer-employee data. These data allow the measurement of labour input in so-called "efficiency units". No empirical evidence is found that the productivity steps taken have been just factitious increases gained by the displacement of the lower educated and less experienced workers through micro level restructuring.

Productivity-enhancing restructuring also has implications for the dynamics of factor income shares. The payroll shares of plants have been reallocated from plants having a low capital-to-value-added ratio to those having a high capital-to-value-added ratio. The reshuffling of the payroll shares of plants has contributed positively to an increase in the capital's factor income share at the aggregate level.

Because micro level restructuring is of vital importance for economic growth, the factors that affect this process deserve careful consideration when the policy actions or reforms of institutions are designed. Innovations and R&D are important, but alone they may not be enough. Product market competition is likely to have a decisive role. In addition, well-functioning financial and labour markets and a high skill level in the workforce are also key factors facilitating the renewal of the economy at the micro level.

KEY WORDS: Micro-level dynamics, productivity decompositions, competition, R&D, catching-up
JEL codes: J23, J24, J63, L60, O12, O33, O47

TIIVISTELMÄ: Tutkimuksessa analysoidaan tuottavuuden kasvun dynamiikkaa mikrotasolla Suomen teollisuudessa. Osoitetaan, että tuottavuutta vahvistava rakennemuutos (niin sanottu ”luova tuho”) on ollut keskeinen tekijä erityisesti 1980-luvun puolivälin jälkeen. Empiirinen näyttö kertoo, että T&K panostukset ja altistuminen kansainväliselle kilpailulle tuonnin ja viennin välityksellä ovat vaikuttaneet positiivisesti pienellä aikaviiveellä.

Tulokset tukevat näkemystä, että innovaatiot ja tekninen kehitys sisältävät kokeilua, valikoitumista ja voimavarojen uudelleen kohdentumista mikrotasolla, mikä on tärkeää talouskehitykselle. Tuottavuuden vaihtelun lisäys näyttää edeltävän luovan tuhon kiihtymistä, mikä myös sopii kuvaan. Samaan aikaan luova tuho kuitenkin myös supistaa tuottavuushajontaa poistamalla heikon tuottavuuden yksikköjä. Ei saatu empiiristä näyttöä siitä, että toimipaikkojen välisellä palkkahajonnalla olisi myönteinen vaikutus. Kansainvälisen kaupan positiivinen vaikutus osoittaa tuotemarkkinoiden kilpailun merkityksen, mitä myös tuore teoreettinen kirjallisuus tähdentää. Lopuksi, pääosa tuottavuutta vahvistavasta rakennemuutoksesta syntyy hiljattain perustetuista toimipaikoista, mikä osoittaa uusien toimipaikkojen tärkeyden luovassa tuhossa.

Aggregaattitason tuottavuuskasvun komponentteja voidaan tunnistaa ja mitata erilaisilla dekomponointimenetelmillä. Osoitetaan, että erilaiset menetelmät tuottavat hyvin vaihtelevia tuloksia. Eräitä uusia muunnelmia esitetään. Näillä välineillä on kaksi olennaista etua. Ensiksi, niillä laskettavat komponentit ovat käyttökelpoisia, kun arvioidaan niin sanotun ”edustavan yrityksen mallin” käyttökelpoisuutta. Toiseksi, tulokset eivät ole kovin herkkiä eräille mittausongelmille, jotka ovat mikroaineistoille luonteenomaisia.

Usein on huomautettu, että tuottavuushajotelmissa ei oteta huomioon työpanoksen laatua. Tähän pulmaan tartutaan yhdistettyjen työantaja-työntekijä -aineistojen avulla. Näiden aineistojen avulla on mahdollista mitata työpanosta niin sanotuissa ”tehokkuusyksiköissä”. Ei löydy näyttöä siitä, että kyseessä olisi ollut näennäinen tuottavuusparannus, joka on syntynyt siitä, että heikosti koulutetut ja kokemattomat työntekijät ovat syrjäytyneet tuotantotoiminnasta rakennemuutoksen johdosta.

Tuottavuutta vahvistava rakennemuutos on vaikuttanut myös funktionaalisen tulonjaon dynamiikkaan. Toimipaikkojen palkkasummaosuudet ovat kohdentuneet uudelleen. Ne ovat siirtyneet sellaisista toimipaikoista, joissa pääoman tulo-osuus on alhainen, sellaisiin toimipaikkoihin, joissa pääoman tulo-osuus on korkea. Aggregaattitasolla palkkasummaosuuksien uusjako on vaikuttanut pääoman tulo-osuutta kasvattavasti.

Koska mikrotason rakennemuutos on erittäin tärkeää talouskasvulle, siihen vaikuttaviin tekijöihin on syytä kiinnittää huomiota, kun politiikkatoimia tai instituutioiden uudistuksia suunnitellaan. Innovaatiot ja T&K ovat tärkeitä, mutta ne eivät aina yksin riitä. Tuotemarkkinoiden kilpailu on keskeinen tekijä. Myös hyvin toimivat pääoma- ja työmarkkinat sekä työvoiman osaaminen ovat tärkeitä tekijöitä, jotka helpottavat talouden uudistumista mikrotasolla.

ASIASANAT: Mikrotason dynamiikka, tuottavuushajotelmat, kilpailu, T&K, kiinnikuronta
JEL: J23, J24, J63, L60, O12, O33, O47

Preface

This study makes use of the central parts of my work in the fields of productivity analysis over the last ten years. My journey into the world of Finnish manufacturing productivity started in 1993, when Matti Pohjola guided me to this area and pointed out that productivity is the most important determinant of the living standards and competitiveness of nations. And what could possibly be more important in economics than the factors behind the living standards of humans?

I began my studies by investigating productivity differences between countries. Bart van Ark, Dirk Pilat and others in Groningen University taught me a good deal about the myriad problems involved in cross-country productivity comparisons. I was instructed on how problems can be handled in the so-called "ICOP approach". I found that it is not unusual at all that some industries are several steps behind the current international productivity leaders even when the analysis is limited to the developed countries.

So, it seemed that climbing productivity ladders is time-consuming and involves challenges that discriminate between nations, industries, firms and establishments. Often large productivity gaps cannot be explained by the differences in human capital, tangible investments or other such observable factors. To understand why an industry in a country is high on the productivity ladders it may be better to try to disentangle how it got there, instead of exploring its current characteristics. Furthermore, we can expect to find the answers at the firm and plant level where the technology choices are made, and the new technologies are implemented and used in production.

I decided to focus on analysing the micro level dynamics of productivity growth. My work in this field started under the supervision of Pekka Ilmakunnas in 1997. I cannot thank him enough for his encouragement and invaluable advice over the years.

I am also indebted to the examinators Eric Bartelsman and Roope Uusitalo for their valuable comments and suggestions. Different parts of this research have also benefited from the numerous comments of many persons including, in alphabetical order, Rita Asplund, Petri Böckerman, Jukka Jalava, Markus Jäntti, Gabor Kezdi, Hannu Piekkola, Pekka Rouvinen and Pekka Sauramo. I thank Satu Nurmi for her assistance and helpful discussions. I would also like to thank the participants of the EARIE 2001 conference, Dublin 2001, the CAED'01 conference, Århus 2001, the 1st HE.V.P.E.M conference, Patras 2001, the EARIE 2002 conference, Madrid 2002, the Summer at CEU Workshop: Productivity and Reallocation, Budapest 2003 and numerous seminars and workshops for their comments. Of course, I am solely responsible for all the remaining errors.

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A number of my friends, colleagues and former superiors in Statistics Finland have helped me in various ways in my research with precious Finnish micro data. At least I should mention, “in order of appearance”, Olavi Lehtoranta, Heikki Pihlaja, Seppo Laaksonen, Perttu Pakarinen, Heli Jeskanen-Sundström, Kaija Hovi, Merja Kiljunen, Markku Virtaharju and Ritva Wuoristo. Many parts of this research have been written at the Research Institute of the Finnish Economy, ETLA. I want to express my gratitude to Pentti Vartia and Pekka Ylä-Anttila for providing me with a flexible and stimulating working environment. My superior Rita Asplund deserves a second mention thanks to her support that has gone beyond and above the making of comments on economic matters. Laila Riekkinen has been of a great support during the final hurried steps to render my work in a publishable form. I thank Kimmo Aaltonen for making up the volume efficiently. Derek Stewart has checked my English.

The greatest debt of all is to my family, my wife Erika and our son Lari. They have radiated to me the energy that I have so badly needed in my research efforts. Through all these busy years I have marvelled at Erika’s ability to find a balance between compassion and strictness when the going was tough.

Helsinki, October 2003

Mika Maliranta

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1 Introduction

Technology and productivity are arguably among the most important fields of research in economics. Productivity growth through technological progress is the main driving force of the growth in prosperity. Moreover, productivity is an important component of the competitiveness and profitability of a sector or firm. The ultimate sources of technological progress lie at the micro-level where the technology choices are made and the implementation of technology is carried out. All through this research on productivity a lot of emphasis will be put on the role of incessant restructuring of production at various levels – between and within industries and between and within micro-level units.

In this study a micro-level unit refers to a firm or more often to a plant. In several contexts the plant and firm concepts are used interchangeably. Most firms consist of a single plant. On the other hand, multi-plant firms account for a significant share of input and output use. It is worth remarking that firm-level dynamics may also involve a lot of restructuring between the plants in multi-plant firms (see Disney, Haskel, and Heden 2003).

Technological progress is a multidimensional process that entails various forms of adjustment. Micro-level analysis provides us with a way to study not only the forms but also the determinants and implications of the various adjustment processes. In the subsequent introduction sub-sections 1.1-1.7 the motivations, goals and focus of the present study are presented.

1.1 The performance level of manufacturing is crucial

Technology and productivity are the ultimate factors behind living standards. GDP per capita, which is a reasonably good indicator of a country's labour productivity, is highly correlated with various indicators of well-being. Hobijn and Franses (2001), for example, point out that those countries that do well in terms of GDP per capita also do well in terms of calorie supply, daily protein supply, infant mortality rates and life expectancy at birth.

Although the manufacturing sector nowadays typically accounts for a third or less of an economy's total value added, analysing the productivity of this sector is important for a number of reasons. The majority of exports comes from manufacturing. Productivity is an important factor in competitiveness, which in turn is essential for a sector that is extensively exposed to international competition. Thus the good productivity performance of the manufacturing sector is essential for a small open economy. Furthermore, a large percentage of technological innovations is made in manufacturing and a large proportion of technological advances is embodied in manufacturing products. Usually these are of great use to the other sectors of the economy as well. All in all, despite the sustained de-industrialisation tendency in most developed countries the technological level and productivity of the manufacturing sector are still very important to the total economy.

Finally, productivity measurement poses great challenges in terms of data. One needs to be able to make a sharp distinction between values, volumes and prices. Unlike the situation in many other sectors of the economy, productivity in manufacturing can be measured with at least reasonable accuracy.

So, both the validity and reliability aspects speak for focusing on the productivity of manufacturing. However, in the same breath it should be emphasised that an analysis of manufacturing deserves to be complemented with analyses of other sectors. The manufacturing sector may have a special role in a small open economy and thus the findings concerning this sector may not be very representative of the other sectors that may be sheltered from the pressures of international competition or may suffer from lack of adequate economies of scale because of limited markets, for example.

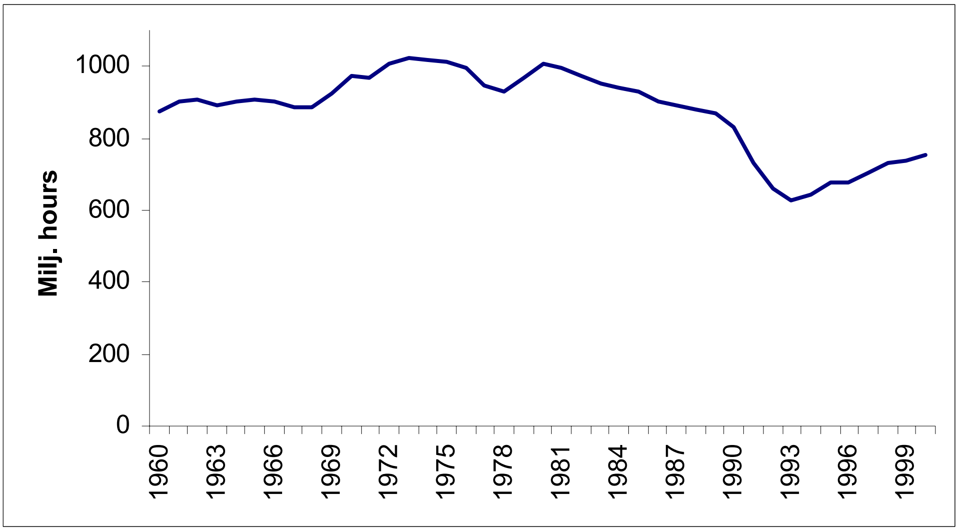
1.2 Turbulent decades in the Finnish economy

The Finnish economy was hit by an exceptionally severe economic depression in the early 1990s. In a few years' time GDP dropped by about 14 per cent. Lots of jobs were destroyed and, as a consequence, employment fell in all the main sectors. Unemployment rose from some 3.5 per cent in 1990 to 18.4 per cent in 1994. Industrial production declined by 12 per cent in 1991. Employment in the manufacturing sector fell by almost one fifth from 1989 to 1991.[1] As can be seen in Graph 1.1 the Finnish manufacturing sector was characterised by a sustained de-industrialisation process during the 1980s. The graph also indicates a noteworthy turn in this trend in the post-recession years following 1993. The other sectors of the economy have also witnessed a substantial increase in employment, but it started a year or two later. From 1994 to 2000 employment increased by 16 per cent in the total economy and by 20 per cent in the market sector.

Several explanations for the recession have been put forward. The Finnish economy had bad luck as the downturn within the OECD area coincided with a collapse of trade with the former Soviet Union in 1991. Furthermore, policy-makers can be argued to have been unsuccessful in fiscal policy and in the deregulation of

[1] Kiander and Vartia (1996) and Honkapohja and Koskela (1999) provide a description of the recession in Finland.

Graph 1.1 Hours worked in manufacturing 1960-2000



Note: The data is from the Finnish National Accounts. The years 1960-1974 are extrapolated from the earlier series obtained with a slightly different classification of industries.

the financial markets, which started in the mid-1980s, as the indebtedness of the private sector rose substantially and the economy overheated in the late 1980s. A strong currency, especially after the revaluation of the Finnish markka in early 1989, reduced the competitiveness of exporting firms. The defence of the markka against speculative attacks kept interest rates high. (See Honkapohja and Koskela 1999). This made the financial situation difficult for businesses with high interest payments per cash flow, such as new firms that had made large investments. Unlike the Japanese economy, for example, the Finnish economy started to recover quite soon. The question as to how much credit should be given to institutions and policy actions for this is an open one. Anyhow, a proper evaluation of this issue should include careful consideration of the various micro-structural adjustments that took place before, during and after the recession.

Although the focus of this study goes beyond short term fluctuations of output and productivity, cyclical variation is of some interest also in the present study, as business cycles can be associated with medium-term productivity growth. There are two opposing views concerning the influence of business cycles on the evolution of productivity. According to one opinion good business conditions are favourable for productivity growth because of learning by doing, expansion of markets and economies of scale (see, for example, Young 1928, Krugman 1987, and Martin and Rogers 1997). A more recent argument in favour of good and stable economic business conditions emphasises the imperfections of financial markets, especially in the presence of uncertainty. The collateral value of R&D investments, from the point of view of a lender, may be doubtful. For that reason internal funds are likely to be an important source for this type of investment. Economic slow-downs may be harmful for future growth because investments that are to a large extent irreversible and that involve specificity with respect to the choice of technology will most likely be depressed in the presence of widespread shortage of internal funds (see Stiglitz 1993). All in all, the functioning of financial markets may be a critical factor for the evolution of productivity during slow-downs or, as emphasised recently by Caballero and Hammour (2000), in the developing countries.

The other opinion is that recessions and crises include beneficial elements. This view also has long traditions, tracing back at least to the seminal works by Schumpeter (1939 and 1942). There are two strands of reasoning. In the works by Schumpeter and more recently by Caballero and Hammour (1994, 1996 and 1998) it is argued that recessions do the job of cleansing the least efficient units from the production system. Another theory is that recessions are the times when it is relatively cheap to innovate and reorganise. This can be called the "pit-stop" or "opportunity cost" view (see Aghion and Saint-Paul 1998, Hall 1991, and Cooper and Haltiwanger 1993).

1.3 Productivity performance in Finland

Rapidly increasing R&D intensity is one of the striking tendencies that has characterised the development of the Finnish economy and manufacturing since the mid-1980s. As late as in 1985 R&D intensity, i.e. nominal gross domestic expenditure on R&D (GERD) per nominal GDP, was 1.6 percent in the Finnish economy whereas the respective numbers for the United States and the total OECD were 2.9 and 2.0 percent respectively. By the year 1999 Finland had overtaken the United States with R&D intensity amounting to 3.1 percent in contrast to 2.8 percent in the United States. Similar tendencies can be found in the manufacturing sector, too. Business enterprise R&D expenditure (BERD) per value added was 2.2 percent in Finnish manufacturing in 1980 whereas the respective number for US manufacturing was 7.3 percent. Since then the increase in R&D intensity has been much more rapid in Finnish manufacturing. In 1997 R&D intensity was 7.2 percent in Finnish and 9.1 percent in US manufacturing.[2]

Investments in the creation of technological knowledge seem to have paid dividends, too. There has been a considerable acceleration in the total factor pro-

[2] The computations of R&D intensity in manufacturing are made by using OECD's STAN and ANBERD databases. See also OECD (2000).

ductivity growth rate in the business sector from an annual average growth rate of 2.1 percent in 1980-89 to 2.8 percent in 1990-96. In the United States, on the other hand, the growth rate remained at a stable and moderate level of 0.8 in both 1980-89 and 1990-97 (OECD 2000, p. 119).

Pohjola (1996 and 1998a) has argued that inefficiency in capital usage made the Finnish economy vulnerable in the presence of free international capital flows and high real interest rates. The inefficiency was a consequence of the long-lasting regulation period from the 1940s up to the mid-1980s.

According to the results by Crafts (1992), growth in Finland was lower than in most of the other countries for the years 1950-60 in the sample, when various factors were controlled in the statistical analysis. However, in 1979-88, Finland outperformed the average growth. The annual growth was 0.73 per cent higher than that predicted by the regression model. The findings of Englander and Gurney (1994) were quite similar. According to their estimates the annual growth of labour productivity was 0.7 per cent higher than predicted. The latter study, in particular, carefully controlled various relevant factors such as capital intensity, education, growth of the labour force, the initial productivity gap to the international frontier and R&D efforts. Another great advantage of the latter study is its focus on the business sector where productivity can be measured more reliably than for the whole economy.

Graph 1.2 illustrates some interesting features in the development of labour productivity (value added per hours worked) in Finnish manufacturing. Firstly, the graph seems to suggest there was a change in the trend towards faster productivity growth in manufacturing in the mid-1980s and that this rapid growth has lasted until now. Secondly, the fast labour productivity growth since the mid-1990s appears to be driven mainly by the electronics industry. This can be seen by looking at the series where the electronics industry is excluded. Henceforth this is called non-electronics manufacturing. This series shows a substantially lower rate of growth in the latter part of the 1990s. Up to the mid-1990s the series labour productivity of manufacturing and non-electronics manufacturing share quite a similar pattern. All in all, this descriptive analysis with aggregate labour productivity indicators seems to indicate three phases in the development of labour productivity in non-electronics manufacturing; a period of reasonable growth in 1975-1985, a period of rapid growth in 1985-1995 and a period of depressed growth in 1995-2000.[3]

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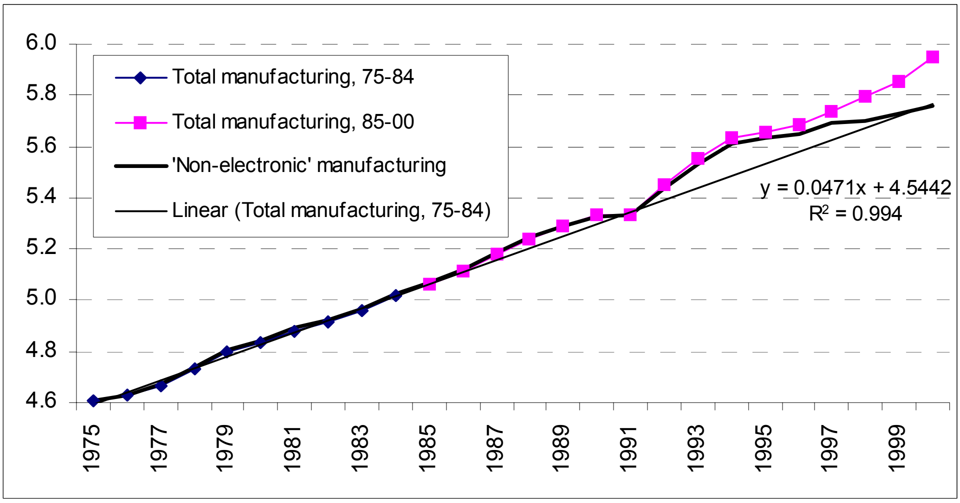
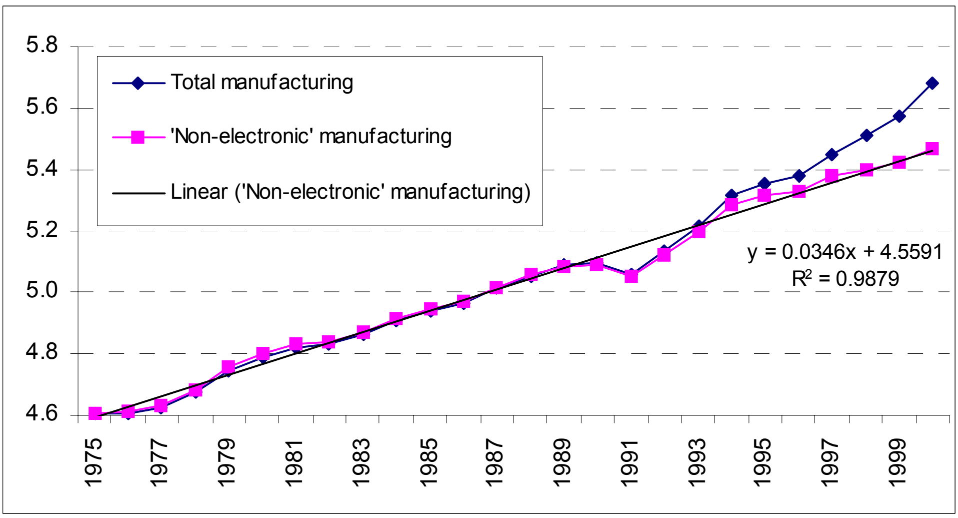
[3] Sauramo (1999) provides a somewhat more comprehensive analysis of the time-series of labour productivity in the Finnish sectors. He emphasises the exceptionality of productivity growth in the period 1992-94.

Graph 1.2 The development of labour productivity in total manufacturing and in non-electronics manufacturing, log scale, 1975 = log (100)



Note: The data is from the Finnish National Accounts.

Graph 1.3 The development of total factor productivity in total manufacturing and in non-electronics manufacturing, log scale, 1975 = log (100)

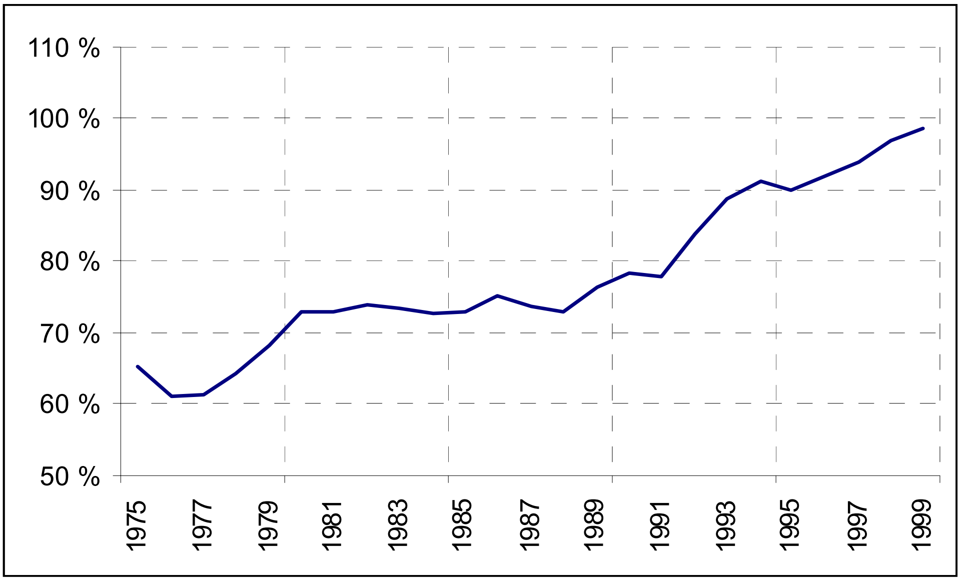


Note: The data is from the Finnish National Accounts.

Since capital input is ignored, labour productivity is an incomplete measure of technology and productivity performance. An investigation with the total factor productivity indicator, summarising labour and capital productivity, supplements the above analysis.[4]

The growth of manufacturing total factor productivity was reasonably stable during the period from the mid-1970s to the late 1990s. Productivity plunged in the

Graph 1.4 Relative total factor productivity level of Finnish manufacturing, 1975 to 1999, USA=100 %



Notes: The figure is based on updated results from Maliranta (1996). The productivity comparisons for the base year, that is 1987, have been made by using the same approach as in the ICOP (International Comparisons of Output and Productivity) project at the Groningen university (see van Ark and Pilat, 1993). In this so-called industry-of-origin approach, value added figures are converted into a common currency by using unit value ratios. These ratios have been calculated for the binary productivity comparisons by using value and physical quantity information on the products obtained from the industrial statistics of the two countries in question. The capital stock estimates needed for the total factor productivity indicator have been calculated from investment series by using the perpetual inventory method by assuming the same depreciation rate for both countries. The investments of each country have been converted into dollars by using the purchasing power parities of investment goods. Extrapolation of the series and measurement of capital stock estimates are based on the information obtained from the STAN database of the OECD. See Appendix 1.

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[4] The total factor productivity measure is calculated here in a traditional way by making use of the Törnqvist index and factor income shares of labour and capital as weights.

recession but bounced back to its historical trend in a couple of years. In non-electronics manufacturing, productivity kept on following the medium-term trend. The total manufacturing sector, however, seems to have witnessed a period of rapid technological change in the latter part of the 1990s, which can be ascribed mainly to the electronics industry.

The total factor productivity gap to the international productivity frontier, which may gauge technological backwardness or technological inefficiency, is one potentially important factor of productivity growth. Graph 1.4 depicts the difference in the level of total factor productivity between Finland and the United States in total manufacturing. Three conclusions can be drawn. Firstly, productivity performance was weak at the onset of the 1980s suggesting a low technology level or inefficient usage of labour and capital inputs. Secondly, the catching-up process was strikingly slow during most of the 1980s. Thirdly, there was considerable acceleration in the catching-up in the late 1980s, and even some further acceleration in the recession period 1991-1993. The improved growth performance has pushed the productivity level close to the international technology frontier. So, it seems that one source of productivity growth had largely been dried up by the end of the 1990s. From this perspective, the stable total factor productivity growth rate up to very recent years in non-electronics manufacturing can be regarded as respectable.

International comparisons of productivity levels for total manufacturing may, of course, hide a lot of variation in relative productivity levels among industries. Productivity comparisons at a more detailed level of aggregation are valuable for a number of reasons:

1. The productivity difference between two countries at the level of total manufacturing may reflect both differences in industry-specific technology and efficiency in its use (see, for example, Harrigan 1999) and differences in industry structures (see, for example, Pilat 1993). Industry-level comparisons of relative productivity levels make it possible to distinguish between these two factors of manufacturing productivity levels.

2. Cross-sectional comparisons of productivity at the industry level provide information on the industries in which the comparative advantages of each country lie. This type of analysis helps us identify the “natural” fields of specialisation in international trade.

3. The identification of industries that have a high relative productivity level provides valuable information when investigating the determinants of high (industry-specific) technology or efficiency in technology use.

All in all, careful cross-country comparisons of productivity levels by industry, which use appropriate estimates of industry-specific price levels (see Sørensen 2001), provide us with valuable information that is useful for the purpose of studying technology, international trade and the determination of price levels.

1.4 Micro-level sources of productivity growth

The seminal work by Romer (1986) has been followed by a large number of other endogenous growth models that focus on the mechanisms and determinants of long-run growth. These models point out that human capital accumulation, R&D and international trade may be the fundamental sources of sustained aggregate economic growth. Micro-level data sets provide a valuable tool by which the empirical relevance of various growth theories can be assessed. Moreover, micro-level data give us an opportunity to study the adjustment processes that take place at the micro-level before the factors of growth have eventually been generated at a higher productivity level.

Technology choices as well as the efficiency with which technology is used in production are determined at the micro-level. Micro-level analysis of productivity is an essential part of any thorough study of the productivity evolution process.

1. In essence the restructuring of production takes place at the plant level. One part of plant-level restructuring takes the form of changing industry structures, while another part is reorganisation of production between plants within industries. Plant-level analysis thus provides us with a way to complete the picture about the determinants of sectoral productivity.

2. Micro-level analysis of productivity makes it possible to distinguish between two main types of adjustment that are needed in the course of technological progress. Productivity growth within plants is achieved through internal restructuring. This may consist of the adaptation of new technologies, organisational changes and alteration of labour composition through hiring and dismissals (see e.g. Bellmann and Boeri 1998). In addition, the productivity progress of a sector or an industry may involve external adjustment that takes place through restructuring between plants. The latter process appears in the form of divergent growth rates of input usage between incumbent plants, or takes place through entries and exits which are 'extreme forms' of the renewal process.

A distinction between these two main micro-level sources of aggregate productivity growth is crucial. The development of these components of aggregate productivity growth may provide us with valuable information on how different forms of adjustment to new technologies are associated with changes in business conditions, for example. It may be less costly to firms to improve their technology by upgrading machinery and retraining workers during economic downturns than during booms. So, instead of laying off personnel to accommodate the decline in demand and production, a firm may decide to assign tasks that are expected to expand production possibilities for the future. This type of "labour hoarding" should be reflected in a pro-cyclical variation of productivity. In particular, a period of prolonged economic slowdown should be followed by a period of extra strong growth within micro-units that cannot be explained solely by improved utilisation of (quasi)-fixed inputs in the production. The cleansing hypothesis of recession instead predicts that external adjustments vary counter-cyclically. Of course, the two versions of explanations as to why recessions may be beneficial for productivity growth need not be mutually exclusionary. So, the two main sources of aggregate growth, within and between components, should be kept clearly separated.

External adjustment is a particularly interesting source of aggregate productivity progress for at least two reasons. Firstly, external adjustment is likely to be painful and costly (see Stigler 1947). This is because micro-structural change requires job creation in some plants and job destruction in others. Firms make investments in some plants, whereas in other plants tangible capital is scrapped or shifted to expanding ones. Thus reorganisation of production entails reorganisation of the capital input shares between plants as well. Secondly, productivity growth through external adjustment can be expected to be particularly time-consuming. It takes time to generate new technological knowledge. Implementation that takes place at plants may also be a lengthy process, as time is needed to build new machines and constructions or an organisation with a suitable mix of skills. Sometimes even the establishment of new plants is required. The value of the new knowledge is typically uncertain and therefore development may entail lots of experimentation and selection.

3. The finding that aggregate productivity growth does not accord with within-firm productivity growth indicates that there is a systematic heterogeneity among firms and that a "representative firm" is an inadequate framework for growth analysis. An investigation of the forms of heterogeneity may reveal important aspects of the growth process. For example, the development of productivity and wage dispersion may tell something about the diffusion of technology, the segregation of labour, the properties of institutions and the forms of adjustment to new technologies.

1.5 Inefficiency and the nature of competition

Baldwin (1993) stresses the differences between two conceptual approaches to the notion of competition. The more traditional and widely adopted approach is to see competition as a state of affairs. An alternative and complementary view that follows the trails marked out by Schumpeter, Hayek and the Austrian school sees competition as a dynamic process.

The static perspective on the functioning of markets consists of two types of efficiency consideration. Imperfect competition can be expected to lead to inefficient allocation of resources. Leibenstein (1966) in turn argued that most of the welfare losses caused by imperfect competition are due to the fact that the lack of competitive pressure brings about inefficiency in the usage of inputs. Dynamic or Schumpeterian efficiency is probably even more crucial (see e.g. Wihlborg 1998). It involves productivity-enhancing reallocation of resources between units. The cumulative effect of this may be sizeable in the longer run.

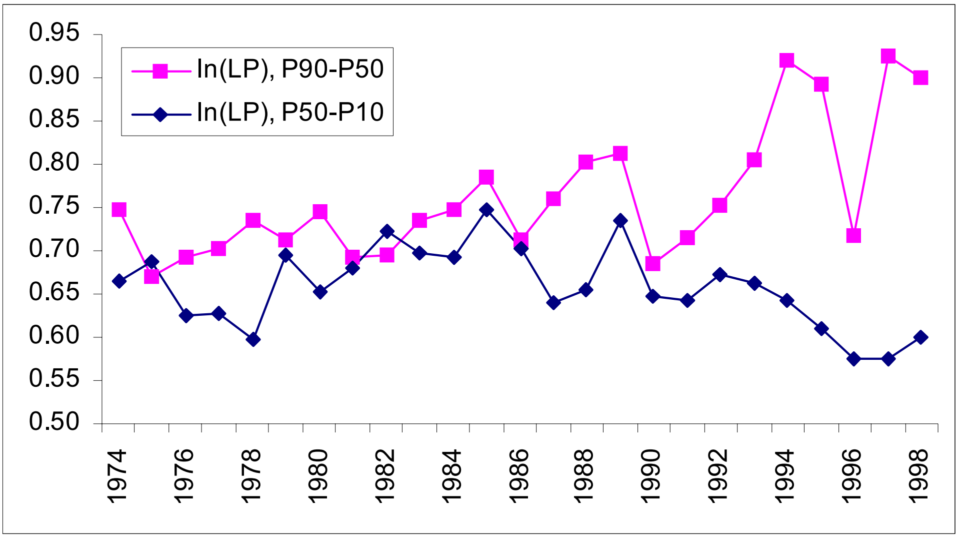
The intensity of competition in its traditional meaning is typically evaluated with indicators such as the number of firms, concentration, advertising ratios, etc. If these measures can be shown to be related to cross sectional differences in profitability, one could argue that they can be used for assessing the intensity of the competitive process.

However, when it comes to productivity and economic development, one should have a long term view (see for example Baumol, Blackman, and Wolff 1989). Firms are maximising the present value of their future cash flows. Technological advancements that are anticipated to open profit opportunities are usually the outcomes of sustained costly development efforts. The presence of high profits found at one point in time does not necessarily mean that these firms have excessive profits over their whole life cycles. These considerations lead us to seek some complementary indicators that better characterise the dynamics of competition.

Mobility measures provide an alternative way to evaluate the intensity of competition. The simultaneous occurrence of declines and rises within an industry suggests that there is a competitive struggle taking place. The fact that someone seems to win over others straight up does not mean that the competitive pressure is missing. On the other hand, as Baldwin (1993) points out, the lack of changes in relative positions does not preclude the possibility that there is hard struggle in the markets. It should be noted that even when the market shares of firms are relatively stable there might be a substantial amount of restructuring taking place within multi-unit firms, as firms are trying to make the best use of their resources.

Boone (2000) and Aghion, Bloom, Blundell, Griffith and Howitt (2002) advocate the view that the magnitude of the difference in profits between efficient and inefficient firms gives us an indication of the competitive pressure in the markets. According to this insight, a strict relationship between technical efficiency and profitability at the firm (or plant) level is characteristic of high competitive pressure. An increase in competitive pressure will strengthen the relationship between technical efficiency and profits. The fate of those low efficiency firms and plants that cannot improve their conduct (by innovation, for example) is disappearance (see e.g. Boone 2000, p. 551). Boone and Aghion et al show that an increase in competitive pressure may increase or decrease the incentives for efficiency improvements through innovation, depending on the situation.

Graph 1.5 Productivity dispersion in manufacturing between plants in the two tails of productivity dispersion



Note: The graph shows the log nominal labour productivity differentials between the 9th and the 5th decile (ln(LP), P90-P50) and between the 5th and the first decile (ln(LP), P50-P10). The measures are weighted by hours worked.

It is useful to consider some factors that may affect the intensity of competition in its dynamic meaning. Bertin, Bresnahan, and Raff (1996) find that the Great Depression in the United States did not have a cleansing effect in blast furnace operations, despite the presence of very substantial interplant heterogeneity and dramatic changes in demand. They argue that the economic explanation for this lies in the poor short-run substitutability of one plant's output for another's. These perspectives on competition lead us to consider some policy implications. For instance, the presence of domestic monopolies may be due to regulation and subsidies. These are factors that may weaken the relationship between technical efficiency and profits, and between efficiency and survival.

The magnitude of industry inefficiency can be gauged by productivity dispersion between plants. A large spread in the left-hand tail of productivity dispersion, i.e. among the low productivity plants, can be expected to be particularly indicative of inefficiency. Graph 1.5 indicates log labour productivity differentials between median and first decile and median and 9th decile plants. The graph reveals that there has been a significant compression of productivity dispersion among the low productivity plants since the mid-1980s. On the other hand, the graph indicates that especially since the mid-1990s there have been plants that have a very high productivity level. As a consequence, above-median dispersion has increased.

1.6 Research questions

We saw empirical evidence that Finnish manufacturing productivity growth and the process of catching up with the international frontier accelerated somewhere in the mid-1980s. At about the same time, productivity dispersion between plants started to compress especially in the left-hand tail of productivity dispersion. Are these developments somehow mutually related? Is it possible to find a link from the micro-level dynamics of productivity growth? How is the intensity of restructuring at the plant-level, i.e. plant-level turbulence, related to these observable facts?

One possible explanation for the accelerated productivity growth and for the compressed productivity dispersion in the left-hand tail is that there has been an intensive and systematic reallocation of factors of production between plants that differ in terms of technology levels. Jobs in low technology and low productivity plants may have been destroyed, which might be behind the rapid increase of the average productivity level. An important question is how much this process has entailed “creative” elements. This is to say how much has there been creation of high productivity jobs for skilled and less skilled workers? One part of the answer is visible in Graph 1.1 Employment declined sharply in the early 1990s, but a substantial recovery occurred soon.

A very important question concerns the role of high skills in production with current technology on the one hand, and with the development, adoption and implementation of new technologies on the other. Can we find lags in the impacts of increased skill levels in the plants? Lags in these impacts are something we would expect to find if high skills are essential for improving the technology of the plant instead of being a factor of production with current technology.

Which factors are likely to have launched the growth process which catapulted Finland to the international top group in productivity and which involved painful restructuring at the micro-level? Is it possible that increased R&D intensity or increased exposure of Finnish manufacturing industries to (western) global markets have something to do with the productivity-enhancing restructuring between plants within manufacturing industries? What has been the role of the deregulation of the Finnish financial markets?

Can the development of the labour income share be understood better by looking at micro-level dynamics? And what about the role of wage dispersion between plants? Are wage differences between plants useful for aggregate productivity growth because they induce workers to change their jobs in low productivity plants to jobs in higher productivity plants? Or is the productivity dispersion between plants to a large degree a reflection of rent extraction by wage bargaining within plants which have varying technologies and rents? In the latter case, a high wage is a kind of tax from the point of view of high productivity plants, which should reduce their labour demand. If this is true then we would expect high wage dispersion to be harmful to productivity-enhancing restructuring. The third perspective is that high wage dispersion between plants reflects segregation of labour by skills, for example, due to the fact that the demand for low and high skills varies between different plants.

Institutions are likely to be important for resource mobility and thus for productivity evolution. The so-called "Scandinavian wage model", which characterises the Finnish labour market, involves some efforts to impede increases in wage differences between industries and companies. This might make the economy particularly apt to productivity-enhancing restructuring in the presence of a technology shock. This is because low productivity plants or industries are not reprieved by low wages and high productivity plants are not punished by high wages. Besides this, temporary or permanent dismissals incur relatively low expenses to enterprises in Finland (and in the other Scandinavian countries), which is another factor that may make the Finnish economy particularly prone to micro-level renewal. One of the goals of this study is to assess whether productivity-enhancing restructuring has been more effective in Finland than in some other countries that have been nearer to the international productivity frontier and have different institutions or different wage struc tures.

1.7 The structure of the study

My efforts to answer the questions raised above are organised in the subsequent chapters in the following way.

In Chapter 2 various theoretical considerations about productivity growth are presented. A sharp distinction between explanations that are based on "representative firm" models and those emphasising the importance of the heterogeneity of firms and plants is made.

Chapter 3 introduces some ways of identifying and quantifying different aspects of productivity evolution. In particular, I focus on the importance of distinguishing between two types of adjustment that are taking place in industry – one related to productivity growth within plants (internal adjustment) and the other involving a reallocation of the factors of production between plants (external adjustment). Some frequently used methods of decomposing industry productivity growth are presented. I also introduce new formulations that are shown to have some desirable properties. The pros and cons of the alternative methods are compared on a theoretical basis as well as with some illustrative examples.

Chapter 4 provides international comparisons of productivity levels in manufacturing.[5] This aggregate analysis provides us with some important insights about the development and structures of productivity performance.

Chapter 5 goes to the micro level by reporting productivity decomposition results for total manufacturing and its industries. Much of the focus is put on the between component of aggregate productivity growth among continuing plants. This component is argued to be quite a reliable and valid indicator of the productivity-enhancing restructuring process and thus it is a good indicator of the "creative destruction" process. For the sake of comparison some results for selected non-manufacturing industries are reported as well in Chapter 5.

In Chapter 5, plants' labour inputs are measured by a raw gauge of hours worked.

In Chapter 6, this simplification is corrected by making labour quality adjustments by means of different labour efficiency indexes. The role of labour skills in productivity growth is evaluated from different angles in that chapter.

In Chapter 7 the roles of different plant and worker characteristics in labour reallocation between plants are studied by examining the job and worker flows of plants. This investigation helps us test and complement some of the conclusions made on the basis of the productivity decomposition exercises in Chapter 5 and 6.

The determinants of the between component of industry productivity growth are studied in Chapter 8. As for explanatory factors, the focus will be on industry's intensity of innovation activity (measured by R&D intensity) and competitive pressure (measured by import penetration and export intensity). The links between innovation activity, productivity dispersion and productivity-enhancing restructuring are also disentangled.

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[5] This chapter summarises some selective parts of my licentiate thesis (see Maliranta 1996).

Chapter 9 examines the micro-level dynamics of labour income shares, which are shown to be directly related to the growth process of productivity.

Chapter 10 provides a summary of the central findings and a discussion on policy implications.

2 Technological progress and productivity evolution

Various theoretical considerations about productivity growth are discussed in this chapter. It is important to make a distinction between explanations that are based on "representative firm" models (Section 2.2) and those emphasising the importance of the heterogeneity of firms and plants (Section 2.3). The former provide us with macro economic explanations of economic growth. Some aspects appear in the literature (e.g. the embodiment issue), and sometimes a close analogy or interface can be found between these two perspectives. In Section 2.4, I characterise some important aspects of productivity-enhancing restructuring, including competitive pressure (Section 2.4.1), selection between heterogeneous micro-level units (Section 2.4.2) and institutional factors (Sections 2.4.3-2.4.6). Wage dispersion is largely related to the institutional features of a nation or sector and to labour market institutions in particular. However, wage dispersion may be related to the micro-level restructuring process in various alternative ways and consequently can be regarded as an important independent element of the "creative destruction" story. Therefore I have devoted Section 2.4.7 to a discussion on the relationship between wage dispersion between plants and restructuring.

Chapter 2 begins and ends with measurement considerations. In Section 2.5, I discuss the measurement of micro-level turbulence that is a prologue to Chapter 3, where characterisations of the micro-level sources of productivity growth are given and methods of quantifying them are introduced. In Section 2.1 the productivity measurement is dealt with. The interfaces between the traditional methods of aggregate productivity measurement and the methods quantifying the sources of productivity growth with micro-level data are expressed. These issues are dealt with when considering appropriate ways of productivity decomposition.

2.1 Productivity measurement

2.1.1 Definition of productivity

Productivity is defined as an output-input ratio:

$$P = \frac{Y}{X} , \qquad (2.1)$$

where Y denotes output and X input.

In the usual cases in which the units of interest (countries, industries or plants) produce products by using various input types, different approaches can be used for gauging productivity. One needs to choose a way by which the different types of outputs or inputs are combined or weighted in an appropriate manner. Typically, researchers choose production functions whose parameters are estimated by statistical methods. Alternatively, a non-parametric approach may be applied, in which output-input ratio is computed by means of mathematical programming (DEA method).

Instead of using econometric estimation or mathematical programming, which both require a relatively large number of observations, the measurement of productivity can be done by leaning on economic and index theory. Then Y stands for an appropriately specified output index and X for an input index. The choice of the index number approach and the functional form for the index can be justified by two main methods: (1) the economic approach and (2) the test (or axiomatic) approach. In the former case the use of index numbers is rationalised by assuming competitive (i.e. price taking) profit maximising behaviour on the part of the producer. In the latter case no behavioural assumptions are imposed, but it is required instead that the index formula satisfies various mathematical properties based on a priori reasoning (see Diewert 1989).

2.1.2 An ideal bilateral productivity index

The productivity index indicates the relative levels of productivity between two or more units or between different points of time (or a combination of cross-sectional and intertemporal comparisons). Törnqvist (1936) formulation has become very popular in productivity measurement. In the case of one output and M input types the productivity index suitable for *bilateral comparisons* takes the form:

$$P_{st} = \frac{A_t}{A_s} = \frac{Y_t}{Y_s} \prod\nolimits_{m=1}^{M} \left(\frac{X_{ms}}{X_{mt}} \right)^{\bar{S}_m}, \qquad (2.2a)$$

where the cost share of input type m is

$$\bar{S}_m = 1/2 \cdot (S_{ms} + S_{mt}),\ S_{ms} = \frac{p_{ms} X_{ms}}{\sum p_{ms} X_{ms}},\ S_{mt} = \frac{p_{mt} X_{mt}}{\sum p_{mt} X_{mt}} \text{ and } \sum \bar{S}_m = 1 \qquad (2.2b)$$

Constant returns to scale and profit maximisation are assumed.[6] This measure can be used for comparing productivity between two points of time t and s ($t>s$) or between two plants called t and s, for example (see e.g. Chambers 1988). This

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[6] For example, Dwyer (1998) finds that in most 4-digit textile industries the returns to scale for capital and labour are quite close to constant. As for Finnish manufacturing plants Maliranta (1997b) finds statistically significant evidence on decreasing returns to scale. In practise the departure from constant returns is, however, quite negligible. The sum of the OLS estimates for output elasticities of labour and capital is .986. When random plant effects are allowed, the respective number is 0.990 (see also Griliches and Mairesse 1995).

index provides us with an exact measure of non-neutral technical change (or technical difference) in the binary comparisons of productivity, if the original production function can be closely approximated by a translog specification (see Caves, Christensen, and Diewert 1982b). Diewert (1976) has called this a superlative index of technical change because it is an exact measure of technical change for a functional form that provides a flexible characterisation of production structure.

2.1.3 *Multilateral comparisons of productivity*

Quite often researchers need to compare the productivity levels of several units at the same time in a consistent way. Caves, Christensen and Diewert (1982a) propose a similar type of formula suitable for multilateral comparisons. In this method one needs to determine a reference point, which is the geometric mean of the output and input levels over all the units that are to be compared. A formula that is less ideal in terms of flexibility but easily computed and suitable for multilateral comparisons is the Cobb-Douglas input index. Comparisons between units s and t and between t and u can be made by using the following formulations:

$$P_{st} = \frac{A_t}{A_s} = \frac{Y_t}{Y_s} \prod_{m=1}^{M} \left(\frac{X_{ms}}{X_{mt}} \right)^{S_m} = \frac{Y_t \Big/ \prod_m^M X_{mt}^{S_m}}{Y_s \Big/ \prod_m^M X_{ms}^{S_m}} \text{ and} \tag{2.3a}$$

$$P_{tu} = \frac{A_u}{A_t} = \frac{Y_u}{Y_t} \prod_{m=1}^{M} \left(\frac{X_{mt}}{X_{mu}} \right)^{S_m} = \frac{Y_u \Big/ \prod_m^M X_{mu}^{S_m}}{Y_t \Big/ \prod_m^M X_{mt}^{S_m}}, \tag{2.3b}$$

where $\sum_{m=1}^{M} S_m = 1$

As above, constant returns to scale and profit maximisation behaviour on the part of the producer are assumed. These computations are easily seen to be transitive:

$$P_{su} = P_{st} \cdot P_{tu} . \tag{2.4}$$

By rearranging the terms in (2.3a) the following formulation is obtained:

$$P_{st} = \prod_{m=1}^{M} \left(\frac{Y_t / X_{mt}}{Y_s / X_{ms}} \right)^{S_m}, \tag{2.5}$$

which illustrates that the multi-factor productivity indicator P_{st} is just a weighted geometric average of partial productivity indicators. Therefore, this formulation is intuitively appealing. Of course, there is a question as to how the weights should be determined in practise. However, if the input ratios are reasonably similar among the units under comparison, the results are not very sensitive to the weighting scheme.

Finally, one may be interested in the differences in one partial productivity measure for its own sake, say labour productivity (*j*). Equation (2.5) can be developed further into the following form:

$$\left(\frac{Y_t / X_{jt}}{Y_s / X_{js}}\right) = P_{st} \cdot \prod_{m \neq j}^{M-1} \left(\frac{X_{mt} / X_{jt}}{X_{ms} / X_{js}}\right)^{S_m}, \qquad (2.6)$$

which indicates that a single partial productivity (e.g. labour productivity) is determined by multi-factor productivity (technology level) and by how much other inputs are used in proportion to the input type of interest (e.g. capital per labour input).

2.1.4 Aggregation of multilateral productivity indexes for an ideal aggregate productivity growth measure

In order to distinguish various micro-level sources of aggregate productivity growth we would need a method that

1. provides us with an input index that is obtained by aggregating *over different input types* for each unit at both points of time, and

2. allows a simultaneous and consistent comparison of productivity levels between all units in the initial and final years, and

3. allows an aggregation of inputs and outputs *over all units*.

We have noted above that the formula (2.2) fulfils the first and the formula (2.3) the second point. Next we look at the weighting scheme by which the plants' productivity indexes calculated by (2.3)[7] can be aggregated to obtain (2.2).

Let us start by first considering an ideal measure of aggregate productivity change from the initial year *s* to *t* now expressed in the following way:

[7] Note that now *s*, *t* and *u* denote plants.

$$P_{st} = \frac{Y_t \Big/ \prod_{m=1}^{M} X_{mt}^{\bar{S}_m}}{Y_s \Big/ \prod_{m=1}^{M} X_{ms}^{\bar{S}_m}} = \frac{P_t}{P_s} \tag{2.7}$$

where $\bar{S}_m = (1/2)(S_{ms} + S_{mt})$ and $\sum_{m=1}^{M} S_m = 1$.

The output and input measures are obtained by aggregating over plants indicated by *i* in the final year and by *j* in the initial year, e.g. $Y_t = \sum_i Y_{it}$ and $X_{mt} = \sum_i X_{mit}$.

So (2.7) takes the form

$$\frac{P_t}{P_s} = \frac{\sum_i Y_{it} \Big/ \prod_{m=1}^{M} \left(\sum_i X_{mit}\right)^{\bar{S}_m}}{\sum_j Y_{js} \Big/ \prod_{m=1}^{M} \left(\sum_j X_{mjs}\right)^{\bar{S}_m}} \tag{2.8}$$

$$\Leftrightarrow \frac{P_t}{P_s} = \frac{\sum_i w_{it} \cdot \left(Y_{it} \Big/ \prod_m^M X_{mit}^{\bar{S}_m}\right)}{\sum_j w_{js} \cdot \left(Y_{jt} \Big/ \prod_m^M X_{mjt}^{\bar{S}_m}\right)}, \tag{2.9}$$

where

$$w_{it} = \prod_m^M \left(\frac{X_{imt}}{\sum_i X_{imt}} \right)^{\bar{S}_{mt}} \quad \text{and} \quad w_{js} = \prod_m^M \left(\frac{X_{jms}}{\sum_j X_{jms}} \right)^{\bar{S}_{mt}}$$

When $S_m = \bar{S}_m$ we see from (2.3) and (2.7)-(2.9) that an ideal measure of aggregate productivity growth can be derived from the plants' productivity indexes that are calculated by using the Cobb-Douglas input indexes. The plants' productivity indexes are weighted by the weighted geometric averages of the plants' input shares in the current year (see Bernard and Jones 1996). Generally $\sum_i w_{it} \neq 1$ and $\sum_j w_{js} \neq 1$ in (2.9).

It is worth noting that when plants' multi-factor productivities are computed for the initial and final years by formula (2.9), different input types are not weighted by their *current* respective cost (or income) share but by their *average* factor shares in the initial and final years. So, in a sense formula (2.9) retracts a little bit from the goal of characteristicity (see Drechsler 1973). This term is used to indicate the degree to which the differences in technology structures between units in the comparison are taken into account. Because input weights are dependent on both initial and final year prices, one could argue that the characteristicity of the weights is not the best possible for the purpose of cross-sectional comparisons in the initial or final years. However, averaged weights are needed to allow simultaneous and consistent comparisons along both the cross-sectional and time dimensions. Secondly, technological structures are likely to change relatively smoothly and slowly, but factor shares may vary quite abruptly due to changes in business conditions or inaccuracy in measurement. The averaging is likely to increase the reliability of estimates that may be important, especially at a detailed industry-level.

2.1.5 Aggregation of plants' outputs for an ideal aggregate growth measure

It was assumed above that each unit produces one and the same product, so that output quantities can be compared across units and points of time and aggregated over units. In reality, of course, the units produce many products and the product variety varies between units. In practise, cross-sectional comparisons can be made with the values of production. There is a case for this approach as the value of output can be assumed to be a quality-adjusted measure of output. Moreover, the approach makes it possible to compare 'apples' with 'oranges'; i.e. plants in different industries. This type of comparison is implicitly behind computations of manufacturing output or productivity. On the other hand, comparisons between different points of time call for some actions to be taken. Output numbers expressed in current prices can be made comparable by the use of price indexes.

Let us consider an index of aggregate output change or difference:

$$\frac{Y_t}{Y_s} = \frac{\sum_{it} p_{ib} q_{it}}{\sum_{is} p_{ib} q_{is}}, \tag{2.10}$$

where p_i denotes the unit price of product i and q_i is its physical quantity. If the formula is used for the measurement of growth between the initial year s and the final year t and if the base year is chosen so that $b=s$, this index is the familiar Laspeyres quantity index. The Paasche quantity index, in turn, is obtained when $b=t$. An ideal measure of aggregate output growth is the Fisher quantity index that is an unweighted geometric average of the Laspeyres and Paasche indexes.[8]

Usually a researcher has no information on physical quantities or unit prices, but only on the revenues, which is nominal value of output $NY_{it}=p_{it}q_{it}$. In this case,

[8] When a value index of output is divided by a Paasche price index, the resulting output quantity (and productivity) index is of the Laspeyres form. Similarly, a Paasche quantity index times a Laspeyres price index gives a value index. Therefore the Paasche and Laspeyres indexes are said to satisfy the 'weak' factor reversal test. The Fisher index in turn satisfies the 'strong' factor reversal test, i.e. a Fisher price index times a Fisher quantity index gives a Fisher value index.

quantity index Y_t/Y_s can be computed by means of deflation if an appropriate price index is available. Let us assume that the industry-specific price index gauges unit price change in each plant and consequently $\tilde{p}_{it} = p_{it} / p_{is}$, where i now denotes a plant. Then aggregate output index can be computed from revenues in two ways:

$$\frac{Y_t}{Y_s} = \frac{\sum_{it} NY_{it}}{\sum_{is} NY_{is} \cdot \tilde{p}_{it}} = \frac{\sum_i p_{it} q_{it}}{\sum_i p_{it} q_{is}} \text{ or} \tag{2.11}$$

$$\frac{Y_t}{Y_s} = \frac{\sum_{it} NY_{it} / \tilde{p}_{it}}{\sum_{is} NY_{is}} = \frac{\sum_i p_{is} q_{it}}{\sum_i p_{is} q_{is}}, \tag{2.12}$$

where (2.11) is an aggregate quantity index of the Paasche type and (2.12) is of the Laspeyres type. We notice that, in the former case, output can be expressed in the final year and, in the latter case, in the initial year prices. So, in this case the aggregate output change can be computed by first converting the plants' outputs into initial year or final year prices and then by summing all plants at both points of time.

An ideal aggregate productivity index should make use of an ideal output index. In many cases, the Laspeyres and Paasche formulations yield reasonably good results, that is to say that the results are quite close to the ones obtained by an ideal Fisher or Törnqvist index. This is the case especially when applied to relatively short time periods, for the purpose of calculating annual growth rates (s=t-1), for example. These can be used for constructing chained output indexes that are ideal when gauging longer term development. One advantage of the Laspeyres or Paache over the Fisher or Törnqvist formulations is that output levels in the initial and final years can easily be expressed in the comparable basis that is needed in equation (2.9).

In the National Accounts outputs are usually expressed in some base year prices. An analogous computation with plant level data would proceed as follows. Let us assume that t is the base year and one wants to calculate aggregate output growth from t+4 to t+5. It is obtained by

$$\frac{Y_{t+5}}{Y_{t+4}} = \frac{\sum_i NY_{i,t+5} / \tilde{p}_{i,t+5}}{\sum_i NY_{i,t+4} / \tilde{p}_{i,t+4}} = \frac{\sum_i p_{it} q_{i,t+5}}{\sum_i p_{it} q_{i,t+4}} = \frac{\sum_i Y_{i,t+5}}{\sum_i Y_{i,t+4}}, \tag{2.13}$$

where

$$\tilde{p}_{i,t+5} = p_{i,t+5} / p_{it} \qquad \text{and}$$

$$\tilde{p}_{i,t+4} = p_{i,t+4} / p_{it}$$

So, first the nominal outputs of the plants are converted into year *t* prices by means of some price index. Then the aggregate output change can be calculated after the summation of the plants' outputs in the initial and final years that are expressed in fixed year prices (year *t* in this example).

One tempting property of the fixed base year method is that it allows simultaneous comparisons of outputs (and productivity levels) between several points of time. However, productivity analysis usually deals with binary comparisons between different points of time (growth analysis) or cross-sectional multilateral comparisons or sometimes, as in the present study, a combination of these two dimensions.

A serious problem with the fixed base year method is that it is likely to generate biased growth rates when the base year is far behind or ahead. Due to the "substitution bias", growth rates can be expected to be biased downward before and upward after the base year. These types of biases emerge if there is a negative correlation between relative price change and relative quantity change. This is the case when consumers substitute the products of decreasing relative prices for the products of increasing relative prices. Because of potential bias like this, the US National Accounts has started to use chained output indexes instead of the more normal fixed base year indexes. As can be seen in Table 2.1, the earlier estimates badly underestimated the growth rate before the base year 1987 and overestimated it after the base year, just as would be expected on the basis of the theory. The bias in the annual productivity growth rate was 0.6 in 1990-94, which can be regarded as very substantial. More seriously, while the earlier figures suggested considerable acceleration in the labour productivity growth rate since the early 1970s, the adoption of the chained index revealed that the development trend was quite different. In reality the growth rate had been reasonably stable over the two decades. One could argue that in a sense the comparability of growth rates between different times is even more important than the growth rate at some particular point in time, because changes in the trends of the productivity series may indicate something important about the growth process. So, the more intensive debate about measuring the quality change of products is not the only important statistical problem in the measurement of productivity and in the analysis of technological change (see also Whelan 2002a).

If those plants that increase their volume of production more than average face below-average price changes, the aggregate productivity growth rates calculated from plant data are biased, when a fixed base year strategy is applied. This problem can be avoided by applying a rolling base year strategy, i.e. the nominal outputs are converted into final year or initial year prices (see Maliranta 2001). In other words, the computation of the aggregate productivity growth rate is based on the chained Paasche or Laspeyres quantity index formulas.

Table 2.1 Growth of labour productivity in U.S. non-farm business sector

	Fixed base year 1987	Chained index
1959-94	1.8	2.0
1960-73	2.9	3.4
1973-79	0.7	1.2
1979-90	1.0	1.1
1990-94	1.9	1.3

Source: 'Monthly Labor Review', Bureau of Labor Statistics, October 1995.

2.1.6 The distinction between technology and inefficiency

Productivity indicators are frequently used for gauging technological change over time or technological differences across units (countries or plants) at a given point of time. This can done legitimately if it is assumed that each unit maximises its profits, which implies that costs are minimised and thus no resources are wasted. However, Leibenstein (1966) argued that units similar in all relevant aspects might have different productivity due to differences in X-inefficiency. A sharp distinction between the low relative technological level and X-inefficiency is difficult to draw, and this is especially the case when technology is given a broad interpretation including, for example, managerial skills. However, the difference may be important to keep in mind.

Productivity can be viewed as determined by the level of technology A (or production frontier), which indicates the maximum technically feasible output with given inputs, and by the amount of inefficiency e:

$$P = A \cdot e, \tag{2.14}$$

where $A \geq P$ and $e \in [0,1]$.

Several authors, e.g. Färe, Grosskopf, Norris and Zhang (1994), Pohjola (1996) and Koop, Osiewalski and Steel (1999) have used this approach of distinguishing two distinct components of productivity, when analysing productivity change. The shift of the production frontier (i.e. the change of A), shows the speed of technological progress. The second component, the change of the distance from the frontier, indicates the change of (in)efficiency.

In practise, computation of the production frontier is a very challenging task, especially when data sets have a lot of noise (see for instance Caves 1992). Furthermore, the view that each unit has the same technology and thus the same production frontier may be regarded as unfruitful. Some units may be stuck with bad tools and methods and there is nothing they can do to improve their performance without large sacrifices.

From the standpoint of aggregate productivity change, the part of measured inefficiency that can be attributed to "remediable defect" (see Torii 1992) or "fat" (see Borenstein and Farrell 1999) may be, however, of some interest. If there exists such inefficiency among plants that is not inevitable and changeless, it would be important to know by which policy action the factors lying behind this type of waste of resources can be renovated, for example. Actions designed for alleviating inefficiencies may have high returns. The fat hypothesis states that a firm is most apt to cut costs to reduce X-inefficiency, i.e. to take steps toward internal adjustment, when it is under financial pressure (see Jensen 1986). Nickell (1996) provides some evidence that competition improves productivity within firms.

Nevertheless, from the standpoint of human welfare one should be ultimately concerned about long-run productivity growth as pointed out by Baumol, Blackman and Wolff (1989) and Barro and Sala-i-Martin (1995). Even though changes in inefficiency may have large effects in the short run on some occasions, sustained growth is likely to be driven mainly by technological change. Factors such as efficiency in innovation activities or success in technology choices (see e.g. Caselli and Coleman 2002), that is to say Schumpeterian efficiency, are likely to be eventually even more relevant than static efficiency in current production activities.

2.2 Macro-level perspectives on aggregate productivity growth

While the current aggregate productivity level and thus economic conditions for well-being are determined by sustained growth in the past, it is useful to look at the determinants of productivity growth. Crafts (1992) distinguishes four types of explanations for aggregate economic growth: (1) neo-classical growth models (2) new or endogenous growth models (3) the catching-up hypothesis and (4) institutional explanations. All these approaches are primarily more or less macro-level explanations and basically ignore the role of micro-level heterogeneity in development. Issues such as the quality of inputs and the embodiment of technology are widely recognised as important points.

2.2.1 Exogenous growth

Foundations for the standard neoclassical growth theory were built in the works by Solow (1956 and 1957) and Swan (1956).[9] Solow (1957) proposed a model that was to become the dominant growth-accounting framework.[10]

In this model, output Y is determined according to the familiar aggregate production function

$$Y = A \cdot f(K, L), \tag{2.15}$$

which is basically similar to the productivity equation (2.1) with P replaced by a technology parameter A and the input index X by a function f which includes raw, i.e. quality-unadjusted, measures of capital and labour.[11]

Constant returns to scale, positive and diminishing returns with respect to each input, and marginal products of each input that approach zero as each input goes to infinity are assumed. Furthermore, the usual neo-classical assumptions of competitive factor markets and profit maximisation behaviour are behind the model.

In this framework, technological progress emerges from nothing and without costs. It makes all types of inputs more productive, irrespective of the age of the plant they are used in, for example.

2.2.2 Quality of inputs

In the base model, both labour and capital inputs are homogeneous. If this were the case, it would be pretty easy to identify the contribution of technology to economic growth (or the differences in the levels of output across countries, for example). It was recognised a long time ago that both labour and capital consist of various input types that differ in terms of efficiency. So the average quality of input is dependent on the composition of the different input types that may change over time (or vary between countries). What is needed is a detailed input index that makes a distinction between heterogeneous types of inputs.

The techniques of separating the effects of raw quantity growth and quality growth can be applied for various kinds of inputs, but for the sake of simplicity let us consider the measurement of labour quality growth. Workers are classified into M

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9 Niitamo (1958) was also one of the important pioneering works in this field.

10 Greenwood and Jovanovic (2001) provide a description of various models of accounting for economic growth.

11 In other words, production is assumed to be efficient.

groups by some relevant labour characteristics (education, age and gender, for example). The labour quality or labour efficiency growth rate, denoted here by $\Delta \ln e$, can be measured by making use of the Törnqvist (1936) formulation. It is the difference of the quality-adjusted labour growth measure, $\ln\left(\hat{L}_t / \hat{L}_s\right)$, and the raw labour growth measure, $\ln\left(L_t / L_s\right)$.

$$\Delta \ln e_{st} = \ln\left(\frac{\hat{L}_t}{\hat{L}_s}\right) - \ln\left(\frac{L_t}{L_s}\right) \tag{2.16}$$

$$\Leftrightarrow \Delta \ln e_{st} = \sum_{m=1}^{M} \overline{S}_{mt} \cdot \ln\left(\frac{L_{mt}}{L_{ms}}\right) - \ln\left(\frac{\sum_{m=1}^{M} L_{mt}}{\sum_{m=1}^{M} L_{st}}\right), \tag{2.17}$$

$$\overline{S}_{mt} = \left(\frac{p_{mt}L_{mt}}{\sum_m p_{mt}L_{mt}} + \frac{p_{ms}L_{ms}}{\sum_m p_{ms}L_{ms}}\right) \Big/ 2,$$

where p_m denotes the price (wages plus supplements) of labour type *m,* and L_m is the labour quantity of type *m*. Therefore, the weights $\overline{S}_m$ are given by the average shares of each labour type in the total value of labour compensation.

This method is suitable for bilateral comparison between *s* and *t*. They may be, again, successive points of time or different units. It is worth noting that the multilateral multi-productivity index shown in Equation (2.3) takes into account the input quality effect to the extent that the classification of inputs into *M* types is successful in distinguishing input types different in terms of efficiency.

Jorgenson and Griliches (1967) made the first efforts to gauge the contribution of changes in the composition of heterogeneous tangible assets. The flow of capital services per capital stock measure for a given time period varies between different types of tangible asset. The ratio is high in those asset types in which the depreciation rate is high or the price increase is low. Thus, if there is substitution toward high-tech equipment where the marginal product is high, and away from structures which have low marginal products, the aggregate capital stock fails to account for the growth of capital quality. Capital quality increase can be measured in a similar way to labour. The capital weighting is measured by using user costs or rental prices.

2.2.3 The embodiment issue

Solow (1960) was among the first to point out that, in earlier growth models, investments in tangible capital have no role to play in technological progress. He found the assumption that old and new capital equipment participate equally in technical progress striking. Indeed, it seems clear that usually the newest innovations need to be embodied in new kinds of durable equipment before they can be made effective. So at least a part of technological progress is investment-specific.[12] Solow (1960) proposed a vintage-capital model in which technological progress is exogenous and embodied in the form of new capital goods.

Embodiment considerations indicate that not only the type of capital good, but also the vintage, needs to be taken into account when constructing an appropriate aggregate measure of capital input that ideally is expressed in efficiency units (see Hulten 1992). The upgrade of capital quality input that takes place when more efficient vintages of a certain capital type are accumulated into the capital stock should be taken into account in the investment price index. To put it in other way, the measurement of the total factor productivity growth rate is biased upward, if the price index of investments fails to account for some of the quality improvements.

Of course, technological change may not be embodied only in the form of new equipment but in other types of inputs, too. Gort, Greenwood and Rupert (1999) argue that new buildings embody a considerable amount of technological progress. Some new technological knowledge needs to be embodied in human capital. Finally, Jovanovic and Rousseau (2001) argue that some of the good technologies are appropriated by the new firms of their day. The technology is embodied into organisational capital that makes a group of people and tangible assets more productive together than apart. I will come back to this issue below when considering heterogeneity across plants or firms.

The embodiment issue is important from many mutually interrelated perspectives:

1. If embodied technological change accounts for a large share of total factor productivity growth, it means that the role of investments in economic growth is much more than its traditional role of capital deepening.

2. Especially when a technology shock is investment-specific it may take a long while before the measured productivity growth reflects the new long-run level

[12] Hercowitz (1998) provides a review on the "embodiment" controversy.

of technological change. For example, in the model by Pakko (2000), the lag comes from the dynamics of capital stock adjustment that is particularly time-consuming in the case of investment-specific technology and may then even involve initial short-run economic slowdown.

3. Thus, the embodiment of technological progress may have implications for cyclical fluctuations and employment.

4. Investment-specific technological change may alter the way in which old vintage capital is used in a firm's production. By making use of Solow's vintage capital model, Whelan (2002b) shows that embodied technological change may lead to reallocation of those inputs that do not embody technology allowing them to work with newer vintages of computers. So, investment-specific technological progress may entail internal adjustment within a (representative) profit maximising firm. In the course of the process the utilisation rate for a capital good falls as it ages.

5. The emergence of new high quality capital goods does not reduce the productive potential of older vintages, but old capital may become obsolete and its economic value may decrease over time. Whelan (2002b) extends Solow's vintage model by allowing endogenous retirement of capital. In his model, embodied technological change entails technological obsolescence. Because of support costs, a firm finds it less and less profitable to operate with old vintage capital and eventually it will choose to retire it, even when it is still productive.

6. The embodiment of technological progress poses big challenges for growth accounting and the measurement of capital in particular. Gort and Wall (1998) and Whelan (2002b) argue that the official estimates of the growth rate of capital stock are biased downward. One problem with the official estimates of capital stock is that depreciation rates not only include physical decay but obsolescence as well. The latter may be substantial, if investment-specific technological progress is rapid. Useful estimates for physical decay are obtained by estimating the quality-adjusted economic depreciation or "partial depreciation rate" (Oliner 1989). Moreover, Gort and Wall (1998) and Sakellaris and Wilson (2001) argue that price-based estimates for embodied technological change understate the true embodied technological change. For example, Bahk and Gort (1993) obtain very high estimates for investment-specific technological growth. Actually according to these estimates there is no residual disembodied technological change.

2.2.4 New growth theories

One important implication of the neo-classical growth model is that, in the long-run, productivity growth is completely determined by exogenous technical progress. An increase in the investment ratio leads only to a temporary acceleration of labour productivity growth. Thus this model does not really explain long-run economic growth.

The endogenous or new growth theory was developed to understand better the factors behind sustained growth. This literature is quite varied encompassing such factors as innovation, increasing returns, production spillovers and the dynamics of competition. Hulten (2000) identifies non-competitive markets, increasing returns to scale, externalities, and endogenous innovation as the key aspects of the new growth theory. I will not try to provide a comprehensive description of this vast literature, but I will pick out a couple of growth factors usually considered in this literature.

Romer (1986) was the first to provide a mechanism and consistent economic explanation as to why capital might not suffer from diminishing returns to scale at the aggregate level, which is one of the basic assumptions of neo-classical theory. Romer showed that spillovers from research and development efforts may generate sustained aggregate productivity growth. Constant returns to scale and diminishing returns may prevail at the micro-level. The level of productivity is dependent on the aggregate stock of some privately provided input

$$Y_i = A(R)\cdot f(K_i, L_i, R_i), \tag{2.19}$$

where subscript *i* represents plant-specific variables, *R* is the aggregate stock of knowledge, and time subscripts are dropped for convenience. There are various explanations and characterisations as to why a plant's ability to generate output with its inputs may be dependent on outside factors, i.e. technology *A* is a function of *R*. Arrow (1962) states that *A(.)* increases over time due to the learning-by-doing involved in the investments in tangible capital. In Romer's (1986) model, technology *A* is determined by the aggregate stock of R&D capital in the economy. Lucas (1988) argues that the continuous accumulation of the stock of human capital drives *A* up.

Coe and Helpman (1995) point out that the R&D stock of international trading partners may be relevant from the point of view of domestic productivity. All in all, a nation may not always be a relevant unit when considering external economies such as technological spillovers. Of course, a common language or culture is likely to make communication more efficient. Sometimes the technological knowledge might be localised in a group of neighbouring countries whose citizens share a similar background and language. Then workers will find it easy to move between countries and carry knowledge with them, for example. Therefore, we would expect that technological knowledge in a neighbouring country is more easily adopted than that in a distant country. Barro and Sala-i-Martin (1995, see pp. 333-334 in particular) provide a great deal of empirical evidence on the regional convergence in real per capita GDP levels. This may be a consequence of convergence in capital intensity or convergence in technological levels, measured for instance by some total factor productivity index.

Much technological knowledge is industry-specific. Therefore, industry specialisation may not only be a *consequence* of a relatively high productivity level but also a *factor* contributing to a high productivity level. Krugman (1991, p. 6) uses the concept of comparative advantage when international trade is beneficial for countries because of their differences. However, if there are increasing returns, international trade may be beneficial also between initially similar countries. Therefore, we would expect that international trade is particularly important for small countries otherwise unable to make use of increasing returns within industries.

If there are increasing returns due to an accumulation of industry-specific technological knowledge, it is quite possible that the labour and total factor productivity levels will diverge between countries at the industry level. If a considerable amount of technological knowledge can only be accumulated through learning-by-doing, a frontier country may have an advantage over others. Krugman (1987) argues that accumulated experience may render a competitive advantage by which a country can capture market shares – and learn more. The role of accumulated knowledge may, of course, differ between industries or different phases of technological development.

Krugman (1991) emphasises the importance of geographical location as a factor of productivity performance and competitiveness. Various types of scale advantages provide us with explanations as to why producers in a certain industry are anxious to gravitate towards each other. Technological spillovers provide us with an explanation as to why two units may be more productive when they operate near each other than when they are located far away from each other. Location is important because information flows locally more easily than over greater distances.

To the extent that relevant knowledge is industry-specific, a positive correlation in the relative productivity levels (relative to some relevant benchmark) of industries between neighbour countries would be expected. In other words, one would expect that, at the industry-level labour and total factor productivity levels, there will be convergence among neighbouring countries even in cases where specialisation leads to divergence at the global level.

With all these explanations, long-run endogenous growth is generated because there may be non-decreasing returns to accumulated inputs at the aggregate level. The literature has pointed out a potentially important role for such factors that are likely to create or transmit positive productive spillovers, e.g. R&D, human capital or international trade. In particular, various new growth models suggest that because there are externalities involved in the process by which technologies are improved in the economy there is a danger of markets generating a sub-optimal outcome. From a social standpoint, market-generated private R&D or education efforts may remain too low.

2.2.5 Catching up and leapfrogging

According to neo-classical growth theory a country may temporarily enjoy abnormally high labour productivity growth after an increase in the investment ratio. In fact, one of the key properties of the neo-classical growth model is its prediction of conditional convergence in labour productivity levels. An economy that starts proportionally further below its own steady-state position tends to grow faster. Technological progress or total factor productivity growth is, however, constant and the labour productivity growth rate stabilises during the transition towards steady-state growth. So in the framework of standard neo-classical growth theory, a change in the relative labour productivity levels between countries can be explained by a change in the relative capital-to-labour input ratio.

Assumptions that each country shares the same technological level seem implausible. This is because substantial and persistent differences in TFP can be found between countries (see e.g. Wolff 1994; Prescott 1998; Bloom, Canning and Sevilla 2002). An almost equally suspect assumption is that TFP differentials across countries persist indefinitely (see e.g. Islam 1995 or Caselli, Esquivel and Lefort 1996).

The so-called “catching-up hypothesis” says that for one reason or other the technological levels between countries may be initially different (see Abramovitz 1986 and 1993). The follower country may imitate or adapt technology from the technology leader. If those countries initially equipped with a low technological level are able to benefit from the greater technological knowledge of the best-practise countries, the low technology countries may be able to experience both greater total factor productivity and labour productivity growth during the process of converging to the international technology frontier. Thus there should be conditional convergence both in labour productivity levels and in total factor productivity levels across countries.

Empirical studies by Bloom, Canning and Sevilla (2002) and by Dowrick and Rogers (2002) allow not only persistent differences in TFP levels, due for example to differences in geographical location or institutions, but also technological diffusion towards low TFP countries. The first of these studies finds that TFP in each country is converging towards a steady state level at a rate of about 1.8 % a year, while the latter study finds that the technological catch-up is 3 % or a bit more per year.

In the basic leader-follower model, initial backwardness helps countries to achieve more rapid total factor productivity growth for some time, but does not give any extra advantages in terms of determining the future leader. However, on some occasions, the current follower may have an advantage in pursuing the leader position at a future date, i.e. there may be a tendency for leapfrogging. For example, Brezis, Krugman and Tsiddon (1993) assume that the current leader has benchmark productivity thanks to its accumulated experience in the use of its current technology. The returns from experience are diminishing, so that the leader has a declining rate of total factor productivity during the life-cycle of the current technology. New better technologies appear occasionally. A better technology may, however, be unattractive for the current leader, if higher productivity is not achieved until substantial learning-by-doing has occurred. This is especially the case if the leader can still improve its productivity with its current technology at a reasonably high rate. However, the new technological opportunities may be worthwhile for a laggard, who is equipped with an obsolete technology and experiencing a low productivity growth rate. Since the new technology is more productive in the long run, the follower eventually becomes the leader.

Catch-up is a potential factor in favour of late development, but its realisation, however, is not guaranteed (see Pilat 1993). Abramovitz (1990) argues that success in the ability to capture the catch-up potential depends primarily on two factors – social capability and technological congruence. The first includes elements such as different institutions, economic policy making and the skill level of the population.[13] More recently, Caballero and Hammour (2000) have emphasised the role of an adequate institutional framework when a developing country is trying to catch up or at least keep up with the international technology frontier. An underdeveloped financial sector and politicised institutions may be major impediments to the catch-up process.

The point here is that the economic environment may be relevant not only from the standpoint of static efficiency, i.e. the current productivity level, but also from the standpoint of dynamic efficiency, i.e. the ability to generate growth.

2.2.6 Institutional sclerosis

As pointed out by Caballero and Hammour (2000), institutions themselves are outcomes of a variety of factors which may affect economic growth indirectly.

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[13] Having examined the role of education in technological diffusions Dowrick and Rogers (2002, p. 380) state that schooling does not seem to capture all the relevant aspects of “social capability”. They note that technological convergence within the OECD countries is three times as fast as among all countries.

In the quest for a general explanation as to why growth rates differ substantially across countries, Olson (1982) adopts an approach that goes beyond the boundaries of economics into history, sociology and political science. According to his theory a long period of political stability lays a foundation for the formation of distributional coalitions that are harmful for growth. These institutions put much effort into rent-seeking that is unproductive from the point of view of the nation.

Crafts (1992) reminds us that institutions may develop differently in an open country where a large proportion of production is exposed to global competition for natural reasons. It is unprofitable to try to seek rents in industries where they are squeezed by hard global competition. On the other hand, if government secures the competitiveness of industries by subsidies or by an active exchange rate policy it may also pave the way to the formation of stronger rent-seeking coalitions. It is also worth remarking that when coalitions are strong and encompassing, the costs of rent-seeking behaviour are internalised.

In Olson's view, only a major political disruption, such as occupation by a foreign power or times of totalitarian regimes, can dismantle the powers of vested interests. Of course, a major economic disaster may destroy sclerotic institutions, too. Williamson (2000) remarks that there are a lot of parallels in hierarchies of firms and nations. Some firms or nations may be unable to adopt new technologies because distributional coalitions within them make them inefficient.

2.3 Heterogeneity of firms and plants

Firms and plants are very different even within narrowly defined industries. They use different technologies and have varying productivity levels and productivity growth rates. Furthermore, there are disparities in growth among firms and plants in terms of employment and capital, that is to say there is a reshuffling of input shares at the micro-level. These aspects should be taken into account in the analysis and in the measurement of industry productivity growth.

As Greenwood and Jovanovic (2001) note, economic progress entails three types of costs that need to be met. Usually (1) *invention costs* are required before a new technology is added to society's menu. Then a new technology needs to be put in operation in the production units which incur (2) *implementation costs*. Finally, there are (3) *production costs* when goods are produced by using various inputs and some technology. The maximisation of a society's welfare calls for efficiency (and cost minimisation) at all three stages. Overall, implementation costs are high and thus a society's total performance is much dependent on its efficiency in implementing new technologies. One of the main hypotheses of the present study is that plant-level restructuring is essential for the efficient implementation of new technologies.

At the micro-level economic development is likely to involve a lot of selection and experimentation. Only a proportion of firms end up spending resources on efforts to create new techniques. Only some of these manage to generate new technological knowledge. Only a proportion of new technological knowledge has economic value and only a proportion of firms and plants are able to implement new technology in an efficient way.

Skills are certainly important at all stages of the growth process, but their role may vary. Engineers may be those whose job is to build the production process at the early stage of a plant's life cycle (Adler and Clark 1991 and see Greenwood and Jovanovic 2001). Bartel and Lichtenberg (1987) show that educated workers have a comparative advantage in implementing new technologies, but the demand for educated workers relative to less-educated workers declines as the experience pertaining to a new technology accumulates. So there are reasons to expect that high education is relatively more important during the early stages of a plant's life cycle.

In the following sub-section I review several explanations for why firms and production units even within a specific industry may use different technologies at a given point of time.

2.3.1 Differences in R&D efforts

Profit maximising firms try to create new firm-specific technologies by means of their R&D efforts. Firms that are initially heterogeneous in their market positions or in their innovation and adoption abilities may end up with different strategic behaviour as regards R&D efforts (see Stein 1997; Leiponen 2000). Those firms that are able to realise innovative opportunities and believe that they are able to make inventions with sufficiently low costs, are likely to be the ones who have the largest investments in the formation of technological knowledge. There are, of course, a number of factors affecting a firm's innovative opportunities and efficiency in research efforts and these factors are likely to explain the disparity in R&D intensity among firms. For example, Stein (1997) considers conditions when only entrant firms do research and when both entrants and incumbents pursue innovations.[14]

Labour skills in a firm (or within its regional labour markets) are likely to affect the propensity to pursue innovations when opportunities emerge. Certain

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[14] See Pakes and Schankerman (1984), Cohen (1995), Lerner (1997) and Klette and Johansen (1998) for discussion and further references to other relevant literature concerning heterogeneity in innovation activity.

types of skills help to realise opportunities, and skills also improve efficiency in inventing activities.

Scientific discoveries may open opportunities for technological innovations that may be industry-specific or more general. If all firms are assumed to be motivated by potential profits, but are different in terms of expected private returns on research, then an increase in technological opportunities can be anticipated to lead to greater dispersion in R&D efforts among firms. To sum up, one explanation for the heterogeneity in technology levels between firms is that they have generated technologies for themselves and have been able to protect their technologies by patents and secrecy, for example.

As mentioned in Section 2.2.4, some theoretical considerations based on the "representative firm" model yield a prediction that market-generated private R&D efforts may remain too low from a social standpoint (see Romer 1990). Aghion and Howitt (1992) introduce a "creative destruction" model. This model points out that the incentives for investment in R&D and thus economic growth are influenced by the process of "creative destruction". There is a race for rents associated with technological advancements among firms and the struggle generates turbulence. The resulting R&D efforts may be below optimal because of spillover effects. However, innovations and growth may also be more than optimal. This is because private firms do not internalise the destruction of the rents of other firms.

2.3.2 *Differences in adopted technology*

Since technology is non-rival, but only to some extent excludable, a firm is usually unable to exclusively reap all the fruits of its own R&D efforts. The corollary is that, instead of creating technology for itself by itself, a firm or a single plant may also absorb technological knowledge that is spread from other innovative firms that may be domestic or foreign. The differences in technology adoption may have various origins (see Greenwood and Jovanovic 2001). There may be differences in technological levels between non-innovating firms or plants because of diffusion lags.

2.3.2.1 Vintage-specific physical capital

An incumbent firm may postpone the implementation of a new technology, if it needs to be embodied in the capital stock and the firm is able to use just one technology at a time. As Hjalmarsson (1973) puts it, "as long as firms find themselves having non-negative quasi-rent, they have their raison d'être with their past choice". So the existence of sunk costs involved in the implementation of technology implies that high technology and low technology plants may operate side by side, even within the same company. As a consequence, the process of technological advance entails persistent technology dispersion among plants that are each stuck with their production modes and with their capital vintages. The insight that plant-level heterogeneity reflects the vintage of the installed capital is included in various models, e.g. Aghion and Howitt (1992), Caballero and Hammour (1994, 1996) and Campbell (1997) (see Foster, Haltiwanger and Krizan 2001).

2.3.2.2 Vintage-specific human capital

The implementation of new technology may require specific skills. A firm may use old vintage technology with its current workforce that has human capital specific to the old technology. Thus the scarcity of up-to-date specific skills may slow down the adoption of new technologies. Skills are likely to promote the learning of the expertise specific to new technology, as emphasised by Parenta (1994) and Greenwood and Yorukoglu (1997) (see also Caselli 1999). The vintage of the manager may also play a role (see Foster, Haltiwanger and Krizan 2001). A firm may hold off the technology upgrade because of difficulties in hiring skilled labour in regional labour markets (Chari and Hopenhayn 1991). The dispersion in technology adoption and thus in productivity dispersion may have an important regional dimension (Böckerman and Maliranta 2003).

As Greenwood and Jovanovic (2001) point out, one important difference between human capital vintage models and physical capital vintage models is that the former implies that a new plant may adopt methods inside the technology frontier.[15]

2.3.2.3 Uncertainty and search costs

Firms may have ended up making different technology choices because of inherent uncertainty about product markets or technologies. This aspect is built into the models of Roberts and Weitzman (1981), Lambson (1991) and Melitz (2002), for example. Because of uncertainty one would expect to find experimentation in the markets (see Jovanovic 1982 and Ericson and Pakes 1995).

Acemoglu and Shimer (2000) show that even if all firms (and plants) and all workers are initially identical, firms may end up using different technologies because of search costs. Identical firms end up with different choices of technology and irreversible investments in their model. In equilibrium some firms have made a

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[15] Earlier I discussed quite an analogous situation where different countries use different technology because of differences in specific knowledge accumulated through learning by doing (Brezis, Krugman and Tsiddon 1993).

lot of irreversible investments in research and have high technology and productivity. At the same time other firms have lower technology and productivity. In this model all workers are assumed to be identical but there are, however, firm-specific differences in wages that are needed to induce the search for workers. High technology firms employ "informed" high wage workers and low technology firms employ "non-informed" low wage workers. Of course, finding out the existence of new technologies, assessing their profitability potentials and exploring all the requirements for implementation may be costly to firms as well. These search costs vary between firms depending on location, networks or the capability of managers, for example. Those having the largest search costs are likely to be the last to adopt a new technology.

A firm may have low productivity because it has judged it to be too costly to collect information on the best-practise technology and how it could be implemented profitably. Knowledge diffusion has been found to involve multi-year lags among firms producing related products (Rogers 1983).[16]

2.3.2.4 Second-mover advantages

The use of a new technology involves a lot of uncertainty. It seems natural to assume like Arrow (1962) that the experience of early adopters helps the followers. Thus there are second-mover advantages that may explain why some firms choose to wait (Jovanovic and Lach 1989, Kapur 1993, see Greenwood and Jovanovic 2001).

2.3.3 Organisational capital

Jovanovic and Rousseau (2001) argue that some of the good technologies are appropriated by the new firms of their day (see also for example Caballero and Hammour 1994 and Campbell 1997). The technology is embodied in organisational capital that makes a group of people and tangible assets more productive together than apart. Jovanovic and Rousseau count firm-specific human capital (Becker 1962), management (Prescott and Visscher 1980) and physical capital (Ramey and Shapiro 2001) and a co-operative disposition in the firm's workforce (Eeckhout 2000) as forms of organisational capital. A distinctive feature of organisational capital is that it is worth more to the firm than it is to other firms. It seems that the concept of organisational capital may be useful when explaining productivity differences between different plant cohorts as well. But certainly much of the technology is

[16] Technology diffusion in Finland is studied in several papers of the book edited by Vuori and Ylä-Anttila (1992).

firm-specific and thus the owner of a plant should matter as well. Maliranta (1999) finds that if a plant's productivity level is high, this situation is usually repeated in the owner firm's other plants in the same industry. One possible interpretation of this result is that the good organisational capital of the owner firm makes its plants more productive.

2.3.4 Heterogeneity in (measured) productivity levels

In practise, researchers do not usually observe the technological level of a firm or plant directly, but they may compute indicators of the productivity level that are wavering indirect reflections of the technological level. The productivity levels of the firms or plants that use identical technology may vary for various reasons. As is widely known, labour productivity may be a particularly inaccurate measure of technology because it is dependent on the ratio of capital to labour that may vary between units (see Equation (2.6)). A more comprehensive multi-factor or total factor productivity indicator may also fail to gauge the technological level of a unit for a number of reasons.

2.3.4.1 Measurement errors

Comprehensive micro-level data sets unavoidably include some inaccuracy in the numbers. The measurement error may be classical, i.e. uncorrelated with the characteristics of interest or not. Certain variables are particularly vulnerable to measurement problems. The capital input measure is certainly one of the most problematic ones. Quite usually the capital input measure is computed on the basis of investments made in the past. The investment information may be unreliable. Moreover, the time series of investments may be too short so that a researcher needs to estimate the initial stock of capital to which subsequent investment flows are accumulated. A firm may also use rented capital and thus a researcher should be able to compute the estimates for rented and owned capital on a comparable basis. Often a firm's or plant's capital input measure includes owned capital only. To the extent that the ratio of rented capital to owned capital varies systematically between units, the analysis is subject to some bias. New firms or plants, for example, may use a larger proportion of rented capital than older ones because of liquidity constraints. Of course, some techniques of productivity and efficiency measurement are more sensitive to noise in data than others.

2.3.4.2 Capacity utilisation

Some of the factors of production are (quasi-)fixed in the sense that it is costly to adjust the amount of input employed in the unit according to changes in demand and production. So, the productivity level of a profit-maximising firm may appear low at a certain point of time, because utilisation of inputs is temporarily (and optimally) low. Similarly, the utilisation of inputs may sometimes temporarily exceed the sustainable long-run level, so that a productivity indicator may give too favourable picture of the underlying productivity performance.

Plants may have spare capacity for reasons that are not related to uncertainty or business fluctuations. Irreversibilities and related non-convex costs involved in investments may induce a firm to create spare capacity. The costs of investing may vary between different types of inputs and thus the ratio of inputs (e.g. capital intensity) may vary over time. Jovanovic and Stolyarov (2000) present a model in which investment in lumpy items (plant or capital) precede investment in other input which are more smoothly adjustable. Their model shows that investments may be asynchronous even when they are extremely complementary. If capital investments involve large fixed costs, firms may first build excess capacity. Thus at first it may seem that capital is used inefficiently, but efficiency may improve at the same time as other factors of production are acquired over time.

2.3.4.3 Learning the potential of a technology

A plant or firm may have a low productivity level despite modern advanced technology, because it lacks expertise on how to use it efficiently. As a consequence two plants using the very same technology may have different productivity levels, because of the differences in the accumulated specific knowledge. As discussed above, Krugman (1987) has provided an explanation for cross-country differences by following analogous reasoning. The importance of learning the technology at the plant level has been emphasised by Bahk and Gort (1993), Greenwood and Yorukoglu (1997) and Greenwood and Jovanovic (2001), for example.

2.3.4.4 Technical inefficiency

Leibenstein (1966) argued that units similar in all relevant aspects may have different productivity levels due to differences in X-(in)efficiency. As has already been pointed out, a sharp distinction between low relative technological levels and X-inefficiency is difficult to draw, and this is especially so when technology is given, as is sometimes useful, a broad interpretation including e.g. managerial skills. The difference is important to keep in mind, however. Borenstein and Farrell (2000) put it strongly: “X-inefficiency is surely among the most important topics in microeconomics”. Borenstein and Farrell (1999) argue that organisations do not generally minimise costs or maximise value. There is sheer inefficiency and rent dissipation. Hicks (1935) once stated that “the best of all monopoly profits is a quiet life”.

2.3.5 Heterogeneity in productivity growth

Plants and firms are different not only in terms of productivity levels but in terms of productivity growth as well. Much of this variation is random and uninteresting; a consequence of measurement inaccuracy or the idiosyncratic differences in capacity utilisation changes between units. However, some of the differences in productivity growth rates can be expected to be systematic. For example, productivity may grow particularly fast among relatively new plants, because they are learning the technology. Quite analogously, plants that have a low productivity level because of X-inefficiency may be able to exhibit extra growth when upgrading their conduct.

2.4 Elements of productivity-enhancing micro-level restructuring

In this section I will discuss some issues that can be expected to be related to the intensity of productivity-enhancing restructuring. The magnitude of productivity-enhancing restructuring is dependent on two factors:

1. How large is the initial productivity dispersion between plants and

2. how strict is the relationship between the productivity level and the subsequent growth of input usage?

The previous section considered the factors behind productivity dispersion. In this section the factors affecting the relationship between productivity level and growth are discussed. The role of competitive pressure is emphasised. It should be stressed that the effects of high competitive pressure may be of two kinds. It may provide firms with an urge to innovate and thus may induce internal adjustment within firms, but it may also lead to selection among firms. How the intensity of micro-level restructuring is reflected in various indicators is considered later. I will also present some considerations of the roles of institutions. I will give a short review not only of the Finnish wage bargaining system that involves centralised agreements on wages and working conditions, but also of bargaining at the level of industry, firm and plant.

2.4.1 The nature and roles of competition

Baldwin (1993) distinguishes two different conceptual approaches to the notion of competition. The more traditional and widely adopted approach is to look at the market structures. An alternative view sees competition as a dynamic process.

The intensity of competition in its more traditional meaning is typically evaluated by indicators such as the number of firms, concentration, advertising ratios, etc. If these measures can be shown to be related to cross sectional differences in profitability, one could argue that they can be used for assessing the intensity of competitive pressure. This static perceptive has a very long tradition in the analysis of how much imperfect competition causes welfare losses due to distorted output prices. Leibenstein (1966) in turn emphasised the role of X-inefficiency. For example, the factors of industry inefficiency in six countries (United States, Japan, Britain, Canada and Australia) have been studied in several papers in a book edited by Caves (1992). The studies investigate various potential determinants of inter-industry differences in efficiency such as competitive conditions (concentration), organisational factors (e.g. prevalence of trade-union organisation), structural heterogeneity (e.g. product differentiation), dynamic disturbances (e.g. some units incompletely absorb technology shocks created by innovation) and regulation.

The productivity differences between firms within a nation or across nations at a given point of time are so great that one might wonder whether this is truly because some of them fail so badly to use their existing production possibilities efficiently. Another interpretation is that they have different technologies, because of differences in their ability to develop and implement new technologies (see e.g. Caselli and Coleman 2002). Observed discrepancies in the productivity performance levels across countries may be consequences of long-lasting dynamic or Schumpeterian inefficiencies that involve a technology race among firms with innovations on the one hand and efficient and productivity-enhancing reallocation of resources between firms (i.e. selection) on the other hand.

When one adopts the dynamic approach, mobility measures provide us with a potentially useful indicator of the intensity of competitive pressure. Simultaneous occurrences of declines and rises within an industry suggest that there is a competitive struggle taking place. Another alternative is to use variables such as import penetration or exposure to global competition (e.g. Baily and Gersbach 1995; Blundell, Griffith and Van Reenen 1995 and Nickell 1996) or to look at what happens to productivity after deregulation (e.g. Tybout and Westbrook 1995; Bottasso and Sembenelli 2001).[17]

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[17] Many Finnish industries, e.g. the paper industry and basic metal industry, have been exposed to global competition for a long time. It may be the case that these industries were not so seriously affected by the increased deregulation that took place in the mid-1980s. Another important turning point in Finnish economic history was the year 1992 when Finland joined the EU. This caused a substantial change in the competitive environment in the food industry, for example. All in all, it seems that there has been a substantial amount of variation in competitive pressure both over time and across industries. Evidence of this will be seen in Chapter 8, where the intensities of import penetration in the period 1975-1998 by industry are depicted.

A major insight emphasised by Boone (2000) and advocated by Aghion et al (2002) is that the intensity of competition can be assessed from the standpoint of how strict the relationship between technical efficiency and profit level is. According to this view, an increase in competitive pressure will improve the competitive position of high productivity firms relative to low productivity ones.

Aghion et al (2002) provide us with a framework by which they show that the relationship between the rate of innovation and product market competition is inverted U-shaped. At a low level of competition an increase in competition stimulates innovation, but it depresses innovations when the level of competition is high. Using the concepts of Boone (2000), firms may become "fainted", because they are so much behind the frontier that there is no chance of being rewarded in the struggle in a very competitive environment. Or if they are very superior, they may become "complacent" and cut down innovations because they will win anyway.

Above, the role of technology and productivity dispersion in productivity enhancing restructuring was considered. Aghion et al (2002) use an expression "technological closeness". They show that the more levelled an industry is in terms of technology the more probable it is that an increase in the intensity of competition will stimulate innovations. When firms are very similar they have great incentives to "escape competition" by innovation.

Boone (2000) states that an increase in competition may raise industry productivity through the adaptation effect. Firms improve their efficiency. This involves internal adjustment in the plants and is reflected within plants in productivity growth. A second channel works through the selection effect. Competition selects more efficient firms from less efficient ones (see Section 2.4.2 below).

As for suitable indicators of competition Aghion et al (2002) give a useful characterisation of competition:

'*… any parameter increase that would result in increasing the relative profit shares of more advanced firms, that is the profitability of a greater technological lead, would be a suitable measure of product market competition*'.

Boone (2000) considers some factors of competitive pressure by examples. One is the degree of substitutability between the products of firms. Competitive pressure is increased as goods become closer substitutes. The number of firms is another factor of competitive pressure. Thirdly, Boone also shows how the competitive pressure of a firm increases when its competitor becomes more efficient.

The fourth example is interesting from the standpoint of evaluating the role of labour market institutions in productivity development. All firms in an industry are assumed to share the same wage levels. A general increase in wage levels leads to higher competitive pressure. It is possible that higher wages raise firms' incentives to improve productivity by innovations (see e.g. Porter 1990). Boone does not, however, consider the effects of wage dispersion or positive correlation between wage and productivity levels between firms. These are other important aspects of different labour market institutions. Obviously, competitive pressure is decreased if the wages of low-efficiency firms are lowered and the wages of high-efficiency firms are increased correspondingly (see Hibbs and Locking 2000). The selection effect is diminished and the incentives for innovation are reduced among both low and high efficiency firms. Progressive profit taxation and subsidisation of low productivity firms can be expected to negatively affect the competitive pressure as well.

2.4.2 Selection between units and reallocation of the factors of production

So selection is one of the channels through which competition may boost industry productivity. The struggle in competitive markets leads to the appearance and expansion of some units at the cost of the decline and disappearance of others. According to the view held by Boone, the declining units are usually inefficient when the intensity of competition is high. In this study a lot of focus is put on restructuring in terms of input usage shares, that is to say we are particularly interested in the differences in the growth of labour and capital that are the two main factors of production of a nation. Due to the inherent uncertainty that is typical of productivity improving activities, there will be a lot of selection and restructuring between successful and unsuccessful firms and plants.

Various types of life cycle models of firms pay attention to the role of experimentation, selection and learning in the restructuring process. In the passive learning model by Jovanovic (1982) a firm makes an entry in order to see whether it has qualifications for profitable activities. On the basis of the information it has gained from the markets, it decides to expand, contract or exit. One important implication of this model is that there is a lot of productivity enhancing-restructuring especially between the younger firms. Indeed this seems to be the case also for Finland according to the results documented by Maliranta (1999, p. 401).

In the active learning model by Ericson and Pakes (1995) a firm makes investments to improve productivity and profitability. Competition continuously discriminates between winners and losers; the former gain and the latter lose market shares. According to this model, firms endeavour to develop the performance level of their plants throughout their life-cycles by R&D investments, for example.

Achieving productivity gains by new technological knowledge requires implementation and embodiment at the plant level. One form of vintage capital model states that only new establishments can adopt new technology (see also Section 2.3.2). This approach emphasises the role of entry and exit (e.g. Caballero and Hammour 1994 and 1996, Campbell 1997). However, even though new technology is embodied in new capital, it can also be implemented among continuing plants through retooling (see Cooper, Haltiwanger, and Campbell 1997). The ability to extend existing technology with more modern technology may, however, vary across different types of plants. Given the cumulative nature of technological progress, as outlined for instance in the model of Klette and Griliches (2000), one would nevertheless expect modern technology to be more easily integrated with relatively new technology vintage and equipment capital than with its older equivalent. Campbell and Fisher (1998) argue that young plants have greater organisational flexibility than old plants, which is likely to be crucial in technology adoption. This insight again indicates that not only new, but also young, plants can be expected to have a central role in the selection process.

Ilmakunnas and Maliranta (2000 and 2002) provide empirical evidence for Finnish manufacturing and the private sector as a whole that relatively new plants had a higher job creation rate and net employment growth compared to older ones. On the other hand, they have also had higher job destruction rates. So there seems to be a selection process in operation among relatively new units (see also Davis, Haltiwanger, and Schuh 1996). However, the updating of the technology may have to be supported by new workers with modern skills and changes in the workforce composition. This is in agreement with the findings on worker flows by Ilmakunnas and Maliranta (2002).

In summary, we have good reason to expect that

1. waves of intensive innovation activity are followed by periods of intensive experimentation and selection, and

2. these will focus more on young plants.

Successful adoption of modern technology is reflected in rapid productivity growth in the plant in question. These plants can be expected to be more often new than old. On the other hand, new plants are usually relatively small (see Maliranta, 1997b, p. 13, for example) and therefore these technological advances are not necessarily reflected clearly in aggregate productivity development.

2.4.3 Product markets

The idea that the functioning of economic and political institutions may be important for the static and dynamic efficiency[18] which determines current and future productivity is by no means new. Olson (1982) states that institutional sclerosis may stifle economic progress.

The potentially important role of competition in product markets in the context of inefficiency was pointed out above (see Boone 2000). Reforms that lead to increased competitive pressure in product markets among firms and plants can be expected to eventually lead to more productive use of resources and increased living standards. This may come in the form of internal adjustment (e.g. firms and plants eliminate inefficiencies that may occur in their operations) or in the form of external adjustments[19] (the share of firms and plants incapable of using resources efficiently is diminished). As shown by Olley and Pakes (1996), the regulatory process in the manufacture of telecommunications equipment appears closely related to factor reallocation and productivity movements in the United States. Among others, McKinsey Global Institute (1996) stresses the importance of encouraging product market competition, lowering barriers to entry and pruning regulations.

Exposure to global competition can be expected to increase competitive pressure in the sense defined by Boone (2000). Greater imports usually means that domestic firms face a larger number of competitors who usually have higher technical efficiency. Exports can be expected to have a central role to play as well. Bernard, Eaton, Jensen and Kortum (2000) argue that international trade plays an important role in determining which firms are capable of surviving and expanding. The lowering of trade barriers is apt to filter out low productivity plants while giving opportunities to high productivity plants to sell more abroad. This is to say that increased outward-orientation is likely to bring about micro-level restructuring (see also Clerides, Lach and Tybout 1998; Bernard and Eaton 1999). This insight is built into a dynamic industry model by Melitz (2002). He argues that international trade does not reshape micro-structures in terms of productivity among firms, if increased import competition is not accompanied by new export markets for high productivity firms.

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[18] Wihlborg (1998) discusses the properties and requirements of static and dynamic (or 'Schumperian') efficiency.

[19] Levinsohn and Petrin (1999) denote this the "rationalisation case".

2.4.4 Capital markets

Börsch-Supan (1998) asserts that without capital market pressure, unproductive firms will not exit even in the face of hard product market competition. If investors allow bad capital management in a firm, the lack of capital market pressure is likely to lead to bad conduct in the effectiveness of operations, product-line management, pricing, capital purchasing decisions, and industry chain management. At the national level this means that some resources are wasted because of bad management. This issue is important, for example, as different countries have had quite different institutions for capital markets.

Richards (1998) stresses that active owners are needed in order to encourage corporate efficiency in the usage of capital and the allocation of resources to those with the best ability. Institutions are likely to have a decisive role in how well the interests of the owners are taken into account. Ramey and Shapiro (2001) find evidence that there was a significant increase in capital reallocation across firms and industries during the 1980s and 1990s in the United States with significant economic consequences. In particular, their results seem to indicate that increased capital reallocation has increased labour productivity growth.

Sometimes US financial markets are blamed for focusing on the short term, as opposite to those of Japan. Recent experiences in Japan, however, suggest that excessively passive patience may eventually jeopardise long-term economic performance, too.

The conditions for capital reallocation at the micro level have changed considerably since the early 1980s in Finland.[20] A large number of steps were taken to deregulate financial markets especially from the mid-1980s. For example, free long-term foreign borrowing for manufacturing and shipping companies was allowed in 1986. Regulation of lending rates was abolished in the same year (see Vihriälä 1997).

The Finnish financial system used to be very bank-centred before deregulation. A firm's financing was usually based on a long-term relationship with a certain bank (see Hyytinen and Kauppi 2002). Sometimes banks were quite patient with their inefficient and unprofitable client firms. The dominance of a few banks combined with widespread cross-ownership echoed the Japanese keiretsu system. It may have led to sclerotic structures at the micro level.

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[20] Hyytinen and Kauppi (2002) argue that changes in the Finnish financial markets have contributed to changes in industry structures. The increasing dominance of market-based financial markets, and of venture capital in particular, has increased opportunities for innovative firms to finance their efforts, which in turn has changed industry structures. Of course, we might expect that the development of the financial markets has stimulated restructuring within industries as well.

Liberalisation steps taken in the financial markets have contributed to an increase in competition in the financial markets. Increased competition and new financing sources opened up opportunities to finance the growth of many firms (and their plants) in the latter part of the 1980s. Indeed, manufacturing investments surged sharply for the years 1987-90. It is probable that this also involved restructuring of capital input shares at the plant and firm level.

2.4.5 Labour markets

Labour is another important factor of production. The functioning of labour markets has attracted a little more notice than that of capital markets in the context of assessing the economic performance of nations. Rigidities in labour markets have often been seen as one of the predominant factors behind the recent economic problems in many European countries (see Caballero and Hammour 1998).

The determination of wages in the "Scandinavian model" within the framework of wage agreements that are negotiated between government, employers and the major trade unions differs considerably from that of the United States. Uniformity in wage increases or even efforts to compress wages have obtained more emphasis at the cost of considerations of the firm's or industry's profitability or "ability to pay". Hibbs and Locking (2000) point out that the central union pay policy may explain at least partly why wage levels across firms and industries in Sweden exhibit no "non-competitive" correlations with profitability, average productivity and capital intensity. This would mean that identical workers (with identical working conditions) receive the same wage irrespective of the profitability, productivity or capital intensity of the industry or firm.[21]

Graph 2.1 illustrates the types of wage settlements that were in force in Finland in the years 1969-2001 according to Marjanen (2002).[22] We see that in 1970-1983 the coverage or tenability of the centralised agreements was not good (1971 and 1976) or that the agreements were made at the industry-level (in 1973, 1980 and 1983). In the period 1984-1987 centralised agreements were in force and both their coverage and tenability were good. In 1988 the agreements were made at the industry level and in 1989 a centralised agreement was made but its coverage and tenability was weak. Since 1992 there has been a centralised agreement in force with a few exceptions, as agreements were made at the industry level in 1994, 1995 and 2000.

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[21] The role of collective bargaining, institutional wage compression and growth is discussed also in Flanagan (1999, see especially pp. 1163-1164).

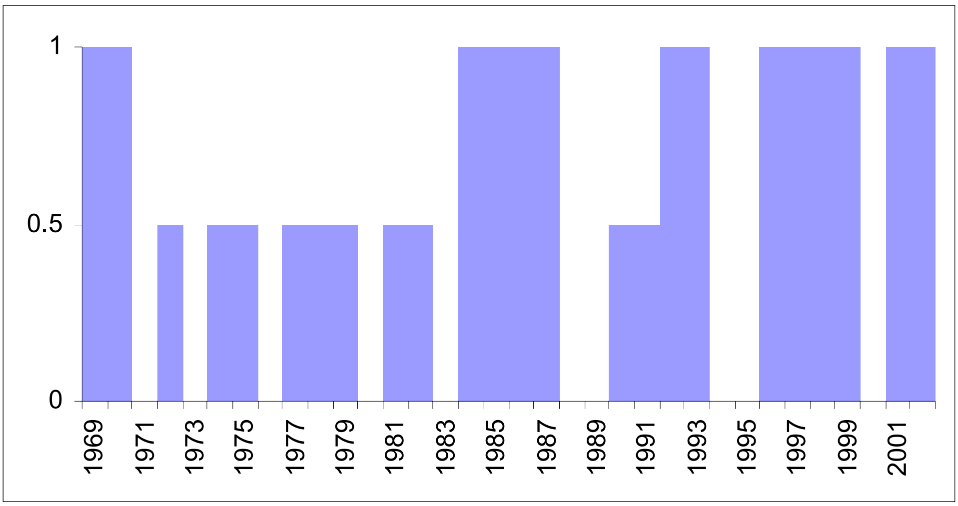
[22] The whole description of the Finnish wage settlement system draws heavily on the work by Marjanen (2002)

A few points are worth mentioning. Strictly speaking, the collective settlements are always made at the industry level. The role of centralised agreements is to co-ordinate and give limits for wage increases.

Secondly, even when a formal centralised agreement is not made this does not mean that there is no co-ordination and pressure for some uniformity among industry settlements. For example, industry agreements are usually negotiated at the same time, which may present an obstacle for a single industry union to try to take off.

Thirdly, the actual wage increase is usually more than the agreed wage increase. As a rule, the agreements define the minimum wage increase for each firm within the same industry. However, each firm may increase wages more if they feel a need for it in order to attract workers, for example. This is reflected in the so-called "wage drift". Marjanen (2002) finds a negative relationship between the negotiated wage increase and wage drift.[23] Further, the estimation results of that

Graph 2.1 Characteristics of the collective agreements on terms of employment in 1969-2002



Note: '1' denotes that a centralised agreement is in force, whose coverage and tenability is good, '0.5' denotes that a centralised agreement is in force, whose coverage and tenability is satisfactory and '0' denotes that agreements are made at the level of industry or that coverage or tenability of a centralised agreement is weak according to Marjanen (2002).

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[23] This is in contrast with the findings made for Sweden by Hibbs and Locking (1996) and for Norway by Holden (1998) who found no relationship between negotiated wage increases and wage drift. In other words, those results do not give support to the view that sizeable wage drift offsets the effect of centralised negotiations (see also Pehkonen and Viskari 1994).

study suggest that a high employment ratio and high inflation lead to large wage drifts. An important finding is that no statistically significant relationship was found between profitability change (or productivity change) and wage drift.

Fourthly, agreements and recommendations made after centralised bargaining give mainly general guidelines for wage increases. Other terms of employment are determined largely at the industry, firm or plant level or even at the individual level.

Acemoglu and Shimer (2000) assess that when there is no wage dispersion, workers do not search enough, and there is a less than an optimal amount of competition for labour. An alternative point of view is that if wages are compressed by, for example, collective agreements, the greater mobility is a result of the fact that there is no "extra tax" for plants capable of using resources efficiently and no "allowance" for inefficient ones. In this type of environment workers try to find new jobs because they have been laid off or feel the threat of losing their jobs shortly.

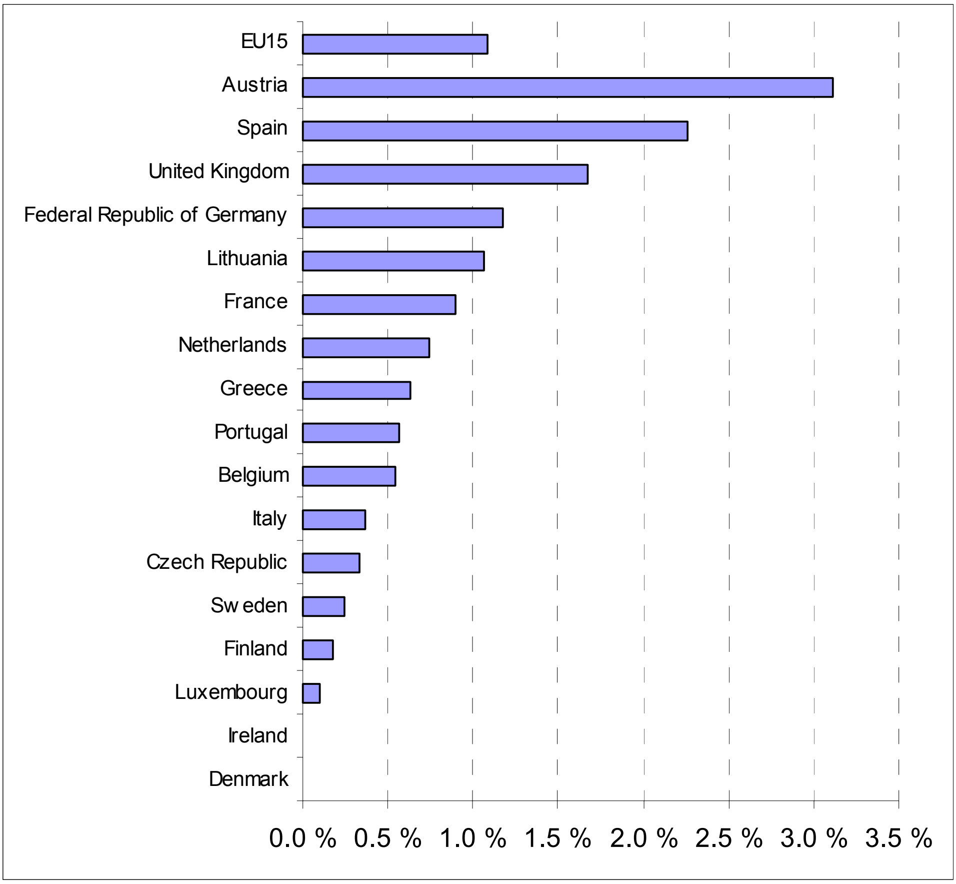
Bertola and Rogerson (1997) point out that the restrictions (firing cost policies) in the labour markets are usually implemented together with wage compression policies. Although wage compression per se can be expected to increase job reallocation, the fact that it is often associated with stricter dismissal restrictions may eliminate the effect. This is an important aspect as a "tax" on job destruction may be harmful to industry productivity. Hopenhayn and Rogerson (1993) show with a general equilibrium model that firing costs reduce steady-state employment, but even more importantly bring about a significant decrease in average labour productivity. The tax on dismissals reduces the job turnover rate and variance in growth rates. The tax on job destruction leads to inefficient use of resources and the welfare loss due to this is sizeable.

However, good social security offered by the government may make the insider workers more agreeable to low statuary labour protection. One distinctive feature of the "Scandinavian wage model" is that employment protection is at a substantially lower level than in most Central or Southern European countries. Graph 2.2 tells that firing costs are comparatively low in Sweden, Finland and particularly Denmark (see also Westergaard-Nielsen 2002). The OECD (1994) gives a broadly similar picture of the level of employment security in firms, the main discrepancy being that Great Britain appears to have lower security than Finland. From this perspective we would expect that the Finnish economy is more exposed to micro-level restructuring than are the Central and Southern European countries.

Although one should be extremely careful when making cross-country comparisons of job or worker flows, it seems that these flows in the Scandinavian countries are comparable to those of the United States, for example (e.g. Davis and Haltiwanger 1999). The analysis by Ilmakunnas and Maliranta (2003c) shows that the Finnish labour market is quite flexible in terms of job and worker flows.

Although wages are settled at the industry level, firm-specific assets generate an ex post bargaining problem over surplus. Rational workers may collude at the plant or firm level to obtain a surplus-share in nonpecuniary form through restriction of effort, as pointed out by FitzRoy and Kraft (1987). This leads to a two-tier bargaining system, where the outcome of the second round is reflected in wage drift. Profit sharing systems can be seen as a reflection of the local bargaining element in the system. These systems have become increasingly common especially in the latter part of the 1990s. As late as 1994 only 15 percent of manufactur-

Graph 2.2 Payments to employees leaving the enterprise, per cent of total labour costs



Source: Eurostat, New Cronos-database, Survey 1996.
Note: Firms with at least 10 employees.

ing workers were covered by profit sharing systems, but by 2000 this had increased to 34 percent (Uusitalo 2002; see also Kauhanen and Piekkola 2002). So even though centralised wage settlements were usual in the 1990s, wage determination at the local level seems to have become increasingly common towards the end of the millennium. Firms where profit sharing systems are adopted are usually large, capital intensive and profitable and they have a lot of highly educated, high wage workers. So these firms have (quasi)-fixed rents and workers capable of rent-seeking behaviour.

It should be noted, however, that it is employers who have normally been more positive to profit sharing and local bargaining than employees. Uusitalo (2000) documents that almost 80 per cent of respondents[24] feel that local bargaining has had a positive effect on productivity and almost 70 percent of respondents believe that it has improved profitability. More than 90 per cent of respondents consider that local bargaining has been beneficial for employers and about 90 per cent that it has been useful to employees.

Econometric analysis made with Finnish data suggests that adoption of a profit sharing system improves productivity by 10 per cent according to Uusitalo (2002) and 6-13 per cent according to Kauhanen and Piekkola (2002). So these systems seem to have positive incentive effects among workers. They also incur expenses for firms, while belonging to this system increases wages by 3 per cent for white-collar and 13 per cent for blue-collar workers according to Kauhanen and Piekkola (2002). Thus, it seems that profit sharing induces efforts among workers and this is compensated in wages. Statistical evidence hence indicates that the adoption of profit sharing stimulates productivity within firms. Further, statistical evidence suggests that these systems are profitable for firms. However, controlling the reverse causality between profit sharing systems and productivity (and profitability) with statistical methods is a challenging task and thus the results should be interpreted with great care.

Local bargaining probably increases flexibility in terms of relative wage levels between firms and the correlation between profitability and wage level. Uusitalo (2000) finds evidence that local bargaining may smooth out fluctuations in labour demand. Furthermore, the results by Uusitalo (2002) indicate that local bargaining has an independent negative effect on labour turnover within firms, when wage level and various labour characteristics are controlled. All in all, it may be the case that firm (and plant) level restructuring may be declining in Finland as local bargaining is becoming more popular. How this will affect industry productivity is an important research question.

[24] The respondents of the survey consisted of 522 employer representatives and 950 employees.

Caselli (1999) argues that technological revolutions in the form of the appearance of new types of machines can be expected to lead to segregation. When a skill-biased revolution comes into being, high skill (and high wage) workers will occupy high productivity plants that have new generation machines. Low skilled workers (or those uninformed about technology possibilities, see Acemoglu and Shimer 2000) will continue to use the old machines. An alternative explanation is that the widening dispersion in plant productivity levels will lead to an increase in between plant wage dispersion because of rent sharing (or differences in "ability to pay"), for instance.[25]

When viewed from the framework outlined by Caselli (1999), we would expect that, in the "Scandinavian wage model", workers using old machines will have to leave their jobs sooner after a technological revolution because of the shutdown of unprofitable production units. Of course, if these workers were using old machines because of inferior (or dated) skills, some adjustment problems are likely to occur, especially if the upgrading of skills is costly and time-consuming. It is possible that some become unemployed, at least for a while, in the process of reallocation (see Aghion and Howitt 1994, and Hall 1995).[26]

So during rapid technological progress, worker mobility may be worthwhile as the greater exposure to modern technology in modern high productivity plants may fuel a faster upgrading of modern skills through learning. "Creative destruction" among low productivity plants incapable of paying high wages may hamper the segregation process with the provision that these workers will not become permanently unemployed. Cross-matching of (initially) low skill and high skill workers in high productivity plants may promote an increase in the average skill level in the nation. This can be expected to occur if the lower-skilled are able to learn from higher-skilled co-workers. On the other hand, Kremer's (1993) so-called "O-ring theory" emphasises that the effectiveness of an entire production operation is limited by the least efficient input. According to this view, cross-matching might lead to losses in production, if the upgrading of low skills is not quick enough.

Hibbs and Locking (2000) maintain that the reduction of inter-industry wage differentials in Sweden has contributed positively to aggregate output and productivity growth. The unemployment records of Sweden, Finland and other Scandinavian countries, at least up to the early 1990s, suggest that the rise in the unemployment rate is not an inevitable consequence of the greater external adjustment that wage

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[25] Aghion, Caroli and Garcia-Penalosa (1999) provide a comprehensive survey on the literature concerning inequality and economic growth.

[26] There do not seem to be very large differences in job reallocation between European and US economies, but worker flows into unemployment and from unemployment are much more voluminous in the United States (see Pohjola, 1998b, 31-36).

compression is likely to generate. On the other hand, it is possible that until the early 1990s the Scandinavian countries had not confronted such abrupt technological revolutions or allocation shocks that could not have been handled with active labour market programmes.

2.4.6 The match of institutions

Of course, in practise the management of labour and capital inputs is so intrinsically interwoven that there is no point in deliberating which one to blame if overall productivity performance lags behind the benchmark conduct. Capital productivity is affected by work practices (Börsch-Supan 1998, 209) that in turn may be subject to bargaining (Haskel and Sanchis 2000). Efficient labour markets may be needed so that managers are able to make sound investments and make best use of the available assets (Richards 1998).

Caballero and Hammour (1998) argue that the failure of European labour institutions to operate in the presence of appropriability of specific quasi-rents explains recent trends in unemployment, labour share, profit rates and capital productivity. Attempts to appropriate capital have induced substitution of capital for labour. They state that deregulation and the integration of EU product and financial markets may have, in the absent of commensurate labour market reforms, reinforced unsound tendencies. This is because the steps that have been taken have probably enhanced factor substitution possibilities.

2.4.7 Wage dispersion between plants and micro-level restructuring

The above discussion has already introduced three separate perspectives on the role of wage dispersion in plant-level restructuring. These hypotheses are not mutually inconclusive, but yield somewhat different predictions concerning the relationship between wage and productivity dispersion between plants. Furthermore, policy implications may vary to some degree.

2.4.7.1 Wage dispersion induces reallocation

One strand of reasoning is based on the idea that dynamic wage differentials might be needed to guarantee optimal reallocation between sectors and ultimately between firms and plants (see Bertola and Rogerson 1997; Acemoglu and Shimer 2000).

Search induced by wage dispersion may be important for both external adjustment and internal adjustment. Regarding external adjustment, wage dispersion may fuel labour reallocation that is important especially for high R&D intensity firms so that expensive vacancies created by costly irreversible investments do not remain unfilled. On the other hand, search activities reduce firms' monopsony power and drive wages up. Harder competitive pressure is likely to impede X inefficiency through internal adjustment.

Acemoglu and Shimer (2000) emphasise that although workers are able to extract rents generated by fixed costs, the outcome may nevertheless be optimal. This view seems to be in sharp contrast with those considerations where intra-firm bargaining over wages or rent sharing leads to distorted investments (see, for example, Acemoglu 1996). The crucial point here is whether wages are set before or after the match, as pointed out by Acemoglu and Shimer (2000).

If variation in wage dispersion reflects changes in the need to induce the reallocation of labour, we might expect that changes in wage dispersion precede rather than follow changes in productivity dispersion. Firms that have invested in high technology set high wage levels. As it is likely to take some time to build the process and as lots of productivity potentials are materialised with a delay (because of the need to learn new technology, for example), the differences between plants in terms of productivity can be expected to arise later.

2.4.7.2 Rent extraction curbs micro-level restructuring

Caballero and Hammour (1996) emphasise the difficulties in writing and enforcing complete long-term contracts that might be needed in the presence of appropriable specific quasi-rents that arise when establishing new jobs equipped with the best techniques available. The "creative destruction" process is affected by the magnitude of contracting problems which are in turn dependent on legislation and institutions, for example. To the extent that the upsurge in wage inequality is a consequence of bargaining between workers and firms (or plants), it is harmful for productivity-enhancing reallocation, as the higher wages of high productivity firms/plants reduce their subsequent job creation (see Acemoglu 1996).

In this case, changes in productivity dispersion can be expected to precede changes in wage dispersion. This is because realising available (quasi-)fixed rents may take some time.

2.4.7.3 Wage dispersion as a consequence of skill-biased technological change

The waves created by skill-biased technological revolution is one possible explanation for the joint movement of productivity, wage and skill dispersion across plants over time, given by a model of Caselli (1999). In this model technological progress entails the adaptation of new types of machines at plants. A major point of the model is that when a skill-biased technological revolution occurs, high-skilled workers will be the first to use the new machines, since it is less costly for them to learn to use new machines. This model predicts segregation of labour after great technological advances. At one extreme of the distribution there are low-wage and low-productivity plants with less skilled workers and old machines. At the other extreme of the distribution there are high-productivity plants with high-wage and high-skilled workers.

Haltiwanger, Lane, and Spletzer (1999) and Ilmakunnas, Maliranta, and Vainiomäki (2003b), for example, provide empirical evidence that differences in productivity levels across plants are systematically related to differences in workforce composition. These two studies as well as Maliranta (2000), however, fail to find an unambiguous positive relationship between *changes* in productivity and *changes* in workforce characteristics. Thus there is not much empirical support for the view that improvements in productivity, due to adaptation of new types of machine for example, are positively correlated with an increase in skill level at the plant level. The failure to find a positive correlation at this point may be due to measurement errors that are likely to be particularly severe in the case of measuring changes (Griliches and Mairesse 1995), or due to problems in timing. An alternative explanation is that firms and their workforce are locked in different modes of production. This is an important point for the analysis undertaken in the present study as it suggests that plant-level restructuring is important for the efficient utilisation of upgraded skills in the economy.[27]

In Caselli's (1999) model an increase in inequality is an immediate consequence of technological revolution. He points out that it is possible that in the long run this process will lead to widespread adoption of leading-edge technology and declining inequality. The economy will also achieve high aggregate productivity performance. However, it is also possible that an economy will get stuck in a steady state in which not all skills are upgraded. There will be little productivity-enhancing restructuring. Labour markets will remain segmented and inequality will remain. In this case an economy will permanently have a long and thick tail on the left-hand side of the productivity distribution.

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[27] Leiponen (1995) and Ilmakunnas, Maliranta, and Vainiomäki (1999) find that high total factor productivity growth is positively associated with the level of education. This is consistent with the conjecture that education has an important role to play in increasing the steady-state productivity growth rate by enabling the workforce to continuously create, adopt and implement new technologies (see Benhabib and Spiegel 1994). Results by Maliranta (2000b) seem to suggest, quite intuitively, that it is the skills in the field of natural sciences and engineering that are essential from this perspective. In this analysis, by the way, the change of "non-technical" skills appears to be positively correlated with productivity growth, which supports the view that at least certain types of skills can be considered as distinct inputs in the production function. Lloyd-Ellis (1999, 67) considers the importance of institutions being able to support the adequate acquisition of technical skills.

One policy implication that arises from this perspective is that the kind of education that can support the learning of new technologies will promote a productivity-enhancing reallocation of labour.

If the technology steps are characterised by the adoption of new types of machines that are immediately more productive when run by skilled high-wage workers, as suggested by the model of Caselli (1999), we would expect wage and productivity dispersion to vary hand-in-hand. However, as it may require some time to learn by doing with new types of machines before all the potential of the machines is discovered, some delay in the change in productivity dispersion should be expected.

2.5 Indicators of plant-level turbulence

The intensity of turbulence in the labour markets is commonly characterised by job and workers flows. It has become standard to use the following definitions (see Davis, Haltiwanger, and Schuh 1996, Burgess, Lane, and Stevens 2000, and Schettkat 1996).

JC: the (gross) job creation rate; i.e. the employment change in plants that has increased employment, divided by the employment average of the initial and final years in the sector under examination.

JD: the (gross) job destruction rate; i.e. the absolute value of the employment change in plants that has decreased employment, divided by employment.

JR=JC+JD: the (gross) job reallocation rate or job turnover rate.

NET=JC-JD: the net rate of employment change.

EJR=JR-|*NET*|: the excess job reallocation rate. This is widely used as an indicator of simultaneous job creation and destruction.

In this study the focus is on the reallocation input shares between plants. The reallocation of resources that can be characterised by the above measures leads to restructuring in terms of resource shares. However, the relationship between reallocation and restructuring is not strict; there may be important restructuring not included in the reallocation indicators presented above, but which may be crucial for long-term economic development. For example, Caballero and Hammour (1999 and 2000) have emphasised the importance of considering the cumulative factor reallocation that follows a recession.

Let us consider input reallocation and restructuring in an economy that goes through a technological transformation during a recession and the subsequent recovery period (see Table 2.2). At the beginning of the recession period a technologically advanced plant employs one person and a plant equipped with an old technology employs 9 persons. Two jobs are destroyed in the latter plant during the recession. As the technologically advanced plant is able to maintain the job, the unemployment rate is 20 % in year t+1. Two jobs are created by the technologically advanced plant during the recovery period and the low technology plant is now able to maintain its remaining 7 jobs.

Table 2.2 documents the case and shows that the excess job reallocation is zero all the time. However, a substantial reorganisation of production has taken place in the period from the beginning of the recession to the end of the recovery. This very simple example shows that an incessant restructuring process is easily missed during the tumult of business conditions. The dispersion of growth rates between plants, however, indicates the presence of restructuring that is particularly intensive during the recovery period in this example.

Quite often the role of output reallocation (or restructuring) for the aggregate productivity change is analysed with micro-level data. There are two aspects that are worth noting. Firstly, input reallocation is particularly interesting not only because it is related to turbulence in the labour markets, but also because technol-

Table 2.2 Input reallocation and restructuring over two periods

	Period		
	t	t+1	t+2
Employment			
Plant A	1	1	3
Plant B	9	7	7
Sum	10	8	10
Flow rate measures			
NET		-22.2	22.2
mean of dlnL		-12.6	54.9
mean of dlnL, employment weighted		-22.3	24.4
JC		0.0	22.2
JD		22.2	0.0
EJR		0.0	0.0
standard deviation of *dlnL*		17.8	77.7
standard deviation of *dlnL*, employment weighted		7.9	45.7

Note: dlnL denotes log difference of labour.

ogy can be expected to be embodied in inputs. Second, a practical aspect is that the usual aggregate productivity indicators can be expressed as a weighted average of plant level productivity levels, where the weights are input shares as we saw in Equation (2.9).

Ramey and Shapiro (2001) have used analogous measures to measure the extent of capital reallocation. Of course, these indicators could be used for the purpose of examining the reallocations of the total input usage. This is interesting when the evolution of total factor productivity is analysed. In this case the flow analysis is made by using a composite index of labour and capital (and possibly material) inputs.

3 Micro-level sources of productivity growth

A technological step does not turn into higher aggregate productivity before some kind of adjustment in production has taken place. It may occur within plants through retooling or reorganisation of production. Or alternatively, it may materialise through the reallocation of resources between units, i.e. through external adjustment. This is the case when technology is embodied in some inputs (physical capital, organisational capital, etc.). Then the challenge of the restructuring process is to reallocate the factors used with less productive inputs (e.g. in low productivity plants) to places where they can be combined successfully with more productive inputs (e.g. in new plants where new technology is embodied).

The following section 3.1 highlights these internal and external adjustments and their relationship to aggregate productivity growth. First, I consider a situation in which the reallocation of resources is carried out by the turnover of plants through entries and exits. Later I consider a case in which resources are reallocated between continuing plants. I provide some graphical illustrations on how the rate of productivity growth and internal adjustment is likely to vary systematically between plants different in terms of vintage or the amount of X-inefficiency.

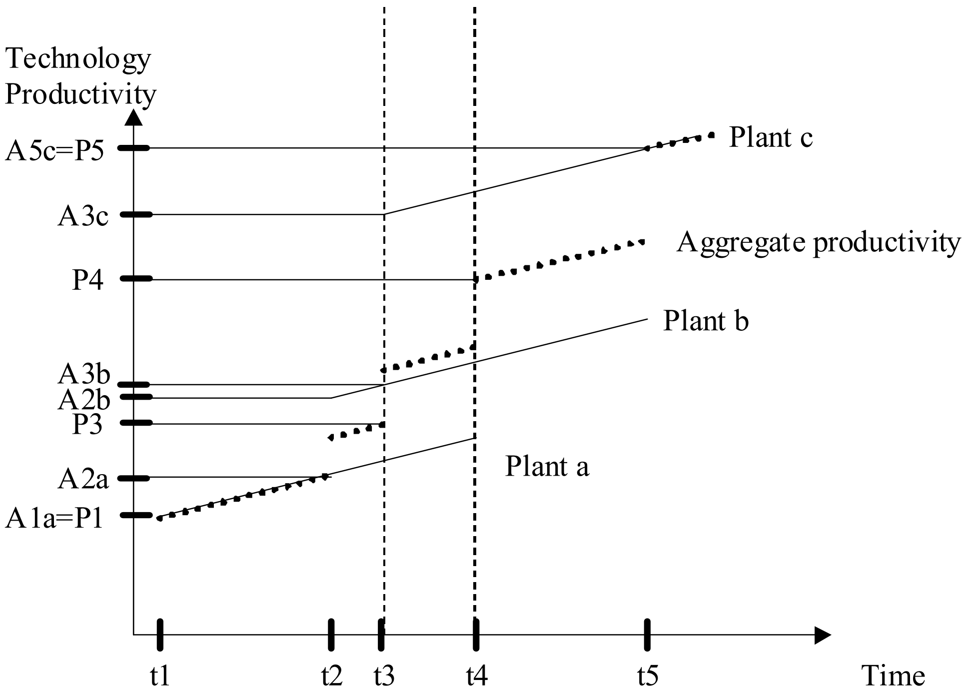
The methods of identifying and quantifying different elements of aggregate productivity evolution empirically will be portrayed in Section 3.2. I present a new variant of productivity decomposition and two versions of it. The properties of these formulations are evaluated and compared to the properties of the formulations that have been applied widely in recent years.

3.1 Internal and external adjustment

3.1.1 External adjustment through entry and exit

Graph 3.1 gives a graphical illustration of the two different ways in which productivity advances made at the level of plants may turn into higher productivity at the level of industries. Three plants (*a*, *b* and *c*) can be found at five points of time (*t1, t2, t3, t4, t5)*. We should take a long-run view and thus the period from *t1* to *t2* may be a decade or so. The period from *t3* to *t4* is a shorter period that is considered in greater detail in the following sub-section. The vertical axis indicates the level of technology or productivity in natural logs and the horizontal axis indicates the passage of time. The upward-sloped straight lines indicate that each plant is able to improve its productivity at a constant rate over its whole life-cycle. Moreover, for now it is assumed that all plants share the same growth rate, i.e. the slopes of the lines are the same. A more detailed consideration of within-plant productivity growth is provided in Section 3.1.3 below.

Graph 3.1 Aggregate industry productivity growth through within-plants growth and through the rotation of plants



Discrete technology steps are taken by entrants. Initially, at *t1* the technology is A1a. A technology step is materialised at *t2*, when plant *b* emerges with technology and productivity level *A2b*, where '*A*' denotes the technology level, '*2*' the point of time and '*b*' the plant vintage. The size of this technology step is |*A2b-A2a*|, which is the difference in productivity levels between the entrant plant *a* and the incumbent plant *b* at the point of time *t2*. It is worth noting that the technology step made by plant *b* is not |*A2b-A1a*|.[28] A bigger technological shock or technological revolution comes to light in *t3*,|*A3c-A3b*|, when plant *c* makes its entry. This means that here the within-plants productivity growth has two important effects on the evolution of aggregate productivity. It improves aggregate productivity growth directly. In addition to this, the within-plant productivity growth has longer term effects as it raises the basis of the next technology step implemented by the next entry. In other words, some technological progress takes place in the plants.

The dashed line indicates the development of industry productivity. We note that this indicator gauges the technological level poorly. Average productivity is normally below the best-practise technology. In this example, the gap is particularly

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[28] Some frequently used productivity decomposition methods measure the entry effect by |A2b-A1a|. These methods are discussed in Section 3.2.

pronounced during the period from *t3* to *t4*. Sometimes this gap is interpreted as technical inefficiency. However, it is quite possible that each plant is making the best possible use of its technology and thus minimising its costs. They are profitable as long as variable costs are met by revenues. Quasi-fixed costs due to irreversible investments explain why technologies of different productivity may appear side by side in a competitive environment in which the present value of profits over each plant's life-cycle may be zero (see Hjalmarsson 1973; Melitz 2002).

Perhaps a more serious problem of the aggregate productivity indicator is that it fails to indicate the timing of the big technology shock which occurs in *t3* in this example. Jumps in industry productivity appear at *t4* and *t5* which are times of stable development of the underlying technology. These steps in aggregate productivity are due to the exit of plant *a* and later of plant *b*.

In the long run (from *t1* to immediately after *t5*) the aggregate productivity measure indicates quite correctly the amount of technological advancement, which is |*A5c*-*A1a*|=|*P5*-*P1*|, where '*P*' stands for productivity. The aggregate productivity measure, however, still fails to identify the different forms of technological change. There are two discrete technology steps that require external adjustment. Their total effect in this example is |*A2b*-*A2a*|+|*A3c*-*A3b*|. The rest of the long-run growth can be attributed to technological progress within plants.

3.1.2 External adjustment among incumbents

Above it was assumed that all plants are of equal size and all job destruction and job creation is due to exits and entries. However, most of the job turnover takes place among incumbent plants. Davis, Haltiwanger and Schuh (1996) report that 15.5 % of annual job creation was due to startups of new plants in US manufacturing in the period 1973-1988. Shutdowns accounted for 22.9 % of annual job destruction. Thus, most of the annual job flows took place among continuing plants in US manufacturing. Ilmakunnas and Maliranta (2000 and 2003c) found that the share of exits and entries may be even smaller in the Finnish manufacturing and business sectors.

Entry and exit indicators may be sensitive to the quality of longitudinal linkages (see discussion in Davis, Haltiwanger and Schuh 1996, p. 192). There might be errors in the plant codes so that the code of a plant is changed even when the plant continues to produce on the line.[29] If there are occasional problems in the

[29] Maliranta (1997b) found more than 1000 breaks in longitudinal linkages in the late 1970s. Most of these artificial deaths and subsequent artificial births could be identified and corrected with the help of the owner firm, industry and location. In some years there were an unexpectedly large number of new plants. The explanation for this is that in some years the registers are checked more carefully than usual to make sure that the Finnish manufacturing census comprehensively covers the plant population. Usually these "new" plants are very small and are not included in the sample in the later years (up to the year 1994 the Finnish manufacturing census covered all plants employing at least 5 persons).

longitudinal linkages in data then we might expect a positive correlation between the exit rate and the entry rate of the next period.[30] Of course, the same outcome will be found when true plant deaths "pull" true new entrants, as they may then have larger markets or unemployed factors of production available (see Johnson and Parker 1994). Still, the relationship between entries and subsequent exits may seem even more natural. New high productivity plants can be expected to have a "displacement effect" on incumbent ones, which characterises the "creative destruction" process.

Baldwin, Beckstead and Girard (2002) provide a robustness analysis by computing job flow numbers by using alternative data sources. They conclude that the entry and exit numbers are quite sensitive to definitions and other factors. These can be expected to vary between countries and so cross-country comparisons from extremely different data sources may be misleading. One of the recommendations of Baldwin et al. is that one should focus on longer periods, for example 5-year periods. Another piece of advice given in the paper is to use the establishment rather than the firm concept.

Besides the above considerations, there are conceptual problems that may make it difficult to give an unequivocal timing for entries and exits. First, a building is constructed for a factory and then some machinery is brought into it. At some point the owner firm starts to search for suitable workers. Similarly, the transitory period of the exit of a plant may be long indeed. Some activities may occur long after the shutdown of the primary production processes.

Entry and exit can be viewed as longer phases of a plant's life cycle. Typically, new plants are small and therefore they account for a relatively small proportion of total labour input.[31] As shown by Maliranta (1997a) a plant cohort increases its labour share and its relative productivity in the subsequent decade. Similarly plants have experienced a decline for many years before their final disappearance in terms of both relative labour productivity and relative size (see also Ilmakunnas, Laaksonen and Maliranta 1999).

Graph 3.2 takes a snap-shot of the whole renewal cycle shown in Graph 3.1 by focusing on the period from *t3* to *t4*. Now sizes are allowed to vary between

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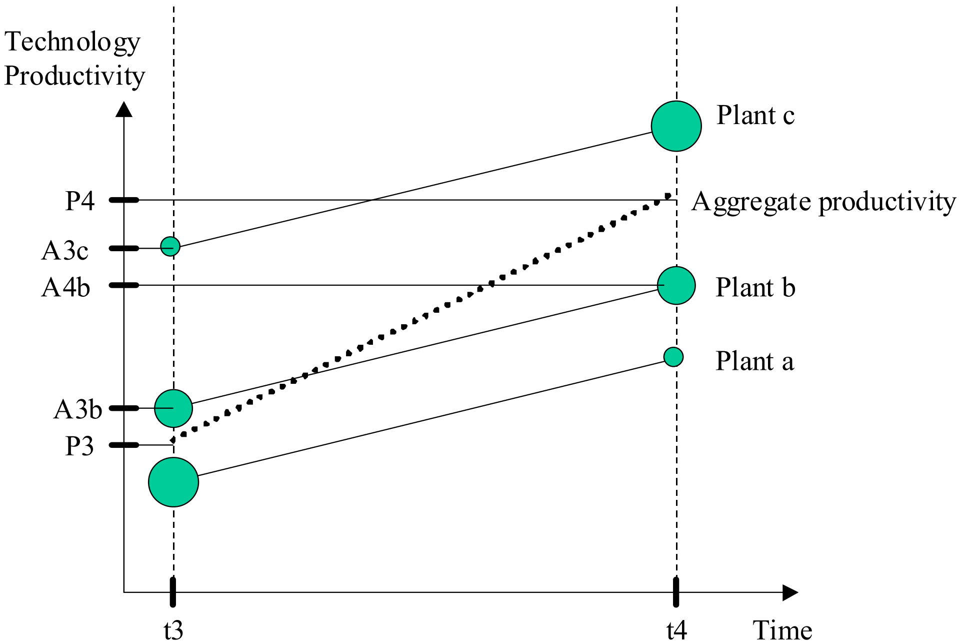
[30] Calculations made with the annual job flow data of US manufacturing from 1973 to 1988 indicated a positive correlation between the current exit and entry rate (0.84) and between the current exit rate and the next year's entry rate (0.61). Both are statistically significant at the 5 % level (two-sided test). The correlation between the current entry rate and the next year's exit rate was almost zero (-0.03). The number of observations was 15 in these calculations (from the period 1974-1987). The data is publicly available at the site http://www.bsos.umd.edu/econ/haltiwanger/download.htm.

[31] Normally a few percentages in Finnish manufacturing.

plants. The size of a ball indicates the amount of input that a plant is currently employing. We observe that a plant's size changes systematically according to the productivity level. The low productivity plant *a* is declining and the high productivity plant *c* is expanding. As a consequence of the reallocation of input shares the growth rate of the average productivity level is more rapid than the growth rate of the productivity within plants, which is still assumed to be constant over time and across plants. So the slope of the aggregate productivity line (dashed) is steeper than the productivity lines of the plants. Some of the aggregate productivity change |*P4*-*P3*| can be attributed to within-plants growth. Because all plants are assumed to share the same rate of productivity growth, it can be gauged by the growth within plant *b,* which is |*A4b*-*A3b*|, while the rest of the aggregate productivity change can be ascribed to the restructuring of input shares between plants.

Graph 3.2 Productivity-enhancing restructuring among incumbent plants



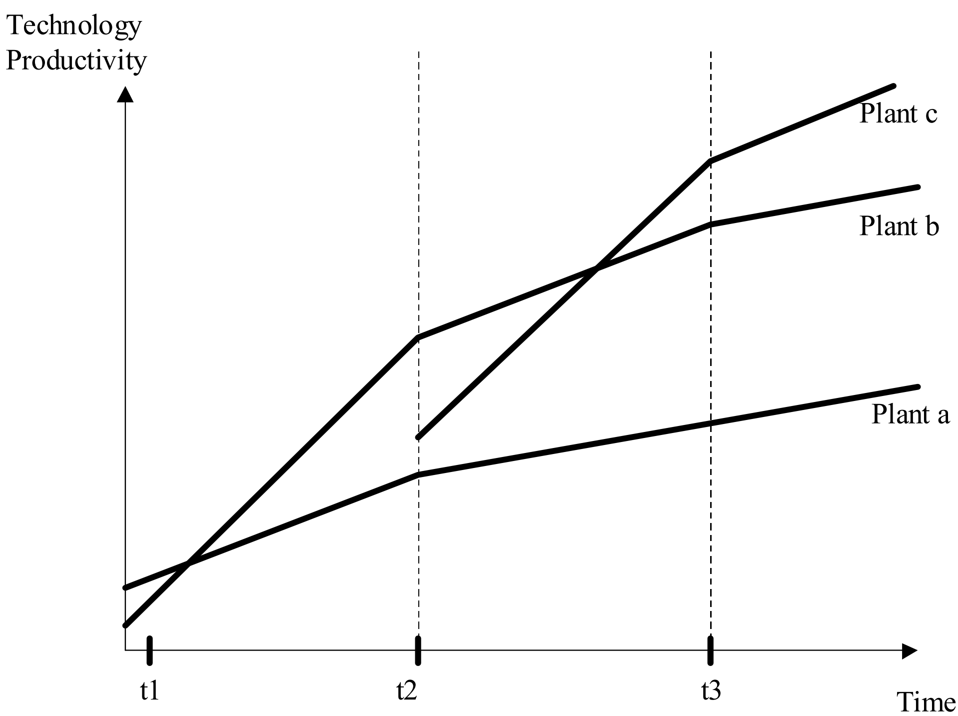
3.1.3 Internal adjustment

So far it is assumed that the productivity growth rate within plants is constant over time and across plants. From the standpoint of various theoretical consideration this seems quite a strong simplification and it is not consistent with the stylised facts obtained with micro data as we will see shortly. Let us now assume that each plant (vintage) has three phases in its life cycle; the periods of rapid, moderate and slow productivity growth. First a plant has fast productivity growth because it is accumulating vintage-specific expertise. At some point the plant has learned the essentials of the new technology and it is no longer able to achieve a very high growth rate. Finally, it has learnt everything that is specific to its technology and it is able to improve its productivity slowly thanks to disembodied technological change and accumulation of general disembodied multi-purpose technological knowledge.

This kind of process is illustrated in Graph 3.3. Plant *c* appears at *t2* at the medium productivity level. With the help of extra-strong productivity growth it surpasses the initial frontier plant *b*. If the size of plant *c* is small up to *t3*, the weighted average of the plant's productivity growth rate can be quite low, something close to the growth rates of plants *a* and *b*. So within-plant productivity growth may fail to spot the productivity step made by plant *c* in the period from *t2* to *t3*. But if there is a lot of reallocation of resources from plants *a* and *b* to plant *c* after *t3*, the technological advance made by plant *c* before *t3* has a delayed influence on aggregate productivity growth that is rapid, thanks to the restructuring among incumbents.

In fact, the empirical findings for Finnish manufacturing obtained by Maliranta (1999) are quite consistent with the picture shown above. The total factor productivity

Graph 3.3 Technological renewal and leapfrogging at the plant level



levels and trends for different plant generations for the period 1981-94 were estimated in the paper. The newest plant generation *A* consists of plants that belong to the first decile class according to their age in 1981. The next plant generation *B* consists of the second decile class and the subsequent generations from *C* to *F* are quintile groups according to the situation in 1981.

The dependent variable was the log of the total factor productivity index. Models included dummy variables for plant generations and trends that were allowed to vary between generations, as it is suggested in the previous graphical depiction. Furthermore, the models had a wide set of other controls including size, multi-unit owner, average annual hours per worker, industry, industry-specific trends, region, foreign ownership, "the shadow of death"[32] (see Griliches and Regev 1995, pp. 193-195), the extent of rents, recent investments, white collar employment, capacity utilisation, export share and outsourcing of service operations. Graph 3.4 shows one of the basic findings of the study. Initially in 1981 plant generation *A* has by and large the same productivity level as the previous generation and somewhat lower than generation *C*. In 13 years' time, generations *B* and *A* were able to surpass generation *C* in productivity. The relative positions are relatively stable among the other plant generations.

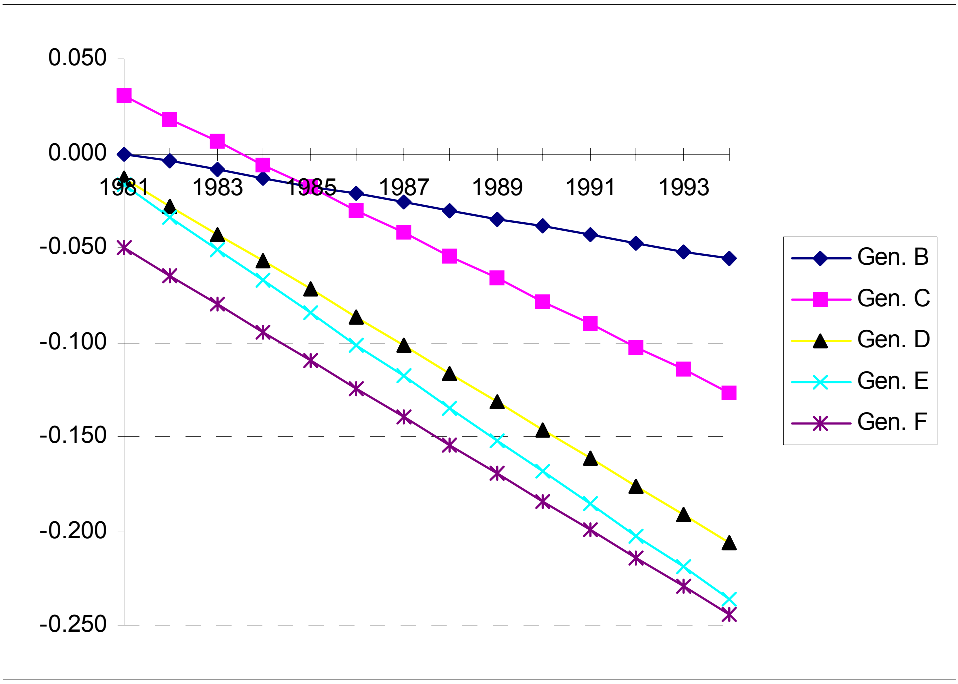
The average plant age in each group is estimated from the panel data from 1974 to 1994 by constructing generation groups for 1994 in a similar way as above. The average age in plant generation *A* is a bit more than one year, in *B* about 4 years, in C about 7 years and in *D* about 13 years. The average age in generations *E* and *F* cannot be estimated, because the year of birth cannot be determined. Only the order of appearance can be inferred. So it can be evaluated that it takes a half of decade or so to reach the frontier and the leading position can normally be maintained for a decade or so.

As to the relative size, generation *A* accounts for 3.1 % of total employment. As it covers 10 % of the number of plants, the average size in generation *A* is 31 percent of that in total manufacturing. The growth in terms of employment is remarkable. The relative average size in generation *B* is more than doubled, 67 percent. Then the increase in relative average size slows down as the figure for generation *C* is 76, for generation *D* 84 percent and eventually for generation *E* 72 %. The largest plants are very old; the relative average size is 220 percent in generation *F*. Dwyer (1998, pp. 437-438) reports broadly similar findings concerning the relative plant sizes in different plant vintages for the United States.[33]

[32] This means that a dummy variable is included, which indicates if a plant will disappear soon.

[33] The employment-weighted average size figures for the different plant generations render a broadly similar picture of the changes in plant size over the life cycle.

Graph 3.4 Log-differences in TFP level, generation A = 0



Source: Maliranta (1999, p. 410)

The illustrative example and empirical findings showed above masked the fact that plants of the same cohort may have widely varying productivity levels despite a wide set of control variables, because some of the plants just do not use inputs in a productive way. Some of them may have simply made an unsuccessful technology choice. A lot of heterogeneity and selection can be expected to be found especially among newer cohorts according to life cycle models (Jovanovic 1982).[34]

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[34] Maliranta (1998) has made estimations with both balanced and unbalanced panels. In both cases, the new plants that made their entry after 1981 were excluded from the sample (see further details of the study).

3.2 Decomposition of aggregate productivity growth

3.2.1 A modified version of the Bernard and Jones (1996) formula, the MBJ method

I now introduce a decomposition method that has several good properties. It is a somewhat modified version of the formula applied by Bernard and Jones (1996) and from now on I call it the MBJ method. The starting point is an ideal measure of aggregate productivity change that is obtained by the Törnqvist index that was presented in Section 2.2. In the one output and M input case it can be expressed as follows:

$$\ln\left(\frac{P_t}{P_s}\right)=\ln\left(\frac{Y_t\Big/\prod_m^M X_{mt}^{\bar{S}_m}}{Y_s\Big/\prod_m^M X_{ms}^{\bar{S}_m}}\right)=\ln\left(\frac{\sum_i Y_{it}\Big/\prod_m^M\left(\sum_{imt}X_{imt}\right)^{\bar{S}_m}}{\sum_j Y_{js}\Big/\prod_m^M\left(\sum_{jms}X_{jms}\right)^{\bar{S}_m}}\right), \qquad (3.1)$$

where $\bar{S}_m=\frac{1}{2}\cdot\left(\frac{p_{mt}X_{mt}}{\sum_m p_{mt}X_{mt}}+\frac{p_{ms}X_{ms}}{\sum_m p_{ms}X_{ms}}\right)$.

Thus, each input type is weighted by the respective average factor cost share in the initial and final years. In competitive markets the factor cost shares are equal to the factor income shares.

Quite usually Y_t and Y_s are expressed in fixed base year prices. As discussed in Section 2.1 a more ideal way is to measure both of them in the initial year *s* or in the final year *t* prices. This may be important especially when the calculations are made at a high level of aggregation. From now on final year prices are used, so that Y_s is measured in year *t* prices.

Aggregate productivity change is gauged by a method that yields a very close approximation to the log-difference of Equation (3.1), that is

$$\frac{\left(P_t-P_s\right)}{\bar{P}}\cong\ln\left(\frac{P_t}{P_s}\right), \qquad (3.2)$$

where $\bar{P}=\left(P_t+P_s\right)/2$.

Now the assumption of a representative firm (or plant) can be dropped and neutral technology differences between the units are allowed. When plant level data is available (3.2) can be expressed as (see also Equation (2.9))

$$\frac{(P_t - P_s)}{\overline{P}} = \frac{\left(\sum_i w_{it} \cdot P_{it} - \sum_j w_{js} \cdot P_{js}\right)}{\left(\sum_i w_{it} \cdot P_{it} + \sum_j w_{js} \cdot P_{js}\right)/2}, \tag{3.3}$$

where $w_{it} = \prod_m \left(\frac{X_{imt}}{\sum_i X_{imt}} \right)^{\overline{S}_m}$, $w_{js} = \prod_m \left(\frac{X_{jms}}{\sum_j X_{jms}} \right)^{\overline{S}_m}$, $P_{it} = \frac{Y_{it}}{\prod_m X_{it}^{\overline{S}_m}}$

and $P_{js} = \frac{Y_{js}}{\prod_m X_{js}^{\overline{S}_m}}$.

These formulations can be used for different productivity indicators. In the case of labour productivity M=1 and then S_{mt}=1. In the case of total factor productivity (TFP) or multi-factor productivity (MFP), the weight w_{it} is an index of the shares of the inputs, that is a weighted geometric average of the input shares of plant i. I will call the productivity measure TFP, when labour (L) and capital (K) are included in the computations. It is also possible to compute a type of productivity indicator that includes intermediate inputs in addition to labour and capital. For clarity we will call this indicator MFP. In the latter case output Y should be measured by gross output, but in the case of labour productivity and total factor productivity the value added measure of output can be used as well. In all cases it is required that $\sum_m S_{mt} = 1$. In the case of TFP, the output elasticity of labour (i.e. S_L) may be defined as the proportion of labour compensation (wages plus supplements) to value added. The output elasticity of capital S_K is then one minus S_L. When intermediate inputs (INT) are included for computing MFP the weight of labour S_L is the proportion of labour compensation (wages plus supplements) to nominal gross output and the weight of intermediate inputs S_{INT} is the nominal costs of intermediate inputs (materials, energy and services) per nominal gross output. Now $S_K = 1 - S_L - S_{INT}$.[35]

The aggregate productivity change defined in (3.3) can be decomposed by using the following formula:

$$\frac{(P_t - P_s)}{\overline{P}} = \sum_{i \in C} \overline{w}_i \frac{\Delta P_{it}}{\overline{P}_i} + \sum_{i \in C} \Delta w_{it} \frac{\overline{P}_i}{\overline{P}^C} + \sum_{i \in C} \overline{w}_i \left(\frac{\overline{P}_i}{\overline{P}^C} - 1 \right) \frac{\Delta P_{it}}{\overline{P}_i} + TURN, \tag{3.4}$$

where

$$TURN = \frac{(P_t - P_s)}{\overline{P}_t} - \frac{(P_t^C - P_s^C)}{\overline{P}_t^C}. \tag{3.5}$$

[35] The weights of different input types are defined at the aggregation level under consideration.

Superscript C denotes continuing plants. The first component on the right-hand side of (3.4) is the within-plant component that shows the weighted average of the productivity growth rates among plants. The second component is the between component that gauges the effect of the reallocation of input shares among the incumbent plants. The third component might be called the catching up (or residual) component. Supposing that size and productivity level are mutually uncorrelated, a negative value suggests that plants having a relatively low productivity level are able to catch up, thanks to an above-average productivity growth rate. Therefore it can be used as an indicator of productivity convergence. Negative values should predict narrowing productivity dispersion.[36]

The last component in (3.4) is the plant turnover effect (*TURN*) or net entry effect. It is here defined as the difference between the productivity growth rate in all plants and the productivity growth rate among continuing plants. It is positive when the renewal of the plant population through entries and exits contributes positively to aggregate productivity, as was the case in Graph 3.1. Equation (3.5) can be decomposed further (see Maliranta 1997a, pp. 359-361). The entry and exit effects can be distinguished by noting that

$$\frac{\Delta P_t}{\overline{P}} - \frac{\Delta P_t^C}{\overline{P}^C} \cong \ln\left(\frac{P_t}{P_s}\right) - \ln\left(\frac{P_t^C}{P_s^C}\right) = \ln\left(\frac{P_t}{P_t^C}\right) + \ln\left(\frac{P_s^C}{P_s}\right) \qquad (3.6)$$

The first term in the third equation is positive if the total aggregate productivity level is higher than the aggregate productivity level among continuing plants (those that appeared also in the initial year) in the final year. Thus this term can be used as an indicator of the entry effect. The second term in turn is positive if the aggregate productivity level among continuing plants (those that will appear also in the final year) is higher than among all the plants that include the disappearing plants in addition to the continuing plants. This term thus provides us with an indicator of the exit effect.

To sum up, the aggregate productivity growth rate measured by $\Delta P_t / \overline{P}$ consists of five components; (1) the within component (*WH*), (2) the between component (*BW*), (3) the catching up component (*CH*), (4) the entry component (*ENTRY*), and (5) the exit component (*EXIT*).

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[36] If the relative productivity levels across the size groups are reasonably stable over time, short-term variation in this component may reveal something interesting about the changes in the economic environment. This term can be expected to be low when productivity improving adjustment among low productivity plants is common.

3.2.2 *The input index method, the INP method*

Let us consider again the equation (3.3), with the plant's i weight now defined as follows:

$$w_{it} = \frac{\prod_m X_{imt}^{S_{mt}}}{\sum_i \left(\prod_m X_{imt}^{S_{mt}}\right)} \tag{3.7}$$

The productivity decomposition measure calculated with these weights is labelled INP. It is worth noting that now $\sum_i w_i = 1$, but generally this is not true in the MBJ method with the exception of single input productivity measures, such as labour productivity. To put it differently, in the case of labour productivity the methods MBJ and INP are identical. Of course, in both cases the plant weights are independent of the units in which each input type is measured.

One advantage of the INP method over the MBJ method is that the entry and exit components can be presented in a way that illustrates the determination of these components:

$$\ln\left(\frac{P_t}{P_t^C}\right) + \ln\left(\frac{P_s^C}{P_s}\right) = \ln\left(1 - w_t^E\left(1 - \frac{P_t^E}{P_t^C}\right)\right) - \ln\left(1 - w_s^D\left(1 - \frac{P_s^D}{P_s^C}\right)\right), \tag{3.8}$$

where E refers to the entering plants (those that appear in t but not in s), D refers to disappearing plants (those that appear in s but not in t), $w_t^E = 1 - \sum_{i \in C}\left(\prod_{m=1}^{M} X_{it}^{S_{mt}}\right) / \sum_i \left(\prod_{m=1}^{M} X_{it}^{S_{mt}}\right)$ is the current input share of the new plants in the year t, and $w_s^D = 1 - \sum_{i \in C}\left(\prod_{m=1}^{M} X_{is}^{S_{mt}}\right) / \sum_i \left(\prod_{m=1}^{M} X_{is}^{S_{mt}}\right)$ is the current input share of those plants in the initial year s that do not exist in the final year t. The cost share of input m, i.e. S_{mt} is calculated as for (3.1).

The first term in the right-hand side of (3.8) is the entry effect and the second term (minus included) is the exit effect. We see that the magnitude of the entry effect (exit effect) is dependent on the input share of those plants in the final year that have appeared after the initial year s (of those plants in the initial year that will appear before the final year t) and the average productivity level of the new plants (the disappearing plants) relative to the continuing plants. One great advantage of this decomposition method is that the productivity of the exiting and entering plants is compared to the other plants in the current year (the year s in the case of exits and the year t in the case of entries). So the elements of technological renewal illustrated in Graph 3.1 can be quantified. However, the INP method is not directly related to a usual measure of aggregate productivity change, unlike the MBJ method. How much aggregate productivity growth rates obtained by INP differ from the usual aggregate measures is an empirical question that will be examined in the empirical part of the present study.

3.2.3 A modified version of the Baily, Bartelsman and Haltiwanger (1996) formula, the MBBH method

A somewhat different formula that bears some resemblance to the one used by Baily, Bartelsman and Haltiwanger (1996) has the form:

$$\frac{\Delta P_t}{\overline{P}} = \sum_{i\in C} w_{is}\frac{\Delta P_{it}}{\overline{P}} + \sum_{i\in C} \Delta w_{it}\frac{P_{is}}{\overline{P}} + \sum_{i\in C} \Delta w_{it}\frac{\Delta P_{it}}{\overline{P}} + TURN\,. \qquad (3.9)$$

This formula will be called the BBH method.[37] The first term is the within component, the second is the between component, and the third is the cross term. The cross term is negative if high productivity growth is typically associated with decreasing input shares. The within component of (3.9) is calculated by using the industry productivity level as the denominator. A rearrangement of the terms in (3.9) lead to an expression where the within component takes a more appropriate form (the other components remain unaltered):

$$\frac{\Delta P_t}{\overline{P}} = \sum_{i\in C} w_{is}\frac{\Delta P_{it}}{\overline{P}_i} + \sum_{i\in C} w_s\left(\frac{\overline{P}_i}{\overline{P}} - 1\right)\frac{\Delta P_{it}}{\overline{P}_i} + \sum_{i\in C} \Delta w_{it}\frac{P_{is}}{\overline{P}} + \sum_{i\in C} \Delta w_{it}\frac{\Delta P_{it}}{\overline{P}} + TURN \qquad (3.10)$$

The first term is the within component and the second the catching up term. I will refer to this modified version of the BBH method as the MBBH method. In both cases, the entry and exit effects can be computed in the same way as in the MBJ or INP methods.

In a multi-input case the plant weights can be determined in a similar manner to the MBJ or INP methods. Output weights could be used as well, if one happens to want it for some reason.

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[37] Baily, Bartelsman and Haltiwanger (1996) used the aggregate productivity level in the initial year as the denominator instead of the average aggregate productivity $\overline{P}$, which is used here.

3.2.4 The Foster, Haltiwanger and Krizan (2001) method, the FHK method

Two decomposition formulations proposed by Foster, Haltiwanger and Krizan (2001) have become quite popular in recent years. In both models aggregate productivity change is defined in a particular way:

$$\Delta \underline{\ln P_t} = \sum\nolimits_i w_{it} \ln P_{it} - \sum\nolimits_j w_{js} \ln P_{js} \ , \tag{3.11}$$

where P_i is again a ratio of output to input. This measure of aggregate productivity change is dependent on how the weighted geometric average of the plants' productivity has changed from the initial year *s* to the final year *t*. In the methods presented in Section 3.2 and 3.3 aggregate productivity levels P_s and P_t were input weighted arithmetic averages. Generally (3.11) does not necessary provide a close approximation to the more usual measures of aggregate productivity change, that is to say

$$\sum\nolimits_i w_{it} \ln P_{it} - \sum\nolimits_j w_{js} \ln P_{js} \not\equiv \ln(P_t) - \ln(P_s) \cong (P_t - P_s) / \overline{P} \tag{3.12}$$

Foster, Haltiwanger and Krizan (2001) have calculated the weights *w* on the basis of labour input for labour productivity and on the basis of the nominal value of production for multi-factor productivity.

The aggregate productivity change defined as (3.11) can be decomposed by using the following formula:

$$\Delta \underline{\ln P_t} = \sum\nolimits_{i \in C} w_{is} \cdot \Delta \ln P_{it} + \sum\nolimits_{i \in C} (\ln P_{is} - \ln P_s) \cdot \Delta w_{it} + \sum\nolimits_{i \in C} \Delta \ln P_{it} \cdot \Delta w_{it} +$$

$$\sum\nolimits_{i \in E} w_{it} (\ln P_{it} - \ln P_s) - \sum\nolimits_{i \in D} w_{is} \cdot (\ln P_{is} - \ln P_s) \tag{3.13}$$

Following custom, I will call this the FHK method. The first term is the within component, the second is the between component, the third is the cross term, the fourth is the entry effect and the fifth is the exit effect.

Maliranta (1997b, p. 19) and Foster, Haltiwanger and Krizan (2001) pointed out that the type of decomposition methods that make use of initial year input weights, as is the case in the BBH, MBBH and FHK methods, may render a distorted view of the micro-level sources of aggregate productivity growth. The input values of the plants may deviate from the true optimal values because of idiosyncratic shocks or measurement errors, for example. The within component is likely to be biased upward. This is because the transitory measurement error in w_{is} leads to a spurious positive correlation between w_{is} and ΔP_{it}. If the input number is too low (too high) in the initial year because of transitory error then the input share number is too low (too high). If the error in input has disappeared in the next period, then the productivity growth rate from the initial year to the final year appears to be lower (higher) than in reality. The between effect is also biased upward because a spuriously high initial productivity (spuriously low input value) is positively correlated with the subsequent input growth Δw_{it}. The role of the cross term is to capture the remaining downward bias in this type of decomposition, which originates from a spurious negative relationship between Δw_{it} and ΔP_{it}. When output shares are used as weights instead of input shares, the directions of the biases are reversed, as explained and demonstrated by Maliranta (2001) and seen in Foster, Haltiwanger and Krizan (2001).

3.2.5 The Griliches and Regev (1995) method, the GR method

It may be useful to use a method that is not so vulnerable to measurement errors. Such are the MBJ and INP methods introduced above that use the average input shares in the initial and final years as weights ($\overline{w}_i$). Another is a variant suggested by Foster, Haltiwanger and Krizan (2001) that is based on the formulation used by Griliches and Regev (1995).

$$\Delta \underline{\ln P_t} = \sum\nolimits_{i\in C} \overline{w}_i \cdot \Delta \ln P_{it} + \sum\nolimits_{i\in C} \left(\overline{\ln P_i} - \overline{\ln P}\right) \cdot \Delta w_{it} +$$

$$\sum\nolimits_{i\in E} w_{it} \left(\ln P_{it} - \overline{\ln P}\right) - \sum\nolimits_{i\in D} w_{is} \cdot \left(\ln P_{is} - \overline{\ln P}\right), \qquad (3.14)$$

where a bar over a variable again indicates the average of the variable over the initial year *s* and the final year *t*. This will be called the GR method.

3.2.6 Contributing plants

In the previous formulations the value of a particular component is calculated by summing over all continuing or entering or exiting plants. We see that each plant *i* can contribute to aggregate productivity through all the components appearing in the method in question. So each component can be broken down in a way that indicates how much different groups of plants contribute to a certain component. We can then evaluate, for example, how much the high export intensity plants contribute to different components. The high export intensity plants can be expected to contribute to the within plant component relatively more than the low export intensity plants, if export stimulates disembodied technological change within plants. Or it is possible to assess whether a disproportionally large share of the between component can be attributed to young plants, as can be expected if there is particularly intensive selection among new technologies as predicted by the life cycle models (Jovanovic 1982).

3.3 A summary of the different methods

Table 3.1 summarises the various decomposition methods that are available for analysing micro-level sources of productivity growth and shows the abbreviations that are used in this study.

Table 3.1 A classification of decomposition methods

Plant weight w_i	Non-log plant productivity Timing of weight		Log plant productivity Timing of weight	
	Average	Initial year	Average	Initial year
Index of input shares	MBJ	MBBH	GR	FHK
Input index	INP	MBBH	GR	FHK
Output		MBBH	GR	FHK

So the methods differ in terms of

1. whether the plants' productivity levels are measured in log terms or not

2. how the plants are weighted in the calculation of aggregate productivity levels (using an index of input shares, input indexes or outputs)

3. the timing of weights (initial year or the average of initial and final years).

All of these methods can be used for labour productivity (LP), total factor productivity (TFP) and multi-factor productivity (MFP). Output can be measured by using the value added or gross output concepts.

Finally, the entry and exit effects can be measured in different ways, as in the INP or FHK methods. Thus, there is a multitude of computations that can be performed. How much these methods differ is largely an empirical question, but before empirical applications some assessment with illustrative examples and theoretical considerations is useful.

3.4 Interpretation of the components of the different methods

In this section the different methods represented above are assessed from the standpoint of what can be learned from them about the micro-level sources of technological progress. I will demonstrate some important differences between the methods by using simple examples.

3.4.1 The roles of entrants and exits

We noted above that the MBJ, BBH and MBBH methods differ from the standard FHK and GR methods regarding the way in which the entry and exit effects are measured. In the former methods the entry effect is positive only if the aggregate productivity growth had been slower without new entries, i.e. if the new plants have higher productivity than the incumbents in the current year. In the FHK method the productivity levels of the new plants are compared to the level of all plants in the initial year and in the GR method to the average level in the initial and final years.

Table 3.2 provides us with some illustrations of the behaviour of the different decomposition methods in different types of cases. In these examples it is assumed that all plants are of an equal size employing one unit of input each, so that the productivity levels indicate the output levels, too. As stated above, in the single input case the MBJ and INP methods are identical. In all four examples each plant is able to improve its productivity at an equal rate, thanks to general disembodied technological change.

Example 1 is a characterisation of the representative firm model and job flows. In example 2 the plants are heterogeneous in terms of technology. A low technology job is destroyed and a high technology job is created. In example 3 the job flows consist of two parts: the part that enhances aggregate productivity growth and another part that is irrelevant from the point of view of technological progress. In fact, example 3 is similar to example 2 except that plants *C* and *C'* are identified as distinct plants. The reason for this may be an error in the longitudinal link, for example. Even if these two plants are truly separate plants, it is worth noting that the productivity level *C'* in the final year was achievable for plant *C* thanks to disembodied technological change. Example 4 demonstrates disembodied technological revolution which has made each plant 10 % more productive in the final year than in example 3. A similar outcome is obtained, if there is a measurement error in the output price index by which the output volumes are computed, for example.

These examples demonstrate a number of important differences in the methods that should be taken into account in the interpretations:

1. The within component of the MBJ and MBBH methods indicates the average productivity growth rate among plants. The determinants of this type of growth are analysed in a large number studies that make use of the differenced specifications in the estimations with micro-level data. For the within component

Table 3.2 Identifying entry and exit effects with different decomposition methods

	Example 1 "Representative plants"		Example 2 "Heterogeneous plants"		Example 3 "Break-offs in longitudinal linkages"		Example 4 "Rapid disembodied technological change"	
	Initial year	End year	Initial year	End year	Initial year	End year	Initial year	End year
Productivity								
Plant A	10.00		9.00		9.00		9.00	
Plant B	10.00	11.00	10.00	11.00	10.00	11.00	10.00	12.00
Plant C	10.00	11.00	10.00	11.00	10.00		10.00	
Plant D		11.00		12.00		12.00		13.09
Plant C'						11.00		12.00
Average	10.00	11.00	9.67	11.33	9.67	11.33	9.67	12.36
Aggregate growth, %								
ΔlnP		9.53		15.91		15.91		24.61
MBJ & MBBH		9.52		15.87		15.87		24.48
FHK & GR		9.53		15.94		15.94		24.64
Within plants, %								
MBJ & MBBH		9.52		9.52		9.52		18.18
FHK & GR		6.35		6.35		3.18		6.08
Entry, %								
MBJ & MBBH		0.00		2.99		2.99		2.99
FHK		3.18		7.25		11.60		17.40
GR		1.59		4.59		6.28		9.18
Exit, %								
MBJ & MBBH		0.00		3.39		3.39		3.39
FHK		0.00		2.34		1.17		1.17
GR		1.59		5.00		6.49		9.39

obtained by the FHK or GR method[38], instead, it is not very easy to give a useful economic interpretation without further information about the input (or output) shares of the entrants and exits that could be used in the "re-scaling".

2. As it turns out, the non-zero entry and exit components of the FHK or GR methods are not inconsistent with the representative firm model. According to the FHK method one third of aggregate productivity growth can be attributed to the entry effect in Example 1 even though all plants are homogeneous in each year. In the GR method this contribution is split evenly between the entry and exit effect; one sixth for each. But with reference to the MBJ and MBBH methods, the heterogeneity of the plants in terms of productivity is a necessary condition for non-zero values for the entry and exit components, as was stated above.

3. A comparison of the results obtained in Examples 2 and 3 provides an illustration of the fact that the MBJ and MBBH methods are insensitive to random errors in longitudinal linkages. The within component of the FHK and GR methods is downward and the entry and exit effects are upward-biased in the presence of artificial entrants and exits due to break-offs in longitudinal linkages.

4. One great advantage of the MBJ and MBBH methods is that they allow us to make a sharp distinction between the two types of technological progress: the type that is embodied in new plants and the type that is disembodied. These two forms of technological change were illustrated in Graph 3.1. The differences between the methods in this respect can be seen clearly when comparing Examples 3 and 4. The within components of the MBJ and MBBH methods quite logically indicate that the rate of disembodied technical change is twice as big in Example 4 as in Example 3 (about 20 % vs. about 10 %), but the technological progress attributable to the turnover (entry and/or exit) is unaltered, which is in sharp contrast to the message obtained from the FHK and GR methods. The FHK method indicates a particularly large difference in the entry effect between Examples 3 and 4.

3.4.2 The components among continuing plants

It is probably very useful to focus on the analysis of restructuring among incumbent plants for a number of reasons. This is the case, for example, when a researcher has only samples of units or when the quality of longitudinal linkages are suspect (see for example, Oulton 2000). Then the measurement of the effects of entry and exit would be an audacious exercise to be carried out anyway.[39] Secondly, as dis-

[38] In all these examples, the decompositions are made by using input index (labour) weights.
[39] But as I asserted above, the entry and exit effects are unbiased in the MBJ and MBBH methods, if breaks in longitudinal linkages are random.

cussed in Section 3.1.2 and 3.1.3, both entry and exit can be viewed as relatively long phases in a plant's life cycle and will for the most part be captured by the between incumbents component.

In order to demonstrate some pros and cons of the different methods three examples are now used. To keep things simple, we have only two plants and 5 years (and thus 4 periods over which productivity changes are calculated). In all three examples it is assumed that the total number of workers (L) is fixed at 20 persons. Of course, the technology and labour input determine the output level. I consider here only the methods based on labour input weights.

3.4.2.1 Errors in labour input values

In the first example the data contain errors in the labour input (or fleeting level input that is unsustainable and not optimal for the plant in question) in the even years (see Table 3.3). The expected values are correct and therefore there is no error at the aggregate level. To keep things simple, output Y is measured correctly in all these examples.

Table 3.3 Errors in labour input data

	Year 1		Year 2		Year 3		Year 4		Year 5	
Firm	Y	L	Y	L	Y	L	Y	L	Y	L
A	100	10	100	11	100	10	100	15	100	10
B	100	10	100	9	100	10	100	5	100	10
Aggregate	200	20	200	20	200	20	200	20	200	20

In reality the plants are similar in respect of size and productivity level, but because of errors in the labour input values (or deviation from a sustainable steady state) in the even years there appear to be occasional differences in productivity level and size. Furthermore, it is assumed that technological change within plants does not actually exist although occasional non-zero productivity change rates may appear. In year 2 there is a small and in year 4 a large error in distributing the total labour input value between the plants.[40]

[40] It should be noted that there is a lot of unreal simultaneous annual job creation and destruction in the previous example. Empirical research in this field suggests that the measurement error problem is not that bad. For example, according to Ilmakunnas and Maliranta (2000) the gross job reallocation, i.e. the sum of job creation and destruction rates, is about 15 per cent in Finnish manufacturing. In the first example, gross job reallocation is 10 percent in years 2 and 3, and 50 per cent in years 4 and 5. Thus this example dramatises the point quite a bit.

Table 3.4 shows the decomposition of aggregate productivity changes with different methods based on the numbers in Table 3.3. Three observations can be made from the table.

1. We find that the aggregated log differences used in the FHK and GR[41] methods are not equal to the aggregate growth rate, which is here zero for each year by construction. However, all aggregate indicators are unbiased in the sense that the average rates for the whole period are correctly zeros. The MBBH and FHK methods both seem to indicate a positive within component, which is a misleading result from the perspective that over a longer period there has not been any sustainable plant level productivity progress. The within component according to

Table 3.4 Decomposing errors-in-variable data, %

Growth rate component	Growth rate, %				
	Year 2	Year 3	Year 4	Year 5	Average
Aggregate					
$\Delta \ln P$	0.0	0.0	0.0	0.0	0.0
MBJ & MBBH	0.0	0.0	0.0	0.0	0.0
FHK & GR	-0.5	0.5	-13.1	13.1	0.0
Within					
MBBH	0.5	0.5	13.3	13.3	6.9
FHK	0.5	0.5	14.4	13.1	7.1
MBJ	0.0	0.0	0.0	0.0	0.0
GR	0.0	0.0	0.7	-0.7	0.0
Catching up					
MBBH	0.5	-0.5	20.0	-13.3	1.7
MBJ	0.5	-0.5	16.7	-16.7	0.0
Between					
MBBH	0.0	1.0	0.0	33.3	8.6
FHK	0.0	1.0	0.0	27.5	7.1
MBJ	-0.5	0.5	-16.7	16.7	0.0
GR	-0.5	0.5	-13.7	13.7	0.0
Cross					
MBBH	-1.0	-1.0	-33.3	-33.3	-17.2
FHK	-1.0	-1.0	-27.5	-27.5	-14.2

[41] In the following illustrative decompositions I use, again, input weights.

the GR method has some variation from year to year, but the average over the whole period gives an undistorted result. The same holds true for the MBJ method as well.

2. The average of the catching-up term over the whole period is zero according to the MBJ method, as we might wish, as there is no longer duration catching up in operation in this example. The MBBH method, in turn, seems to suggest a positive catching up term that can be argued to be a misleading finding.

3. As discussed in Section 3.2.4, the between component is positively and the cross term negatively distorted in the results obtained with formulations MBBH and FHK. In contrast, the MBJ and GR methods suggest no between effect (and no within effect) in the long run.

3.4.2.2 Structural change at the plant level

The second example has more economic content (see Table 3.5). Now there are no errors in the data. As in the previous example, there is no productivity change whatsoever within the plants either. However, there is positive aggregate productivity growth because of a systematic labour input reallocation from the low productivity plant *B* toward the high productivity plant *A*.

Table 3.5 Structural change data

	Year 1		Year 2		Year 3		Year 4		Year 5	
	Y	L	Y	L	Y	L	Y	L	Y	L
Plant A	125	10	137.5	11	150	12	162.5	13	175	14
Plant B	75	10	67.5	9	60	8	52.5	7	45	6
Aggregate	200	20	205	20	210	20	215	20	220	20

As there are no random errors-in-variables, all the methods yield the correct result that there is no productivity growth within plants and, consequently both the within component and the cross term correctly have zero values. In short, all the methods seem to work equally well in this kind of situation when applied to continuing plants.

3.4.2.3 Catching-up process at the plant level

In the last example there are long-lasting differences in the productivity growth rates that can be attributed to differences in the productivity levels. Again, there is no technological progress within plants. More precisely, there is no productivity growth at plant *A*, which is on the technological frontier. Plant *B,* on the other hand, is able to achieve continuous positive productivity growth as it manages to gradually catch up with the frontier technology level. As can be calculated from Table 3.7 plant *B* achieves the benchmark level in the final year 5. As long as plant *A* is ahead

Table 3.6 Decomposing productivity change in structural change data

Growth rate component	Growth rate, %				
	Year 2	Year 3	Year 4	Year 5	Average
Aggregate					
ΔlnP	2.5	2.4	2.4	2.3	2.4
MBJ & MBBH	2.5	2.4	2.4	2.3	2.4
FHK & GR	2.6	2.6	2.6	2.6	2.6
Within					
MBBH	0.0	0.0	0.0	0.0	0.0
FHK	0.0	0.0	0.0	0.0	0.0
MBJ	0.0	0.0	0.0	0.0	0.0
GR	0.0	0.0	0.0	0.0	0.0
Catching up					
MBBH	0.0	0.0	0.0	0.0	0.0
MBJ	0.0	0.0	0.0	0.0	0.0
Between					
MBBH	2.5	2.4	2.4	2.3	2.4
FHK	2.6	2.6	2.6	2.6	2.6
MBJ	2.5	2.4	2.4	2.3	2.4
GR	2.6	2.6	2.6	2.6	2.6
Cross					
MBBH	0.0	0.0	0.0	0.0	0.0
FHK	0.0	0.0	0.0	0.0	0.0

Table 3.7 Catching-up process data

	Year 1		Year 2		Year 3		Year 4		Year 5	
	Y	L	Y	L	Y	L	Y	L	Y	L
Plant A	120.0	10.0	132.0	11.0	144.0	12.0	156.0	13.0	168.0	14.0
Plant B	80.0	10.0	79.7	9.0	78.4	8.0	75.9	7.0	72.0	6.0
Aggregate	200.0	20.0	211.7	20.0	222.4	20.0	231.9	20.0	240.0	20.0

of *B* in productivity level, it is also able to capture labour input share. In other words, there is also structural change in operation in this example.

The within component is qualitatively the same in all the methods considered here. The same holds true for the between plant effect. The cross term has negative values in the MBBH and FHK methods. Concluding that a negative cross term comes into being from the fact that an extra-rapid productivity growth rate can be achieved by downsizing would be a mistake at this point. In this case, the persistently low productivity level entails two simultaneous developments, both of which can be understood by economic reasoning. The low productivity plant is not able to sustain all of its jobs in contrast to the benchmark plant *A*, which has greater labour demand due to the high productivity level. This is reflected in the positive values of the between plant component. On the other hand, plant *B* experiences extraordinarily high productivity growth rates (around 10 per cent) because it is reaping the

Table 3.8 Decomposing productivity in catching-up data

Growth rate component	Growth rate, %				
	Year 2	Year 3	Year 4	Year 5	Average
Aggregate					
ΔlnP	5.7	4.9	4.2	3.4	4.6
MBJ & MBBH	5.7	4.9	4.2	3.4	4.6
FHK & GR	6.6	5.6	4.6	3.5	5.1
Within					
MBBH	5.1	4.6	4.1	3.5	4.3
FHK	5.1	4.6	4.1	3.5	4.3
MBJ	4.8	4.3	3.8	3.3	4.1
GR	4.8	4.3	3.8	3.3	4.1
Catching up					
MBBH	-0.9	-0.6	-0.4	-0.1	-0.5
MBJ	-0.9	-0.6	-0.3	-0.1	-0.5
Between					
MBBH	1.9	1.4	1.0	0.5	1.2
FHK	2.0	1.5	1.0	0.5	1.3
MBJ	1.7	1.2	0.7	0.2	1.0
GR	1.8	1.3	0.8	0.3	1.0
Cross					
MBBH	-0.4	-0.4	-0.5	-0.5	-0.5
FHK	-0.5	-0.5	-0.5	-0.5	-0.5

catching-up potential. This can be concluded from the negative catching-up term. As there is less and less divergence in productivity levels, the absolute value of the catching-up term diminishes over time. We observe that the within component declines as well. However, at the plant level there is no decline in productivity growth – the productivity growth rate of plant A is zero and that of B is ten per cent. The reason for the falling within component is that the labour input share of plant B with fast productivity growth is declining in this example.

3.5 An assessment of decomposition methods

To conclude Chapter 3, I will evaluate the different methods that can be used in the identification of the micro-level sources of aggregate productivity change. A good method should have the following three qualifications:

1. It should be related to a proper (or ideal) and a common measure of aggregate productivity growth (see Section 2.1).

2. It should enable the identification and quantification of important aspects of technological change that were considered in Section 2.4 and illustrated in Section 3.1. In particular, it should make it possible to sharply differentiate between the different forms of adjustment involved in technological progress.

3. The method should be able to churn out results that are not spurious due to the usual features and imperfections inherent in detailed and comprehensive microdata. Usually data include measurement errors and lack measures for the utilisation rates of different inputs at the plant level.

3.5.1 The relationship with an ideal aggregate productivity measure

We noted in Section 3.2 that the MBJ method (and MBBH, when the plants are weighted by an index of input shares) is directly related to an ideal aggregate measure of productivity growth with the extension that now technology levels are allowed to vary between plants in a neutral way. The aggregate productivity growth rate obtained by the FHK and GR methods, on the other hand, differs from those usual productivity indicators that can be computed by using aggregated output and input numbers.

It is interesting to note what can be expected to bring a gap between these two aggregate growth measures. Let us consider a case where the MBJ and GR methods are applied to continuing plants, so that the entry and exit components are now dropped. Then the within components of these two methods are approximately the same when the growth rates are reasonably small, that is to say

$$\sum_i \overline{w}_i \frac{(P_{it} - P_{is})}{(P_{it} + P_{is})/2} \approx \sum_i \overline{w}_i \cdot \ln\left(\frac{P_{it}}{P_{is}}\right). \tag{3.15}$$

Similarly, we would expect that the values of the between components are roughly of the same magnitude, i.e.

$$\sum_i \Delta w_{it} \frac{\overline{P}_i}{\overline{\overline{P}}} \approx \sum_i \Delta w_{it} \cdot \ln\left(\frac{\overline{P}_i}{\overline{\overline{P}}}\right). \tag{3.16}$$

So, it can be inferred that

$$\frac{(P_t - P_s)}{(P_t + P_s)/2} - \underline{\Delta \ln P_t} \approx -1 \cdot \sum_i \overline{w}_i \left(\frac{\overline{P}_i}{P_t} - 1\right) \frac{(P_{it} - P_{is})}{\overline{P}_i}, \tag{3.17}$$

where is the aggregate productivity growth rate as measured by the GR method (with input weights), and the term on the right-hand side of the equation is the opposite number of the catching up term of the MBJ method. As the catching up term should, on certain conditions discussed in Section 3.2.1, reflect convergence in the productivity levels of the plants we can conclude that the GR method may render biased results when the productivity dispersion changes due to the divergent productivity growth rates among plants (see also Tables 3.7 and 3.8).

The correct measurement of aggregate productivity growth is particularly important when the contributions of the micro-level components are expressed as shares of aggregate productivity growth, as is rather common now.

3.5.2 The forms of productivity growth

As discussed above, the MBJ and MBBH methods are useful in quantifying the type of technological progress that can be implemented within continuing plants separately from the type of development that entails plant level restructuring of input shares, i.e. the entry, exit and between components. As the productivity-enhancing restructuring involves the cleansing of low productivity jobs, one would expect that the between component is negatively related to the change of input weighted productivity dispersion. Hence, this type of productivity growth can be expected to be related to the changes in productivity dispersion.

The weighted average of plant-level productivity growth, i.e. the within component of the MBJ and MBBH methods, may mask a lot of variation in the growth rates among continuing plants. Much of this may be idiosyncratic differences or noise. However, some of the differences may be explained by the fact that, for those plants that have low productivity level due to inefficient use of technology and inputs, it is easier to improve productivity than for the best practise plants. So we might expect to find beta convergence among the incumbent plants. This is to say that there is a tendency for the low productivity plants to catch up with the high productivity plants (see e.g. Barro and Sal-i-Martin 1995). This may be reflected in the form of the negative values of the catching up components. The MBJ and GR methods are especially useful because they are not so exposed to the regression towards mean problems (e.g. Friedman 1992). This is because they make use of the relationship between the average productivity level (in the initial and final years) and the productivity growth rate instead of between the initial productivity level and the subsequent growth. However, a closer look at the catching up component reveals that it also includes a term which gauges plant size. If the size of the plants is correlated with the productivity growth rate or with the productivity level, the proper interpretation of the catching up component becomes difficult and thus this component may be regarded as a residual term. On the other hand, the variation in the catching up term over time may still reveal something interesting about the changes in competitive environment. For example, one may expect that the catching up component is particularly low when the economic environment is such that there is great pressure among inefficient plants to improve their conduct, as is predicted when considering the determinants of firm inefficiency. If a negative value of the catching up term indeed reflects beta convergence, a positive correlation between the catching up component and the change in input-weighted productivity dispersion should be expected. So the reliability and the validity of this component can be evaluated empirically with micro data.

Finally, it is worth noting that all these methods directly measure the role of *restructuring* or *reallocation of input shares*, not necessarily reallocation of inputs. Some inputs may have just become idle, which may be reflected in a positive between or exit effect. Destruction is not "creative" in a sensible meaning of the expression unless it is accompanied or followed by creation of high productivity jobs by brand new or incumbent plants. The question of whether the restructuring has entailed reallocation of resources or whether it has had positive welfare effects requires a wider and longer perspective. This issue will be touched on later in Chapter 6 when the relationship between skill upgrading and productivity-enhancing restructuring is analysed. We will study whether the restructuring has contributed to aggregate productivity positively by cleansing the low-skilled workers. Or could it be that some low-technology plants are cleansed by reallocating both low- and high-skilled workers to high-technology plants?

4 International comparisons of productivity in manufacturing

4.1 Conducting international productivity comparisons

In this chapter the aggregate productivity performance of the Finnish manufacturing sector is evaluated by using cross-country comparisons of productivity levels. The comparisons are mainly made by using the United States as a benchmark. It serves this purpose very well as the United States has traditionally been the leader country in productivity.

A critical point in productivity comparisons between two points of time or between countries is how successfully the distinctions between values, prices and quantities of output are made. The easiest way to perform a productivity comparison between countries is to convert the values of output into a common measure by using official exchange rates. This is an eligible method if the price levels are the same in the countries in question. According to the OECD's STAN database nominal value added per hour in Finnish manufacturing was 91 per cent of that in the United States in 1987. In 1990 the corresponding number was 118 per cent. The fact that the relative nominal productivity level varies abruptly from year to year clearly indicates that nominal productivity indicators cannot be used for the purpose of evaluating the difference in the technological levels between countries.

An appropriate analysis is based on a careful measurement of the relative price levels. One quite frequently applied method is to use expenditure purchasing power parities (PPPs). They are calculated for national accounts categories such as gross national product, private consumption, government consumption and capital formation. The basic problem of the expenditure approach is that they refer to the price levels of expenditures, not the price levels relevant from the standpoint of the producers and production. It is quite possible that the relative price levels vary a lot between different industries and it may be difficult to take this into account when using expenditure PPPs. One reason for this is that expenditure PPPs apply to the final output. As a consequence, the price level of the output of the paper industry, which is still a very important industry in Finnish manufacturing, cannot be determined properly.

The so-called "industry-of-origin" approach provides us with a methodology that is particularly useful when analysing the cross-country differences in productivity levels by industry. This methodology has been used and further developed by the ICOP (International Comparisons of Output and Productivity) project conducted at the University of Groningen since 1983 for international comparisons of productivity levels.[42]

[42] For a description and presentation of the ICOP project, see van Ark and Maddison (1994) and van Ark (1993 and 1996). Summary results for 30 countries are available in the ICOP website at http://www.eco.rug.nl/ggdc.

The basic idea in the ICOP methodology is to derive the unit value ratios (UVRs) for different levels of aggregation by using the unit values for the matched products in the two countries that are to be compared. Information on the quantities and values needed in the calculation of UVRs is obtained from manufacturing census or Industrial Statistics survey data. Product UVRs are aggregated in a stagewise procedure to higher levels: sub-industry, industry and finally to the total manufacturing level. This procedure yields estimates of the relative price levels for industries in the different levels of aggregation and gives an appropriate weight for each product in the aggregate in question.

More technical details on the method are given in Appendix 1. However, two points are worth bringing up at this point. First, ideally industry PPPs should be based on specified product prices. Detailed output prices are not, however, available on a large international comparable scale and some inaccuracy in the measurement needs to be accepted, which emerges due to the fact that broader product categories are used in the computation of UVRs. Secondly, as UVRs refer to product prices, they are suitable deflators for gross output. On the other hand, when gross output is used in the productivity indicator, it is important to control the intermediate input use, which is difficult. This is because it is often impossible to get an appropriate deflator for it. Quite usually the value added measure of output is used. Even though UVRs are not a theoretically ideal tool for deflating value added, in practise they are usually applicable (see discussion in van Ark (1993)). However, when the relative price level of final output is very different from the relative price level of the intermediate input, the so-called "double-deflation" procedure might be recommendable, if it is possible to implement properly.

4.2 Relative price levels

Table 4.1 shows the number of matches, the matching percentages, the resulting unit value ratios and the relative price levels in comparisons between Finland and the United States by industry. These computations and those made in the comparison between Sweden and the United States, which are documented by Maliranta (1996), reveal some interesting regularities.

1. The price level in Finnish manufacturing was high. The UVR for total manufacturing indicates that the price level in Finnish manufacturing was 27.8 % higher than in the United States. Quite interestingly, the corresponding figure for Swedish manufacturing was very similar being 26.7 % (see Maliranta 1996).

2. The industry structure of the price levels relative to the United States was very similar in Finland and Sweden. There were 30 sub-industries for which the UVRs and price levels could be determined in both Finland and Sweden. Graph 4.1 shows that there is a very strong correlation in the relative price levels of indus-

Table 4.1 Number of Matches, Matching percentages and Unit Value Ratios, Finland/USA, 1987

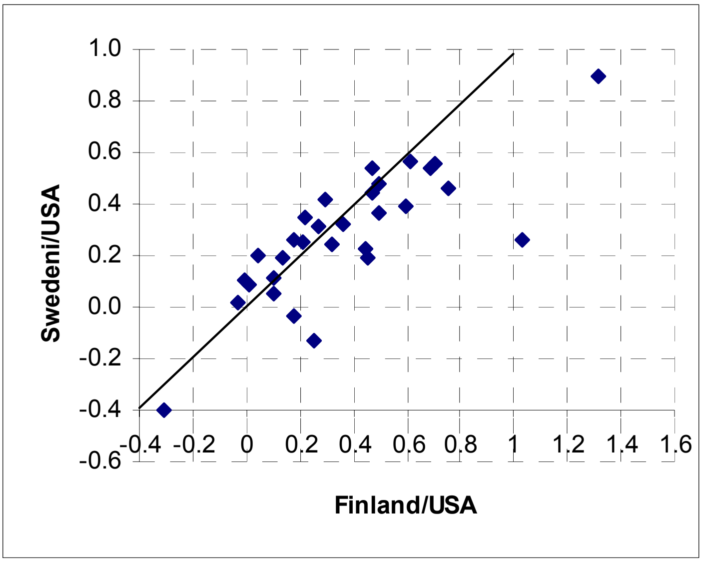
	Unit value ratio Quantity weights			Coverage of matched products, %			Finnish price level
	Finland	USA	Geometric average	Finland	USA	OBS	USA=100
Food products	7.81	9.02	8.39	62.11	43.74	67	191
Beverages	6.91	7.19	7.05	72.95	70.59	14	160
Tobacco	3.29	3.15	3.22	96.01	81.55	3	73
Textile	7.75	8.76	8.24	31.85	46.20	18	187
Wearing apparel	5.16	7.03	6.03	59.12	39.90	28	137
Shoes and leather	4.88	5.93	5.38	77.37	52.84	13	122
Wood and furniture	5.71	6.84	6.25	54.04	17.14	16	142
Paper industry and publishing	4.62	5.65	5.11	58.11	17.55	22	116
Paper, pulp and paper products	4.29	5.06	4.66	80.22	39.49	22	106
Printing and publishing	5.28	5.98	5.62	0.00	0.00	0	128
Chemicals	5.12	6.02	5.55	27.51	8.92	25	126
Oil refining	5.43	5.39	5.41	86.50	30.03	2	123
Rubber and plastic	5.28	5.98	5.62	0.00	0.00	0	128
Non-metallic minerals	6.33	7.04	6.68	20.59	19.83	13	152
Basic metals and metal products	4.68	5.06	4.87	34.84	13.81	40	111
Machinery and transport equip.	4.69	4.69	4.69	7.14	14.76	4	107
Electrical equipment	6.65	6.19	6.42	15.91	4.57	10	146
Other manufacturing	5.28	5.98	5.62	0.00	0.00	0	128
Total manufacturing	5.28	5.98	5.62	42.91	19.90	275	127.8

Source: Maliranta (1996).
Note: *OBS* is the number of matched products. Unit value ratios for printing and publishing, rubber and plastics and other manufacturing are obtained from the total manufacturing level.

tries between Finland and Sweden. In fact, remembering the inaccuracy that certainly occurs in this type of comparison, the results shown in Graph 4.1 indicate that in most industries the price levels are reasonably similar in Finland and Sweden. However, there seems to be a couple of outliers where the Finnish price level is substantially higher than in Sweden.

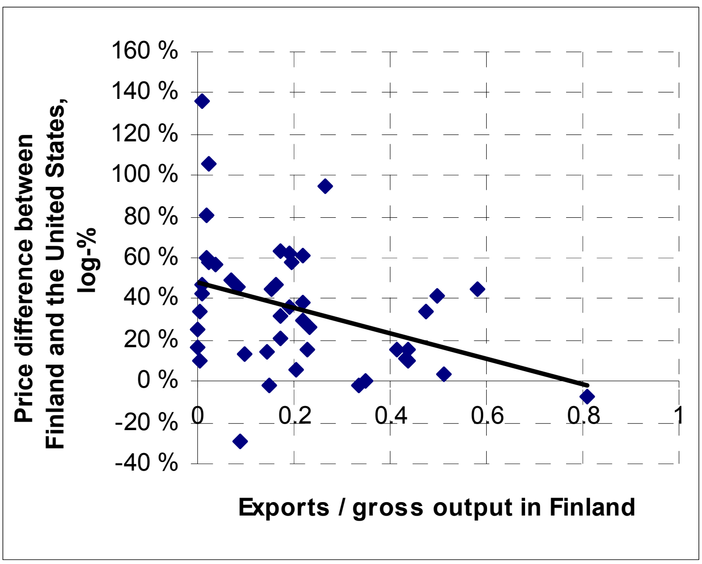
3. The relative price level of an industry is related to the export share. Maliranta (1996) shows that the price differences between Finland and the United States by industry are negatively related to the openness that is measured by the exports to gross output ratio. For example, the price differences between Finland,

Graph 4.1 Log price differences between countries by industry in manufacturing in 1987, USA=0



Source: Maliranta (1996).

Graph 4.2 Price differences between Finland and the United States by industry and share of exports



Source: Maliranta (1996).

Sweden and the United States were negligible in the paper industry. This is something we would expect, as a large proportion of the paper output of Finland and Sweden is exported and the deals are usually made in dollar terms. In the manufacture of food products, on the other hand, the price level of Finnish production is very high indeed being 91 percent above the level of the United States in 1987, which can be explained by the strict trade protection in Finland in those days.

All in all, the fact that cross-country price differences by industry appear to be systematic in an anticipated way increases the confidence in this approach to estimating productivity levels.

4.3 Relative labour productivity levels

Table 4.2 shows value added per labour hour in Finland and the United States expressed in Finnish prices (Paasche price index) and US unit prices (Laspeyres price index) as well as their geometric average (Fisher). Again, the results refer to 1987. A number of conclusions can be drawn from the productivity comparisons.

1. The level of labour productivity in Finnish manufacturing was clearly below the level of the United States. As can be seen in Table 4.2 manufacturing labour productivity in Finland was 74.3 % of the US level in 1987. In nominal terms the Finnish manufacturing sector did quite well as nominal labour productivity was 95 per cent of the US level. The failure to produce output with labour input productively in the leading edge manner is thus largely reflected in a higher price level of output.

2. There is a substantial amount of variation in relative productivity levels by industry. Industry level results show that two traditionally important industries in Finland, i.e. the paper industry and basic metals (and metal products), performed reasonably well in 1987.[43] The food industry is an example from the other extreme, with a labour productivity level that is clearly less than half of the level in the United States.[44] We also note that labour productivity was low in the textile, wearing apparel and shoes and leather industries. These industries had a lot of exports to the former Soviet Union. Obviously there is a negative correlation between an industry's relative productivity level and the relative price level. The

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[43] Maliranta (1997c) found similar results in a separate study made for the benchmark year 1992 in metal industries. Later I will use the results by Maliranta (1997c) for metal industries as they are more up-to-date than those by Maliranta (1996).
[44] Maliranta (1994) provides a detailed analysis between Finland and USA and between Finland and Sweden in the manufacture of food products, beverages and tobacco.

Table 4.2 Value added per worked hour by industry, Finland/USA, year 1987

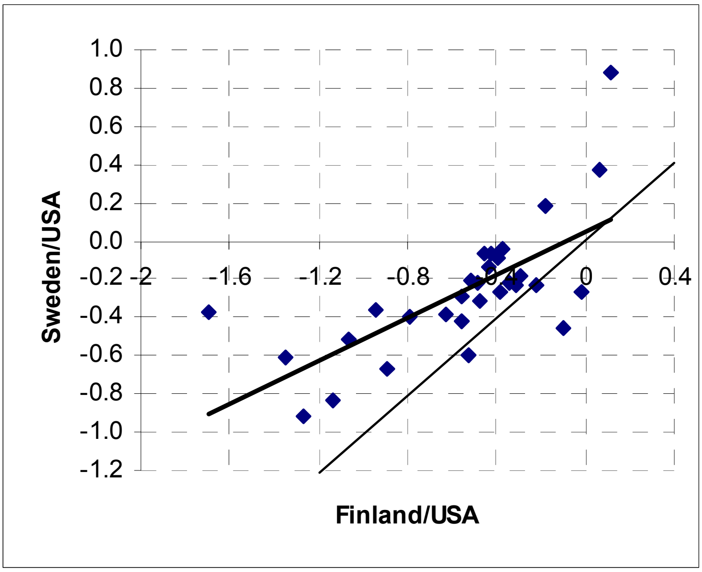
Industry	Laspeyres UVRs			Paasche UVRs			Fisher
	Finland, Fmk	USA, Fmk	Finland/USA (%)	Finland, USD	USA, USD	Finland/USA (%)	Finland/USA (%)
Food products	128.7	340.6	37.8	16.5	37.8	43.6	40.6
Beverages	274.4	505.1	54.3	39.7	70.3	56.5	55.4
Tobacco	261.5	381.5	68.6	79.4	121.2	65.5	67.0
Textile	93.4	156.7	59.6	12.1	17.9	67.4	63.4
Wearing apparel	65.8	114.4	57.5	12.7	16.3	78.3	67.1
Shoes and leather	67.0	103.8	64.5	13.7	17.5	78.3	71.1
Wood and furniture	96.8	138.0	70.1	16.9	20.2	83.9	76.7
Paper industry and publishing	184.9	192.7	96.0	40.0	34.1	117.4	106.1
Paper, pulp and paper products	215.8	211.4	102.1	50.3	41.7	120.6	110.9
Printing and publishing	150.2	184.9	81.2	28.5	30.9	92.0	86.4
Chemicals	199.0	367.8	54.1	38.9	61.1	63.6	58.7
Oil refining	361.8	337.8	107.1	66.7	62.7	106.3	106.7
Rubber and plastic	104.7	154.9	67.6	19.8	25.9	76.6	72.0
Non-metallic minerals	143.9	211.7	68.0	22.7	30.1	75.6	71.7
Basic metals and metal products	124.4	140.5	88.5	26.6	27.8	95.7	92.0
Machinery and transport equip.	119.6	158.3	75.6	25.5	33.8	75.4	75.5
Electrical equipment	124.3	187.1	66.4	18.7	30.2	61.8	64.1
Other manufacturing	113.6	196.1	57.9	21.5	32.8	65.6	61.6
Total manufacturing	134.4	192.6	69.8	25.5	32.2	79.1	74.3

Source: Maliranta (1996).
Note: The data is from the US Manufacturing Census and from the Finnish Industrial Statistics survey. Original (census) value added concepts differ somewhat between the countries. Therefore the Finnish numbers are recalculated so that they are comparable with the US figures. Nominal value added figures are converted into common currency by UVRs.

variation in nominal productivity levels is much less than in real productivity levels. The unweighted coefficient of variation of the real relative labour productivity levels of the industries shown in Table 4.2 is 25.3 % and the respective number for the nominal relative productivity levels is 21.5 %. So the relative output prices seem to do the job of equalising the competitive positions of the industries. These results indicate that ignoring the differences in the relative price levels between industries, as is done in Bernard and Jones (1996) and Landesmann and Stehrer (2001) for example, may lead to a distorted picture of the comparative advantages of the nations (see also discussion in Sørensen 2001).

3. The industry structure of the comparative advantages is similar in Finland and Sweden. In most industries Swedish productivity performance was higher than in Finland. This is shown in Graph 4.3 by the fact that all except four dots lie above the thinner line with the slope 1. What is interesting and consistent with the findings made with the price comparisons above is that we see that the same industries perform well or badly relative to the United States in both Finland and Sweden. There is a statistically very significant correlation (r=0.63) between the productivity levels of the industries between Finland and Sweden that is illustrated by the upward sloping thick line.[45]

Graph 4.3 Log productivity differences between countries by industry in manufacturing in 1987



Source: Maliranta (1996, pp. 74).

Maliranta (1996) has also examined the industry structures of the comparative advantages in the context of multilateral comparisons. Estimates for 14 industries were collected in a number of binary labour productivity comparisons with the United States (see the notes of Table 4.3). The (weighted) average labour productivity level in international prices was estimated by using the Geary-Khamis tech-

[45] This type of relationship may occur if there is a lot of inaccuracy in the US productivity estimates. However, we have little reason to expect that the US numbers are particularly inaccurate.

nique. The average labour productivity in the country sample was used as the benchmark for multilateral productivity comparisons.

Table 4.3 documents the similarities and dissimilarities in the industry structures of the comparative advantages in eight countries. Again, we note a positive significant correlation between Finland and Sweden. Similarly, we find very strong statistical evidence of the similarity of the comparative advantages between the neighbouring countries France and the former West Germany and suggestive evidence for similarity between Japan and Korea. It would be interesting to know which factors might explain that, in certain industries, Finland and Sweden or France and Germany perform relatively well. These empirical findings are consistent with the conjecture that there is diffusion of industry-specific technology within broader geographical areas.

Table 4.3 Correlation matrix of the productivity log differences by industry (14 industries). The benchmark is the average productivity in the country sample, year 1987

	USA	Finland	Sweden	Germany	France	Japan	Korea	UK
USA	1							
Finland	-0.102	1.000						
Sweden	0.086	0.577**	1.000					
Germany	0.225	0.124	0.443	1.000				
France	-0.047	0.057	0.525	0.771***	1.000			
Japan	-0.643**	-0.231	-0.212	-0.269	-0.129	1.000		
Korea	-0.409	0.231	0.206	0.331	0.398	0.476*	1.000	
UK	0.235	-0.133	0.256	0.248	0.280	0.180	0.043	1

Source: Maliranta (1996).

Note: Germany refers to the former West Germany. Labour productivity is value added in international prices calculated by the Geary-Khamis method per hour worked. Country results are obtained from the following binary comparisons: the former West Germany/USA and Japan/USA from van Ark and Pilat (1993), France/USA from Ark and Kouwenhoven (1994), Korea/USA from Pilat (1993), the United Kingdom/USA from van Ark (1993). Finland/USA and Sweden/USA are from the study by Maliranta (1996).

* significant at 10%

** significant at 5%

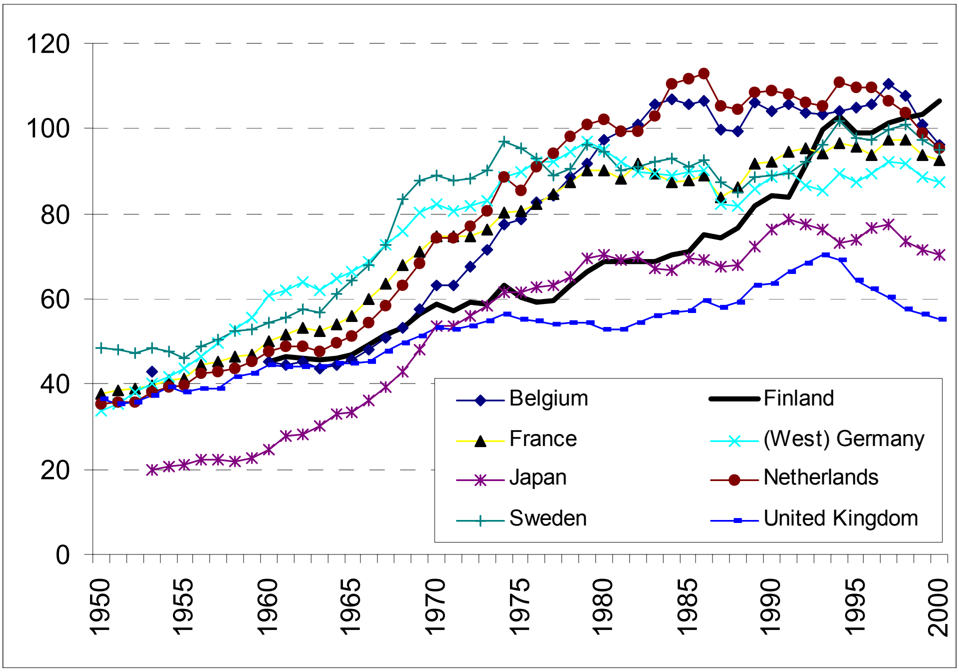
*** significant at 1% level

4. The dispersion of the relative productivity differences between plants is greater in Finland than in Sweden. There are a fairly large number of sub-industries in Finnish manufacturing that had a very poor labour productivity level in 1987. There are 5 out of 30 sub-industries in Finland where labour productivity is more than 100 log-% behind the US level.[46] The corresponding number for Sweden is zero. So a relatively large variation in the productivity performance between (sub-)industries seems to be one distinctive feature of the Finnish manufacturing sector in the pre-recession period.

4.4 Development of relative productivity performance

Graph 4.4 provides us with a wider and longer perspective on labour productivity development in Finnish manufacturing. We note that Finnish labour productivity has improved not only relative to the United States but also relative to many other

Graph 4.4 The relative labour productivity level of Finnish manufacturing, 1950 to 1999, USA=100



Note: The relative labour productivity level in 1987 is from the study by Maliranta (1996). Results for other years in the Finland-USA comparison as well as the comparisons of other countries are obtained from the ICOP industrial database maintained by the Groningen growth and development centre (data and references to other binary comparisons can be found in http://www.eco.rug.nl/ggdc/index-dseries.html#top)

[46] Four of these happen to be sub-industries of the manufacture of food products and the fifth is the manufacture of beer.

competitors during recent decades. The graph seems to indicate a couple of productivity clubs, one consisting of Belgium and the Netherlands and another consisting of France, the former West Germany and Sweden. The Finnish manufacturing sector seems to have broken through to the international top group in the mid-1990s. It is worth remarking that many countries have started to regress in relative terms during the 1990s, Japan and the United Kingdom in particular.

Graph 1.4 depicts the development of the total factor productivity level relative to the United States, which suggests that Finland's success in catching up has largely been based on technological development, not just on increased capital intensity in production.

The relative total factor productivity levels between Finland and the United States by industry are given in Table 4.4. The classification is now based on the ISIC Revision 2 scheme. The development of these relative levels in 1976-1996 is given in Graph 4.5. They are obtained by updating the results in Maliranta (1996 and 1997c).

Relative total factor productivity is measured here in the conventional way by using factor shares of the two inputs considered, labour and capital. More precisely, the weights of the two input types needed in the calculations are obtained by taking arithmetic averages of the income shares in the two countries. The capital stock estimates needed for the total factor productivity indicator have been calculated from an investment series by using the perpetual inventory method and by assuming the same depreciation rate for each country.[47] Finnish investments have been converted into dollar terms by using the purchasing power parities of investment goods. This information has been obtained from the International Sectoral Database (ISDB) by the OECD. Extrapolation of the series and the capital stock estimates is based on information obtained from the STAN Industrial Database by the OECD, DSTI (further information about the data and methods used in the computations is provided in Appendix 1).[48] The productivity comparisons for the base year (1992 for metal industries and 1987 for the others) have been made using the ICOP approach.

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[47] Typically somewhat less than 10 percent, depending on the industry. We have determined the depreciation rate so that the series generated from an investment series by the PIM method for the United States has a pattern over time that is as similar as possible to the official capital stock series. The results for relative productivity performance are not sensitive to the choice of the depreciation rate as long as the same rate is used for both countries under consideration. The computations of standardised capital stocks involve estimations of initial capital stock (in 1970).

[48] Printing & Publishing is dropped from the analysis. For that industry it was not possible to compute an industry-specific unit value ratio that is used in converting outputs into comparable units in the Finland/US productivity comparison.

Table 4.4 indicates that Finnish manufacturing industries were quite heterogeneous in terms of relative productivity performance before the recession. The aggregate productivity level is high in basic metal industries, paper and paper products and non-electrical machinery. The backwardness appears to be worst in the food industry, transport equipment and textiles, etc.

There seems to be a considerable amount of divergence in developments over time across industries as well (see Graph 4.5). Electrical machinery is from one extreme – the relative performance level has climbed from 70 per cent to slightly over the US level in a few years' time. Food and wood industries used to be at the other extreme. Despite their very low productivity level they managed to catch up with the US level gradually. On the other hand, a marked acceleration in catching up can be found in the post-recession period (i.e. since the early 1990s). Productivity performance has typically been quite poor in the non-metallic minerals and textile industries.

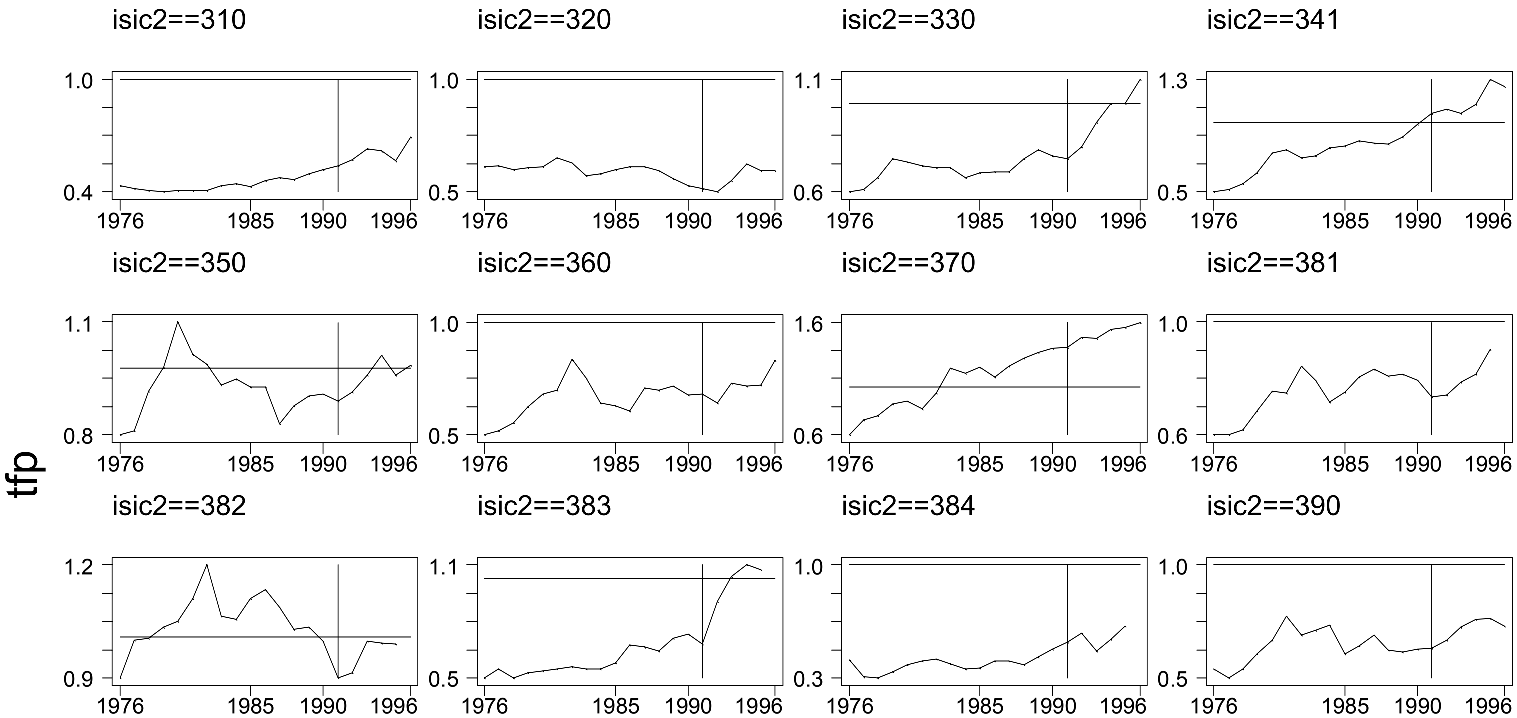
Table 4.4 Relative total factor productivity performance in Finnish manufacturing industries in 1990 (USA=100)

Industry	isic2	LP	TFP
Food, Beverages & Tobacco	310	50	48
Textiles, Apparel & Leather	320	60	56
Wood Products & Furniture	330	90	75
Paper & Products	341	127	98
Chemical Products	350	89	92
Non-Metallic Mineral Products	360	72	71
Basic Metal Industries	370	117	135
Metal Products	381	81	78
Non-Electrical Machinery*	382	91	99
Electrical Machinery**	383	67	72
Transport Equipment	384	47	50
Other Manufacturing	390	67	62

* Excludes computers.

** Includes computers, instruments and other professional goods. *lp* denotes labour productivity and *TFP* total factor productivity.

Graph 4.5 TFP levels in Finnish manufacturing industries relative to the United States (USA=1)



Graphs by ISIC2.

4.5 Aggregate level explanations for cross-country productivity differences

Above we saw substantial differences in productivity levels between countries. Moreover, the differences were found to vary greatly between different industries and between different points of time. The fact that there are considerable gaps in TFP levels suggests that the basic neo-classical growth theory provides us with an inadequate framework for understanding productivity performance.

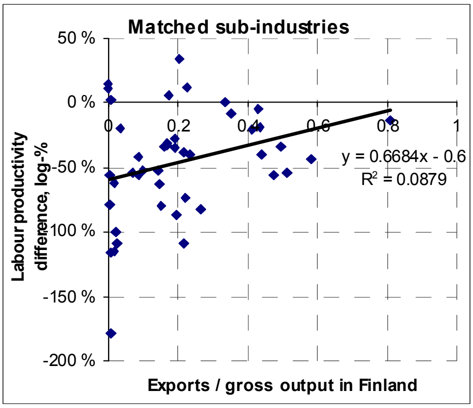
Maliranta (1996) tried to find explanations for the substantial labour productivity differences between Finland and the United States at the total manufacturing level by aggregate data. The effects of industry structures and plant sizes were investigated. Generally, both of these factors were about as unsuccessful as capital intensity, which is controlled in a TFP indicator, in explaining the labour productivity gap. Controlling these factors, if anything, seems to increase the unexplained gap between the two countries. The labour productivity gap seems to have been wider at the sub-industry and industry-level than at the total manufacturing level. This finding suggests that labour productivity difference at the total manufacturing level most likely does not overrate the extent of technological laggardness of the Finnish manufacturing sector in the latter part of the 1980s, rather the opposite. When the sub-industry structures were controlled,[49] the relative labour productivity level decreased most in those Finnish industries where the relative labour productivity level was highest. For example, the relative labour productivity level of the paper industry dropped from 111 % to 87 % after the control of sub-industry structures in Finland and the United States. The variation in relative labour productivity levels between industries declined after the control of the industry structures or plant-size structures. Capital intensive sub-industry structures or large plant sizes seem to have been characteristic of particularly those Finnish industries that had high labour productivity in relative terms. A slightly higher education level in the United States provides, at best, only a partial explanation for the productivity gap.

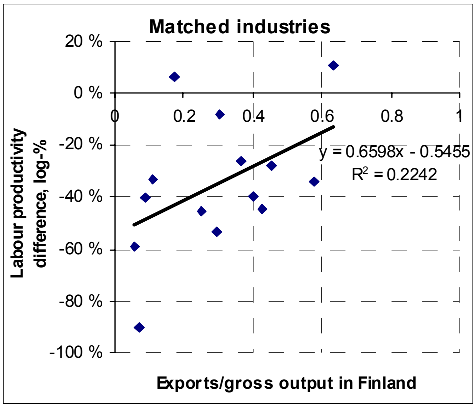
So the explanations for the productivity differences must be somewhere else. Graph 4.6 indicates that the export share is positively associated with the relative labour productivity level. The diagram on the left-hand side plots sub-industries (44 sub-industries) and the diagram on the right-hand side industries (14 industries). Only the "matched" industries and sub-industries are included, because for these industries the relative productivity levels can be computed reliably. Both of these diagrams suggest that the Finnish industries that equal the United States in productivity are those which export at least 80 % of their production to international mar-

[49] This was done by first computing the relative productivity levels at a detailed industry level and then aggregating these ratios by employment share weights (see for example van Ark 1993).

kets. The predicted gap for totally sheltered industries is 55-60 log percentages. Of course, a lot of variation can be anticipated, while the intensity of domestic competition, for example, is likely to play a role.[50] Besides, the direction of causality remains open.

Graph 4.6 The productivity difference compared with the United States and the openness of Finnish industries





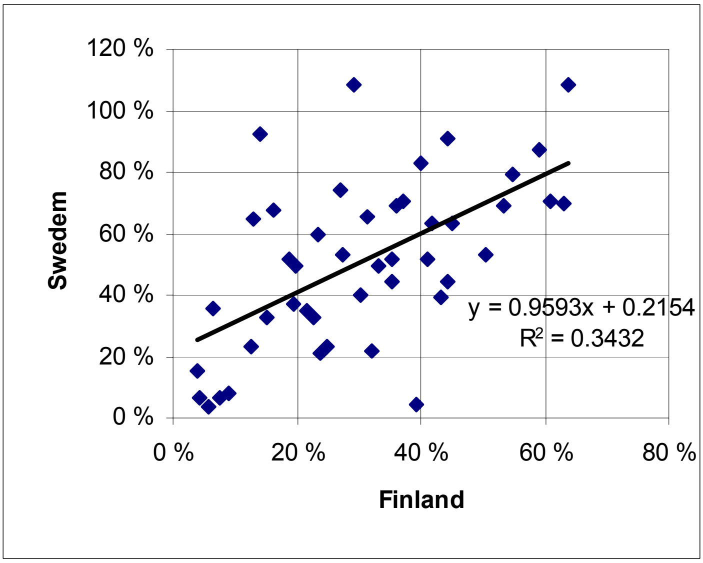
Source: Maliranta (1996).
Note: only those (sub)-industries are included whose UVR is calculated by its own products.

Above we saw that the comparative advantages (relative to the United States) are quite similar in Finland and Sweden. Graph 4.7 in turn demonstrates a great similarity in the revealed comparative advantages between Finland and Sweden at the detailed industry level. The pattern appearing in the graph accords perfectly with the earlier findings concerning the industry structures of the relative labour productivity levels and the relationship between exports and the relative labour productivity.

One possible explanation for these results is that Finland and Sweden (or Germany and France) share similar "natural" factor endowments. This seems a plausible explanation as to why both these countries have relatively high productivity levels in the paper industry. On the other hand, it is not perfectly clear why a large supply of wood material makes Finland and Sweden productive in converting

[50] There is statistical evidence on heteroscedasticity in these regression models. There is a statistically significant negative relationship (t=-2.3) between the exports share and the squared residual term in the model shown in the left-hand side diagram.

Graph 4.7 Exports per gross output in sub-industries in 1990



Source: OECD, Industrial Structure Statistics.

wood material into paper by using labour and capital. It is perhaps easier to understand why these countries have focused in their innovation efforts more on the paper industry than on some other. Further, it is seems quite possible that both countries have benefited from intra-industry knowledge spillovers between them. Thus, high exports in both countries in certain industries can be seen as a reflection of high productivity performance, which is based on the sustained accumulation of technological knowledge in the past and possibly on the increasing returns of knowledge creation. In addition, exports and exposure to global competition as such may have contributed positively to static and dynamic efficiency.

5 The patterns of productivity development in Finnish manufacturing plants

The micro-level components of aggregate productivity change are explored in this chapter. Both labour and total factor productivity changes are analysed. We use a variety of different decomposition methods in order to compare the methods and to check the robustness of the conclusions.

5.1 Data

The main data source is the Longitudinal Data on Plants in Manufacturing (LDPM), which is constructed especially for research purposes from the annual Industrial Statistics databases. In principle, a plant is defined in the Finnish Industrial Statistics survey as a local kind-of-activity unit. In other words, it is a specific physical location, which is specialised in the production of certain types of products or services. A single local unit may consist of several plants that have activities in different industries. In some special cases a plant is delineated to include parts that are located geographically detached from it. However, it is required that the units are located within the same municipality. This solution seems to be well justified, especially when the geographically separated units are closely attached to each other operationally. This way of grouping plants may help firms to provide more accurate information on their activities within a certain specific industry.

The Industrial Statistics survey annually compiles comprehensive information on the economic activity of industrial plants. This electronic database now contains information from 1974 to 2000. Up to 1994 it includes basically all plants with at least 5 persons. Since 1995 all plants owned by an enterprise with at least 20 persons have been included in the surveys. As there is a relatively large number of single unit firms employing less than 20 (but more than 5) persons, the number of plants drops by almost one half due to this change in the applied criteria. However, the number of persons diminishes only moderately, by a few per cent. Thus, there is a break in the series between 1994 and 1995 that needs to be taken into account in handling and interpreting the time series. In particular, there may appear to be some artificial exits in 1995. One way to generate a continuous time series could be to exclude all units with fewer than 20 persons engaged. The analysis covers all production units that have positive value added.

For the labour and total factor productivity indicators, output is measured by value added or gross production. In the case of multi-factor productivity only a gross production measure is used. Nominal output measures are converted into final year prices by means of industry-specific (103 industries in manufacturing) producer price indexes. Labour input is measured by total hours worked. Capital stock, which is used as a measure of capital input, is estimated by using the perpetual inventory method and assuming 10 percent annual depreciation. More details and descriptive statistics concerning the data are given in Appendix 2. The links of the LDPM data to the Finnish statistical system are described there, too.

Following the practise applied by Mairesse and Kremp (1993) I have dropped those plants whose log productivity differs by more than 4.4 standard deviations from the input-weighted industry average (2-digit industries) in the year in question. In addition, I have dropped some seemingly erroneous observations.[51]

5.2 Properties of productivity decomposition results

5.2.1 Fixed base year bias

In this study the outputs in the initial year and final year are expressed in final year prices, i.e. I use rolling base years. Usually, however, productivity growth analysis is carried out by using fixed base year prices instead (see for example Oulton 2000). In order to assess how serious a bias may be caused by using such a procedure in the analysis of aggregate productivity, I have depicted in Graph 5.1 the difference between aggregate labour productivity growth rates when calculated by fixed year prices versus rolling base year (i.e. final year) prices. The bias is defined here as productivity growth with fixed year prices minus productivity growth with final year prices. The trend in the bias is very much in agreement with expectations. The use of the fixed-base-year strategy yields negatively biased growth rates before the base year (in this case 1990) and positively biased rates thereafter. According to these calculations the growth rate for the year 2000 is overrated by 8 percentage points![52] [53] The recent upsurge in the bias can probably be mostly attributed to the electrical machinery industry, where the volume of output has increased rapidly and the prices have gone down annually about 20 percent. These results indicate that the use of the fixed-base-year strategy may overstate the acceleration in productivity growth at the manufacturing level in a serious way (see also Table 2.1).[54]

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[51] For calculating labour productivity decompositions for the period 1975-2000 I have dropped 9 plants from the more than 10,000 plants appearing in the period in question (in addition to those dropped on the basis of the criteria described in the text). The number of dropped plants is 10 for calculating the TFP and 12 for calculating the MFP indicator.

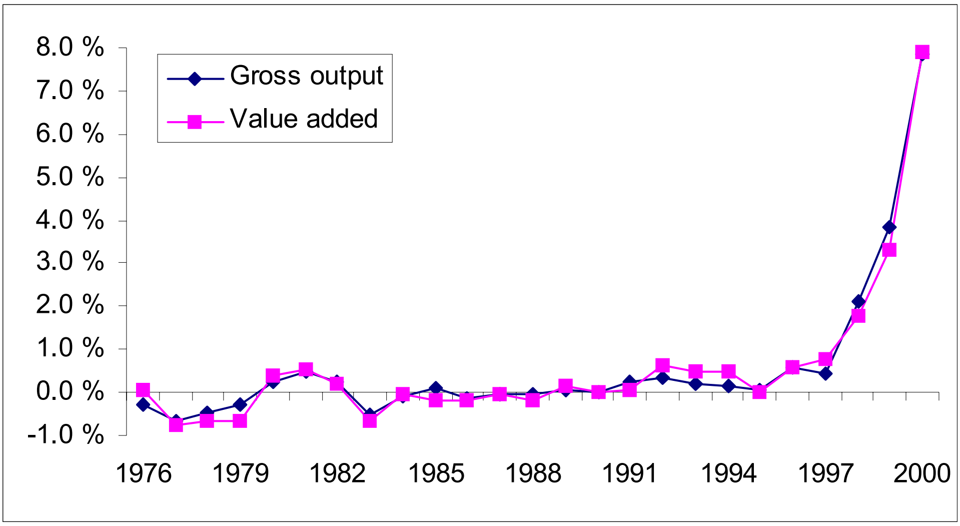
[52] When the base year is 1995 the magnitude of the bias is 5 percentage points.

[53] It should be noted that these results differ to some extent from those obtained from the National Accounts. The main difference is that in this study the volume of output is derived by using producer price indexes whereas the National Accounts make use of the quantity indexes and unit values obtained from the production survey. Because the quality changes are controlled with somewhat greater care in the producer price index, the results for productivity growth reported here are likely to capture quality improvements more accurately.

[54] See for example Corrado, Gilbert, and Raddoc (1997) and Varjonen (1994).

For the most part the bias comes from the catching up and between components. The within component is, of course, unbiased because at the plant level the output volumes expressed in fixed base year prices indicate the output growth correctly. The output growth rates of the plants are weighted by current input shares and these are, of course, independent of the unit in which the output is expressed. The cross term and turnover components show no clear systematic trends in bias.

Graph 5.1 The fixed base year bias in the aggregate labour productivity growth numbers (base year 1990)



5.2.2 The biases in the aggregate numbers of the GR and FHK methods

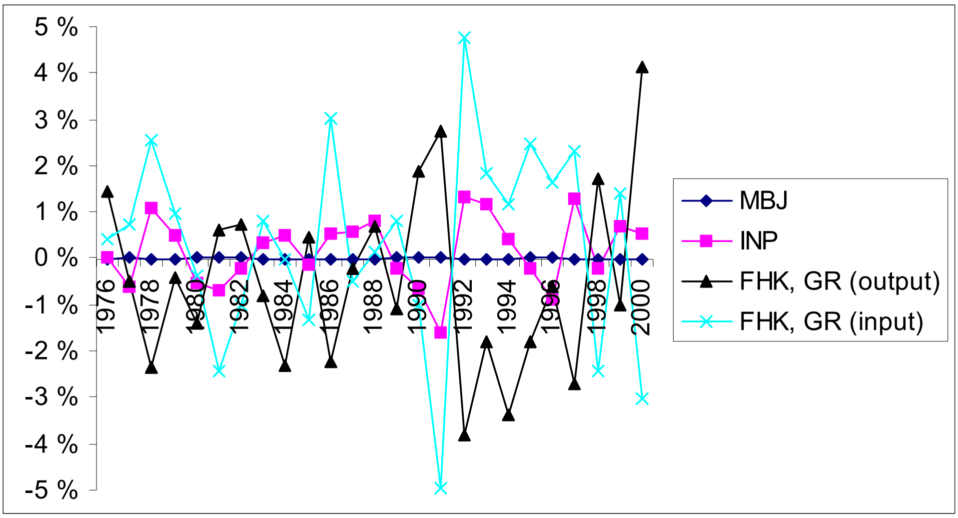
In the FHK and GR methods the aggregate productivity change rate is computed by aggregating the plants' logarithmic productivity levels. This aggregation is made by using input or output shares. It is important to note that these rates of aggregate growth might differ substantially from conventional aggregate measures, in contrast to the MBJ method. This is shown in Graph 5.2, where the aggregate productivity growth rates computed with the different methods are compared to those obtained by an ideal aggregate Törnqvist productivity index. The graph shows how much the results differ from those obtained by the Törnqvist index. As stated in Section 3.2.1 the MBJ method provides us with a very close approximation of an ideal aggregate index. The absolute difference here is always less than 0.01 percentage points. The standard deviation of the discrepancy is 0.003 percentage points.

As for the FHK and GR methods the discrepancy is frequently quite large. On average, the FHK method with output weights underrates the growth by 0.48

percentage points, whereas with input weights it overrates the growth by 0.32 percentage points. The standard deviation of the discrepancy is 1.94 percentage points for the input-based and 2.13 percentage points for the output-based weighting scheme. We also see that there is some, but clearly less, inaccuracy in the aggregate productivity estimates obtained with the INP method. The average bias is 0.15 percentage points and the standard deviation is 0.74 percentage points.

While the focus of this study is on the contribution of the restructuring or external adjustment rather than on the rate of aggregate growth, the inaccuracy of methods in this respect may not be too critical. However, as mentioned earlier the productivity components are quite often presented as proportions of the aggregate productivity growth rates and in that case the bias in the denominator may be quite harmful.

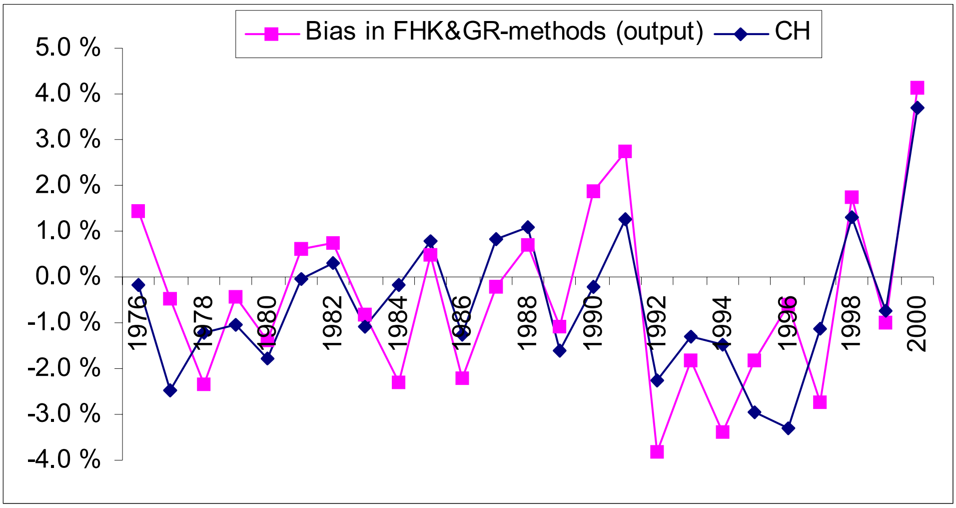
Graph 5.2 Biases in the aggregate productivity growth rates. Comparison with the ideal Törnqvist measure



Note: Aggregate TFP is calculated here by using the value added concept of output.

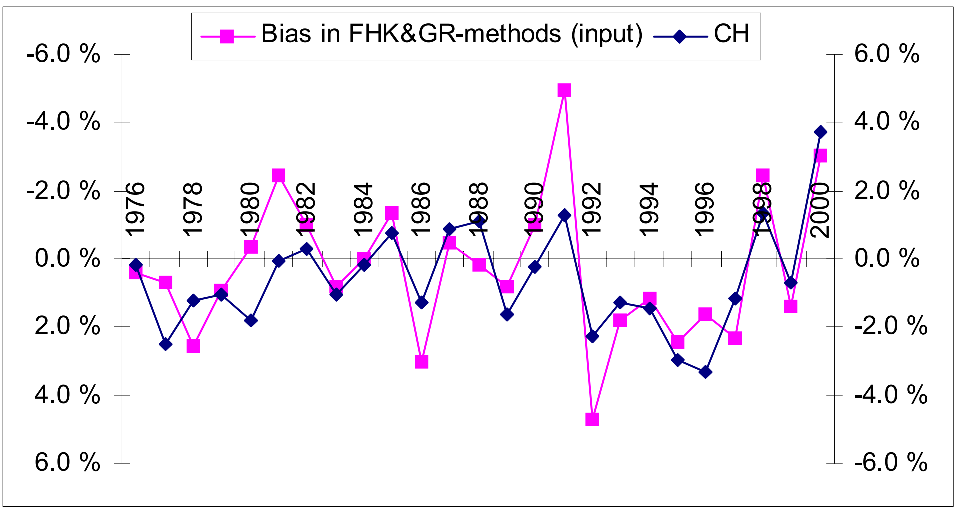
Next, the biases in the aggregate growth numbers obtained by the GR and FHK methods are shown to be directly related to the catching up component of the MBJ method, as was predicted in Section 3.5.1. Graph 5.3 illustrates the co-movement of the bias in the GR and FHK methods applied by output weights and the catching up component of the MBJ method. We see that the connection is quite strict. For example, the GR and FHK methods with the output weights give us downward biased growth numbers in the recovery period, and the catching up

Graph 5.3 Bias in the aggregate TFP growth rates of the GR and FHK methods, calculated by output shares and the catching up component of the MBJ method



Note: Output is measured by the value added concept.

Graph 5.4 Bias in the aggregate TFP growth rates of the GR and FHK methods, calculated by input shares (left scale is reversed) and the catching up component of the MBJ method (right scale)



Note: Output is measured by the value added concept.

component was clearly negative at those times. Graph 5.4 depicts the corresponding series for the input index-weighted GR and FHK methods. Now we find a negative but still very tight relationship between the bias of the GR (and FHK) method and the catching up term (note that the left scale is reversed).[55]

5.2.3 The timing of the weights

When the weights are determined by inputs, those methods that make use of the initial year weights (the FHK and MBBH methods) give systematically higher numbers for the between and within components than those that make use of the average period weights (the GR, MBJ and INP methods).[56] The remaining gap is captured by the cross term that usually has negative values (see Tables A3.1-A3.5 in Appendix 3).

When output weights are used, the outcomes are reversed, as predicted in Chapter 3 (for further evidence see also Foster, Haltiwanger and Krizan (2001) and Maliranta (2001)). In this case, the within and between components are lower in the FHK and MBBH methods than they are in the GR, MBJ and INP methods. Now the cross terms of the FHK and MBBH methods are typically positive. The difference is particularly large when output is measured by the value added concept (see Tables A3.2 and A3.4 in Appendix 3). Large transitory variation in plants' value added is likely to explain the fragility of the results obtained by the FHK and MBBH methods.

The fact that the magnitude and even the signs of the components of the FHK and MBBH methods are very much dependent on whether input or output weighting is used poses some challenges for interpretation. When one wants to analyse the role of input reallocation for an economy's or industry's growth, input-based weighting is a natural choice. But the fact that output weights would give qualitatively very different results may raise some suspicions about the reliability and interpretability of the FHK method. It is worth remarking that when the GR method is used, the results for the between and within components are reasonably similar irrespective of whether input or output is used in the weighting scheme, even when output is measured by value added (see Table A3.4 in Appendix 3).

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[55] The catching up components of the INP and MBBH methods are reasonably similar to those obtained by the MBJ method. In fact, the bias of the FHK and GR methods calculated by input weights can be best predicted by the catching up component of the INP method.

[56] The entry effect is also usually slightly higher in the FHK method than in the GR method. The opposite is true for the exit effect.

These results are totally consistent with the conjecture that the methods that make use of initial year weights are sensitive to the noise in micro data, as discussed in Section 3.2.4 and demonstrated in Section 3.4.2.1.

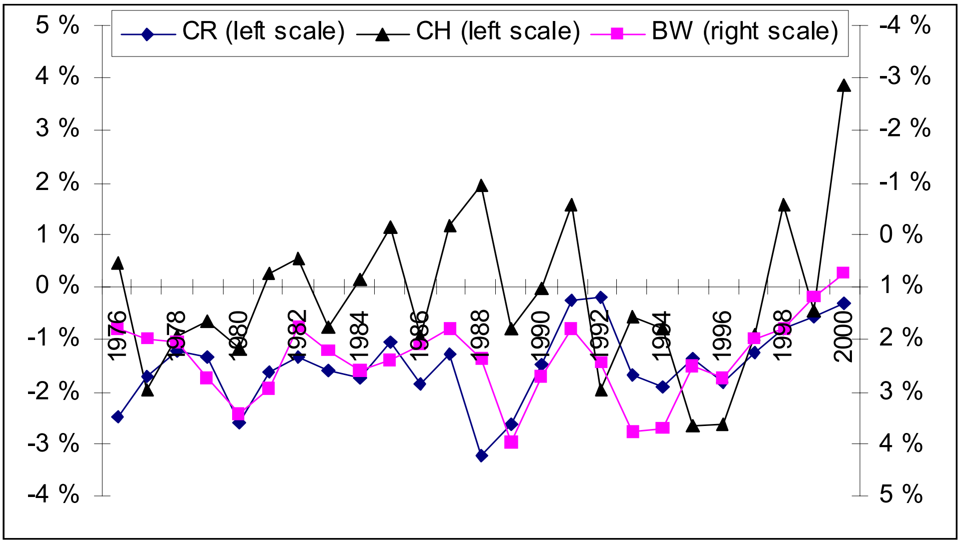
Foster, Haltiwanger and Krizan (2001) argue that one advantage of the FHK method over the GR method is that the former includes a cross term that gives valuable information on micro level development. It could be used to identify periods of productivity-enhancing downsizing, for example.

The catching up component provides us with another alternative for such a purpose. The MBBH method includes both components and they are depicted in Graph 5.5. The two series seem to share some similar variation in the period under consideration but substantial differences in the patterns can be found as well. The catching up term obtains negative values in the periods 1977-80 and 1992-97. The former was a period of quite severe recession in the Finnish manufacturing sector (see also Graph 1.1), while the latter was a period of strong recovery. Finding evidence of intensified internal adjustment by the catching up component in these seemingly quite different periods is not very surprising, however. Both periods can be expected to be times of adjustment to a changed economic environment. The negative catching up component in these periods could be interpreted to mean that many low productivity plants were "struggling", à la Boone (2000), in order to improve their relative productivity level through internal adjustment. A positive correlation between the catching up component and the change in productivity dispersion would give support to this conjecture. This is examined in Chapter 8.

The cross term, on the other hand, does not render any clear indication of changes in development. The cross term was very low in the boom of 1988-89 and relatively high during the recession of 1991-1992. I have also included the between component to show that its pattern is very much a mirror image of the cross term, which is consistent with the view that the variation in the magnitudes of the transitory errors in data may drive the between component and the cross term of the MBBH method (note that the BW has a reversed scale).[57] The fact that there is a negative correlation between the between component and the cross term (-0.55) and between the between component and the catching up component (-0.46) may, of course, indicate that the same factors drive both components. The values of the catching up components of the MBJ and MBBH methods are quite similar. The correlation between them is .992. The catching up component does not seem to be very sensitive to the use of the weights of the initial year or the period average, unlike the within and the between components.

[57] The FHK method gives quite similar patterns for the between and the cross component with the MBBH method.

Graph 5.5 The cross term and the catching up component of the MBBH method



Note: Productivity is measured by TFP by using the value added concept for output.

5.2.4 Output or input weights?

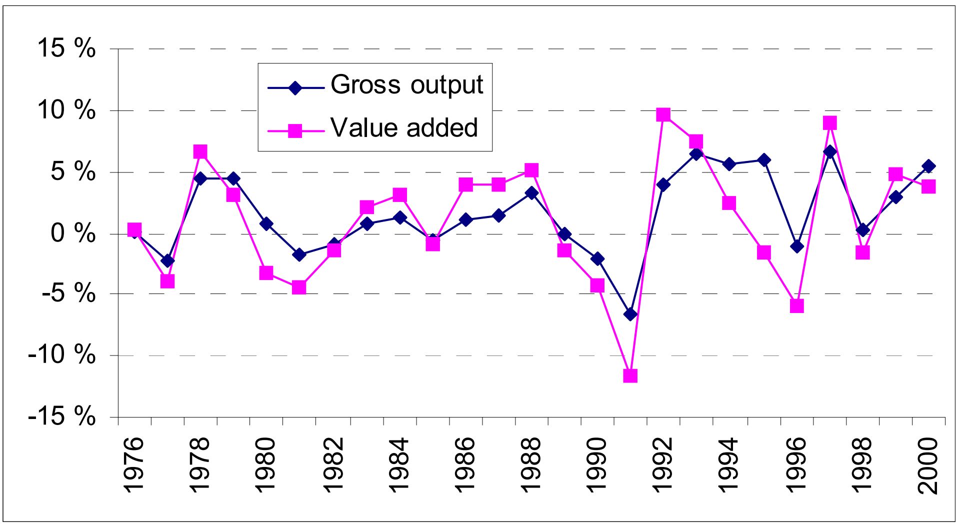
I already commented on some considerable differences in the results depending on whether the plant weighting schemes are based on outputs or inputs. One advantage of the use of input-based weighting over output-based weighting is that then the decomposition can be directly linked to the more usual (and ideal) measures of aggregate productivity change by using the MBJ method. If, despite the problems, one decides to use the FHK or MBBH methods, the use of input index weights is likely to yield more robust and reliable results, because the input numbers may involve smaller transitory measurement errors. This can be concluded from the results reported in Tables A3.1-A3.5 of Appendix 3. The difference in the between (and the within) components of the FHK and GR methods is larger when output weighting is used instead of input weighting. In fact, when the input index includes many input types, as with the TFP and MFP indicators, the difference between the FHK and GR methods may not be insupportably wide (see Table A3.5 in Appendix 3 in particular).

5.2.5 Gross output or value added?

For the sake of a robustness check I have performed computations by using both the gross output and value added concepts for output. The results and conclusions are not very sensitive to the choice of output concept. Some differences can be found, however. As Graph 5.6 indicates, both concepts yield similar patterns over time. However, the average growth rate of TFP within plants in 1976-2000 is different for each of the two concepts, being 1.6 percent with the gross output concept and 1.0 percent with the value added concept. The gross output measure gives somewhat more stable estimates of the productivity growth within plants than the value added gauge. The standard deviation is 3.3 percentage points with gross output and 5.1 percentage points with the value added output concept. One problem with the value added concept is that a theoretically correct price index is not available for it. I have used the producer price index instead, which is related to gross output.

Despite its obvious limitations, the value added concept might have some advantages over the gross output concept in cross-section comparisons of productivity, which is another important dimension of productivity measurement in decomposition computations. For example, value added per hour may be a better gauge for a plant's relative labour productivity performance than the gross output to hour ratio, as the value of purchased services and materials are netted out in the former. An appropriate measure for plants' productivity levels is essential, especially for the computation of the between component (and the catching up component). As the magnitude of the between component is dependent on the correlation between

Graph 5.6 The within component of TFP growth with the alternative output concepts



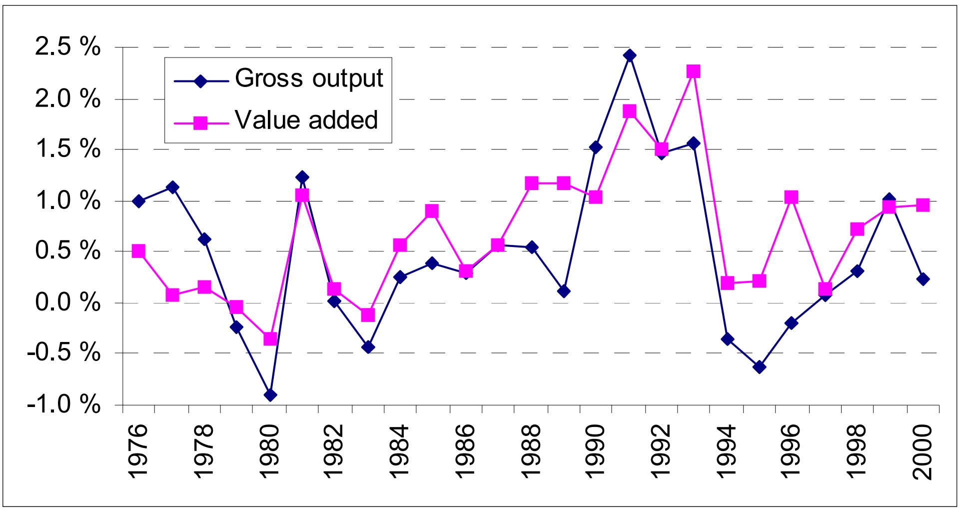
Note: TFP growth is decomposed by the MBJ method.

productivity level and the growth of input usage, accurate measurement of the productivity level is, of course, a highly critical point.

The time pattern of the between component of labour productivity is broadly similar when output is measured by the gross output or value added concepts (see Graph 5.7). The use of gross output, however, underlines the exceptionality of the years 1990-94 whereas the use of the value added concept suggests that the between component exhibits a positive trend in the period from the early 1980s to 1993.

The choice of the output concept appears to be important for the analysis of entry and exit as well. This can be seen in Tables A3.1-A3.5 in Appendix 3.

Graph 5.7 The between component of labour productivity growth with the alternative output concepts



Note. Labour productivity growth is decomposed by the MBJ/INP method.

5.3 Components of aggregate productivity growth in Finnish manufacturing

5.3.1 The "creative destruction" components

In this section the magnitudes and patterns of the between, entry and exit components are examined. These components can be described as the "creative destruction" elements of the aggregate productivity growth process.[58] I consider three measures of productivity – labour productivity, total factor productivity and multifactor productivity.

5.3.1.1 Labour productivity

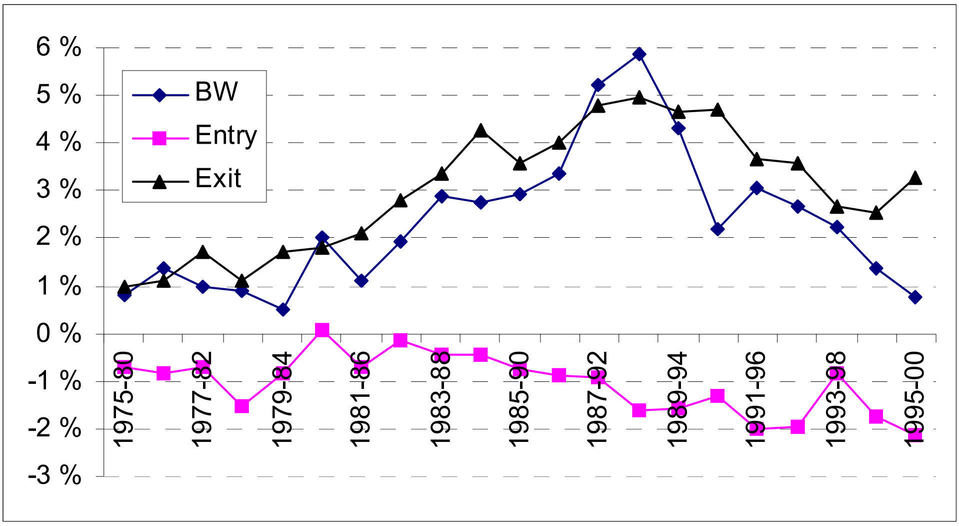
Graph 5.8 depicts the "creative destruction" components of aggregate labour productivity growth in total manufacturing using the MBJ/INP methods.[59] In order to better capture the time-consuming growth process, I have used 5-year moving windows. We see that the between and exit components are quite closely related. Both started to soar in the latter part of the 1980s and peaked during the first part of the 1990s. Both components exhibit downward tendencies in the latter part of the 1990s. The entry effect in turn has been usually clearly negative, indicating that the new plants have a lower labour productivity level than the older ones. This tells us that the current average labour productivity growth would be higher without the appearance of new plants in the previous 5 years.

As shown in Section 3.2.2 two elements can be distinguished in the exit component of the INP method. A higher exit component is obtained the lower is the relative labour productivity level of the disappearing plants relative to the continuing plants, and the larger is the input share of the disappearing plants in the initial year (see Equation (3.8)). Graph 5.9 indicates that the rise of the exit effect up to the

[58] I report and use in this chapter and in the following chapters the absolute numbers of the components obtained from the various decomposition formulas. It should be noted that the productivity growth rates and the components of the productivity decompositions are measured on interval scales. Unlike productivity levels they may have negative values. If the measurement is made on an interval scale, operations of addition and subtraction produce meaningful results. Multiplication and division is legitimate only when the numbers are constrained to be positive. This is to say that the measurement is made on the ratio scale (see Vasama and Vartia 1980, pp. 46-52 or Abranovic 1997, pp. 19-20). It is thus a bit surprising that it is now so common to express the components of growth decomposition as shares of the total aggregate productivity growth rate (see Foster, Haltiwanger and Krizan 2001; Scarpetta, Hemmings, Tressel and Woo 2002; Disney, Haskel and Heden 2003, for example). Of course, when an aggregate growth rate is arbitrarily close to zero, the shares of each component explode towards positive or negative infinity.

[59] Note that in a single input case the MBJ and INP methods are identical.

Graph 5.8 The "creative destruction" components of labour productivity growth, moving 5-year windows

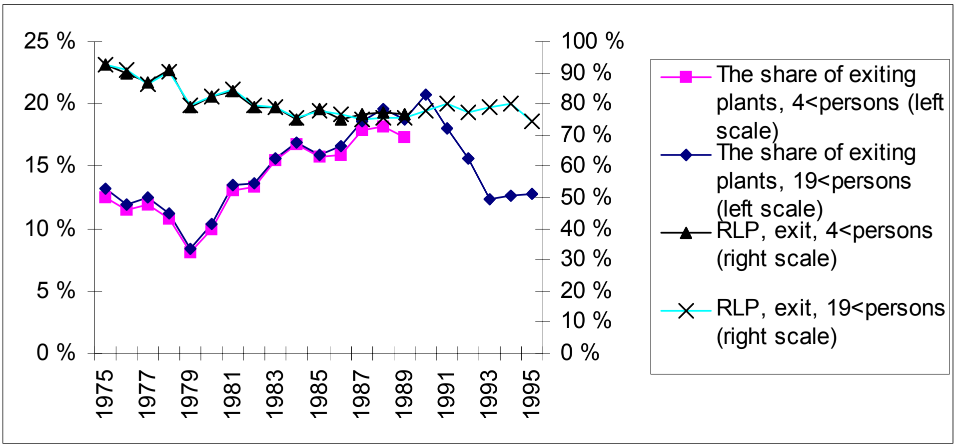


Note: Output is measured by the value added concept and growth is decomposed by the MBJ/INP method. Plants employing fewer than 20 persons are dropped due to the break in the cut-off limit in 1995. The results up to 1989-94 are quite similar when 5 employees is used as the cut-off limit (see Graph 5.21 below).

early 1990s was based on both ingredients. The average relative labour productivity level (*RLP*) in 1975 among those plants that would disappear before 1980 was 92.5 percent. After then, the relative labour productivity level began to fall and was about ¾ in the late 1980s (see also Maliranta 1997a). Meanwhile the input share of the exiting plants grew substantially. One might expect that the relative labour productivity level would increase rather than decrease with an increase in the share of the disappearing plants. These results suggest that job destruction was increasingly focused on low productivity plants during the 1980s.

As there is a break in the cut-off limit between the years 1994 and 1995, I have depicted the results for plants having at least 20 persons in order to guarantee comparability over time up to the year 2000. A potential problem with these calculations is that the results include some artificial deaths due to the fact that some plants may have become smaller than 20 persons and thus appear as exits. However, it turns out that the bias is negligible. For the initial years from 1975 to 1989 I have also made computations by using 5 persons as the cut-off limit. We see that the difference between the results is hardly visible.

Graph 5.9 The sub-components of the exit effect of labour productivity, 5-year moving windows



Note: Output is measured by the value added concept and productivity growth is decomposed by the INP method.

The increased exit and between components suggest that the correlation between productivity level and subsequent growth has increased.[60] This can be regarded as evidence of increased competitive pressure in Finnish manufacturing. High productivity has become increasingly important for survival and subsequent growth.[61]

Some may find it surprising that we found clearly negative entry effects with the 5-year periods in Graph 5.8 above. I have also used much longer periods in the computations, for example twenty years, and still found clearly negative effects. Graph 5.10 depicts the two sub-components of the entry effect, i.e. the relative productivity level and the labour share of entrants in the final year (see Equation (3.8)). We note that the input share of the new plants started to increase after the early 1980s. The relative productivity level of the new plants is normally less than 100 percent and this seems to have had a downward tendency after the early 1980s. So there was an increasing number of new plants, but their relative labour productivity level became lower over time.

It should be noted that the results are extremely sensitive to the choice of decomposition method. The FHK method yields positive estimates for the entry

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[60] Or the difference in the growth rates between high and low productivity plants.

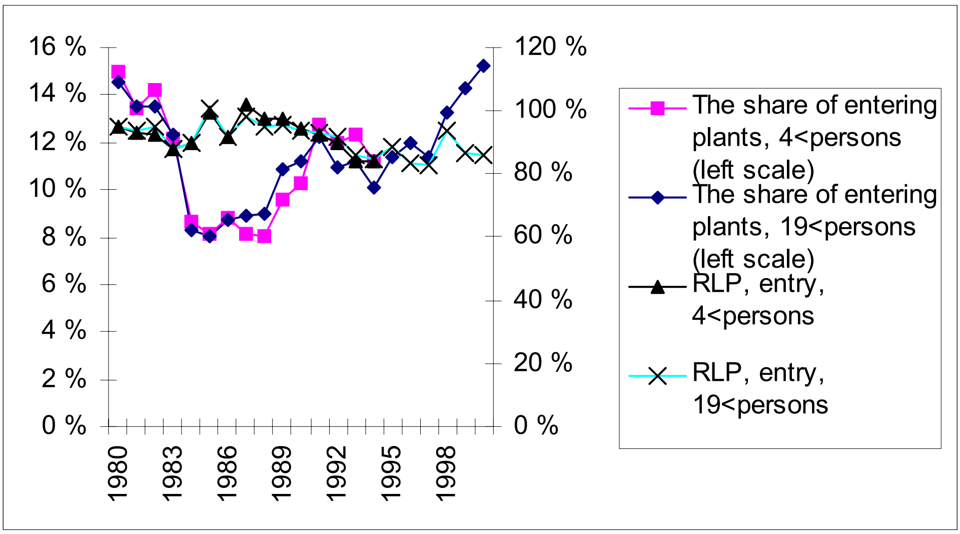
[61] Boone (2000) might predict that high productivity (or technical efficiency) has become more important for profitability.

effect for the 5-year windows and they were particularly high in the periods 1984-89 and 1985-90, about three percent in each period. A positive entry effect for the year 1989 in the FHK method, for example, indicates that young (those appearing after 1984) plants in 1989 had a higher labour productivity level than all plants in 1984.[62]

The new plants have lower labour productivity than the continuing ones in 1989, however, because there was productivity growth within the incumbent plants after 1984. Secondly, the high positive exit and between components obtained by the INP method indicates that there was a lot of selection and restructuring among the incumbents during the period, which raised the weighted average productivity level of the continuing plants.

As argued in Chapter 2, entry is likely to be a time-consuming process that involves learning by doing and selection in the early stages of the life cycle. Much of this process is likely to be captured by the between component. We will come back to the role of the young plants later in Section 5.3.

Graph 5.10 The sub-components of the entry effect of labour productivity, 5-year moving windows



[62] Therefore it is hard to give a meaningful economic interpretation for the entry components that were computed for the 5-year windows by the FHK method (or the GR method) in the OECD's firm-level growth project, for example (see Barnes, Haskel and Maliranta 2002; Scarpetta, Hemmings, Tressel and Woo 2002).

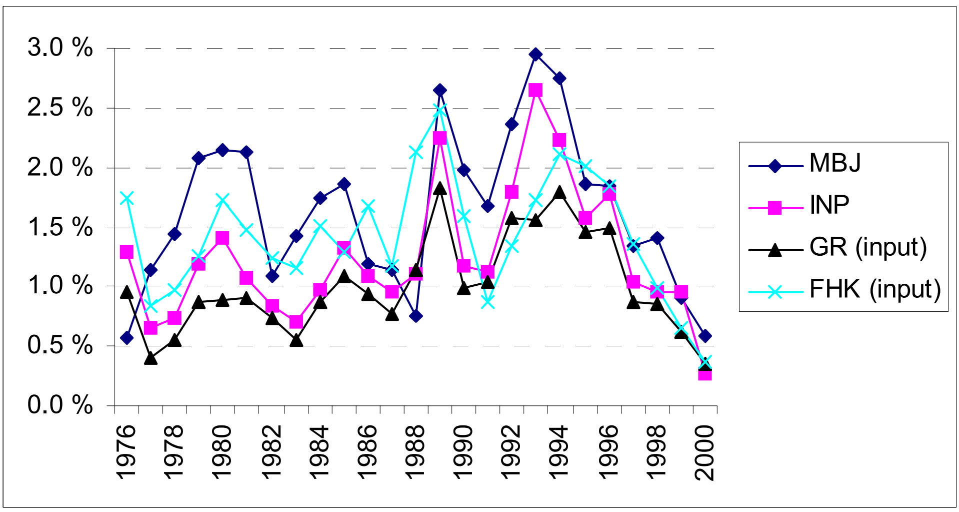
5.3.1.2 TFP

Graph 5.11 gives results for the between component of TFP growth based on the different methods. Again, all the methods applied with input-based weighting schemes yield broadly similar patterns for the between component over the period under consideration. The component was high in 1989 just before the recession and in the years 1992-96.

Unlike the other methods, the MBJ method suggests that productivity-enhancing restructuring was also quite intensive during 1978-81, a period of sharp decline followed by an increase in employment (see Graph 1.1).

In all these methods the weights are determined by using both labour and capital inputs. Disney, Haskel and Heden (2003) have performed decomposition of multi-factor productivity by using employment weights. I have also made decompositions by using employment weights instead of input index weights. It turns out that the between component is clearly smaller when the capital input is not included (results are not reported here). This implies that the restructuring of the capital shares among plants is also an important part of external adjustment.

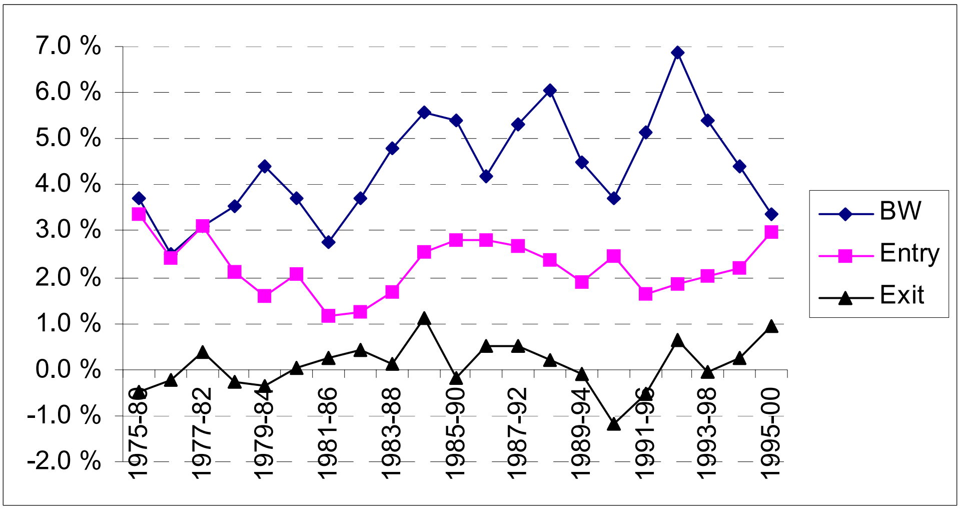
Graph 5.11 The between component of the aggregate TFP growth



Note: Output is measured by the value added concept.

By using the INP method the entry and exit effects can be determined for TFP growth in an analogous way to that used for labour productivity above.[63] The results for the 5-year windows are reported in Graph 5.12. We see that now the entry effect is clearly positive and the exit effect does not differ much from zero.

Graph 5.12 The "creative destruction" components of TFP growth, 5-year moving windows, the INP method



Note: Plants employing at least 20 persons are included. Output is measured by the value added concept.

5.3.1.3 MFP

The between component of the most comprehensive indicator of productivity performance, which I call MFP, also suggests an upward tendency until the first part of the 1990s (see Graph 5.13). We note, however, that the between component of MFP is substantially lower than in the case of labour or total factor productivity. As shown by Equation (2.6) the productivity index can be expressed as a weighted average of partial productivity indexes. Because the cost share of the intermediate inputs amounts typically to 60-70 percent of the total costs, the MFP indicator is largely dominated by the gross output to intermediate input ratio.

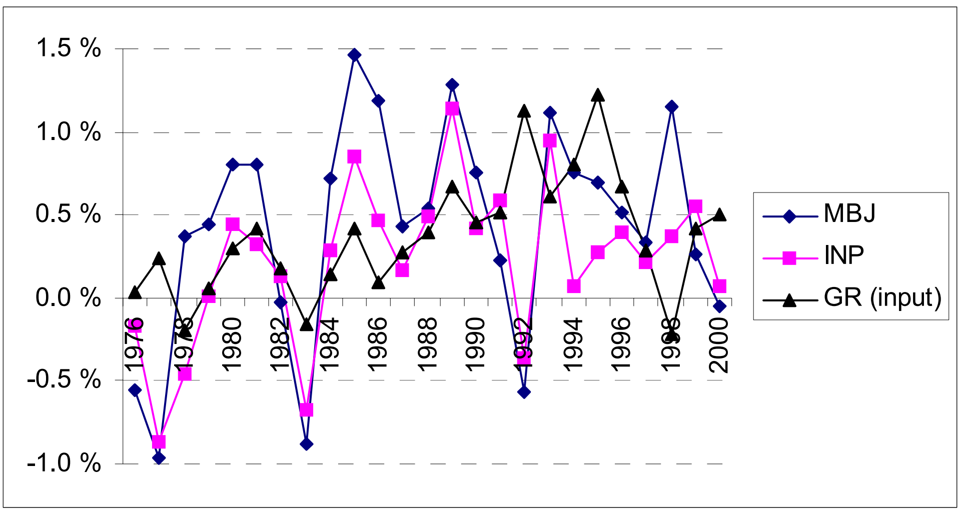
[63] The turnover (or net entry) effect is reasonably similar in the INP and MBJ methods.

The issue of including the intermediate input in a way symmetrical with the primary inputs, i.e. labour and capital, is often dealt with carefully in sectoral productivity measurement. As Gollop (1979) states, the rate of sectoral technical change that is defined by a model including intermediate inputs in addition to primary inputs is less than the corresponding growth rate based on the model, where output is measured by value added and only primary inputs are included (as in the TFP indicator). The economy-wide measure of productivity growth equals a weighted average of the sectoral rates of technical change. The appropriate weights in the aggregation are the ratios of each sector's gross output to the aggregate value added. It should be noted that the sum of these weights over all sectors exceeds unity.

Of course, these considerations can and should be performed down to the plant level. If one chooses to analyse the micro-level growth process in total manufacturing, for example, with an MFP model that includes intermediate inputs, the decomposition method should be constructed so that it takes into account the fact that an important proportion of the intermediate inputs used in the plants are produced by other manufacturing plants. We see that the computations made with an MFP indicator yield clearly lower rates of growth than those made with a TFP indicator for the within component.

The decompositions with the MFP measure of productivity performance suggest, as with the TFP indicator, that entry has an immediate positive contribution to aggregate productivity growth (see also Table A3.5 in Appendix 3).

Graph 5.13 The between component of aggregate MFP growth



Note: Output is measured by the gross output concept.

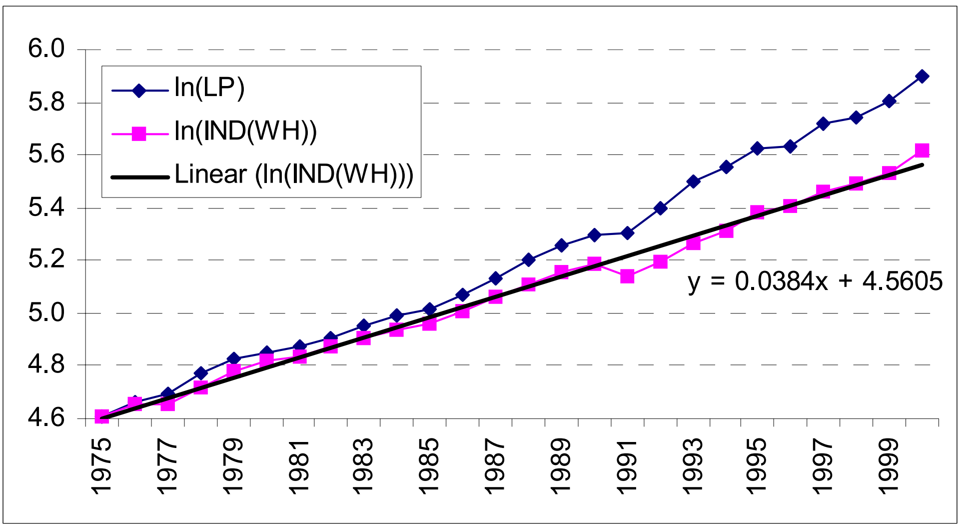
5.3.2 Productivity growth within plants

Plants may be able to improve their productivity over time thanks to learning-by-doing, disembodied technological change, increased managerial skills or work efforts, the reorganisation of tasks, etc. Lundberg (1961, pp. 130-131) reports that a Swedish steelworks called Horndal was able to improve its labour productivity by almost 2 per cent per year for fifteen years without any investments other than replacement of worn-out equipment. Carlsson (1981) presents a similar example for another ironworks. These pieces of anecdotal evidence indicate that disembodied technological change may be substantial and that sustained, but clearly less rapid, productivity growth can be maintained without turnover of plants or restructuring among plants. Of course, labour productivity and the total factor productivity of a given plant may have increased due to investments in tangible capital that may embody more advanced technology. So the within component probably does not reflect solely the rate of disembodied technological change.

5.3.2.1 Labour productivity

The within component of the annual labour productivity growth rate shows a lot of short-term variation over time. The productivity index series depicted in Graph 5.14

Graph 5.14 Cumulative within plants and aggregate labour productivity growth in manufacturing 1975-2000, 1975=log(100)



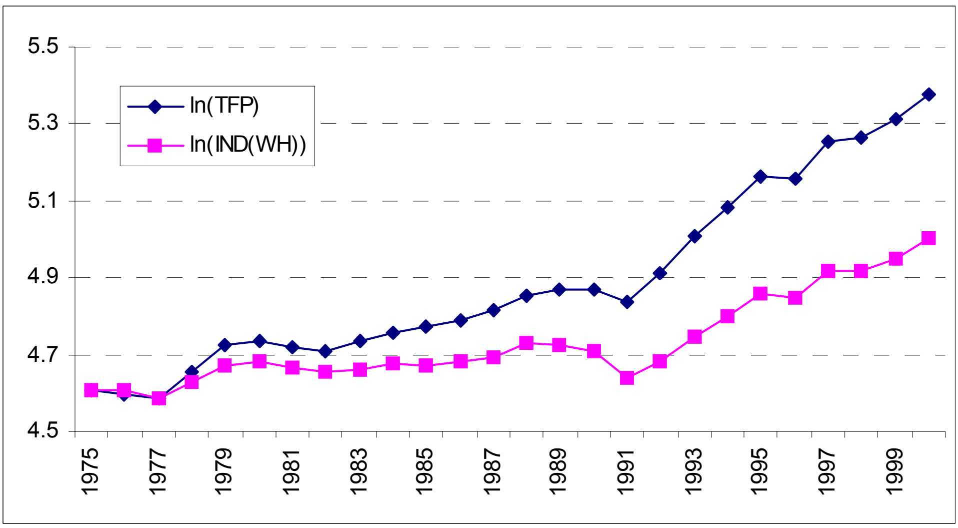
Note: Productivity growth is decomposed by the MBJ/INP method. Output is measured by gross output. The cumulative effect is measured by the log of index $IND_t = IND_{t-1} \times (1+0.5\times a_t) \times (1-0.5\times a_t)^{-1}$, where a_t is the component of the annual growth rate in year t. $IND_{1975}=100$. Ln(LP) denotes the logarithm of aggregate labour productivity index, ln(IND(WH)) the logarithm of within plants productivity index and Lin. (ln(IND(WH))) is a linear trend of ln(IND(WH)).

better shows the trends in labour productivity growth within plants. As a matter of fact, it turns out that labour productivity development within plants has followed astonishingly closely a log-linear trend in the period from 1975 to 2000. For the sake of comparison, I have also included an index of aggregate labour productivity growth in the same graph. The expanding gap between the two series indicates nicely that the acceleration of labour productivity growth since the mid-1980s is largely attributable to micro-structural factors (the between and exit components in particular).

5.3.2.2 TFP

Graph 5.15 shows the development of TFP over time. We see a substantial increase in the growth rate of TFP within plants after the recession years 1991-92. We saw earlier some signs of decline in the restructuring component of productivity during the 1990s, but these pieces of evidence suggest that those plants that survived or were established in the period of intensive restructuring have been able to achieve substantial productivity improvement in later years. Also the results for the MFP indicator give some support to the view that productivity growth within plants accelerated in the 1990s (the results are not reported here).

Graph 5.15 Within plants and aggregate TFP growth in manufacturing 1975-2000, 1975=log(100)



Note: Productivity growth is decomposed by the MBJ method. Output is measured by gross output. The cumulative effect is measured by the log of index $IND_t = IND_{t-1} \times (1+0.5 \times a_t) \times (1-0.5 \times a_t)^{-1}$, where a_t is the component of the annual growth rate in year t. $IND_{1975}=100$. Ln(TFP) denotes the logarithm of the aggregate TFP growth index and ln(IND(WH)) the logarithm of the within plants TFP growth index.

5.3.3 Plant groups

5.3.3.1 New vintage plants

We saw in Section 5.3.1 that the entry effect did not seem to contribute positively to the aggregate labour productivity growth rate. It was mentioned there that one possible explanation for this may be that the entry process is a time-consuming process that involves selection. Hence, to an important extent the renewal process may take place among continuing plants. Next, I analyse the role of plant births with the between component among continuing plants. The decomposition is made by using the GR method that gauges the effects in a robust way. One advantage of the GR method over the MBJ or INP methods is that the GR method is less sensitive to outlier observations. For each period the plants are classified into three groups according to their age, so that each group covers one third of the input usage.[64] I report here the results for the 5-year moving windows.

Information about the timing of plants' birth that is needed to define plant cohorts is incomplete before 1974. However, it is possible to apply a strategy that, despite its obvious limitations, has proven useful in other contexts (see for example, Maliranta 1999; Ilmakunnas and Maliranta 2003c). The order of appearance of the plants in the plant register system can be inferred from the identification numbers of the plants with at least reasonable accuracy. Making use of this property I have formed three broad cohorts. Then, each component can be split into three parts attributable to certain types of plants. As the groups are formed so that each covers one third of input usage, the magnitudes of a certain component across the groups are directly comparable. The sum of the between components of each of the three groups equals the total between component.

Graph 5.16 discloses that a dominant part of the between component among continuing plants can indeed be ascribed to young plants. The group of the youngest plants consists of plants aged about 13 years or less (the average age is a bit less than 6 years). We also see that there was a particularly strong increase in the between component of young plants in the latter part of the 1980s. On the other hand, the effect plunged sharply in the latter part of the 1990s. Contrary to what one might believe, there is no evidence that labour productivity growth has been particularly high within young plants, as can be seen from Graph 5.17.[65] This seems to contrast with the results obtained by Maliranta (1999).[66] However, much broader

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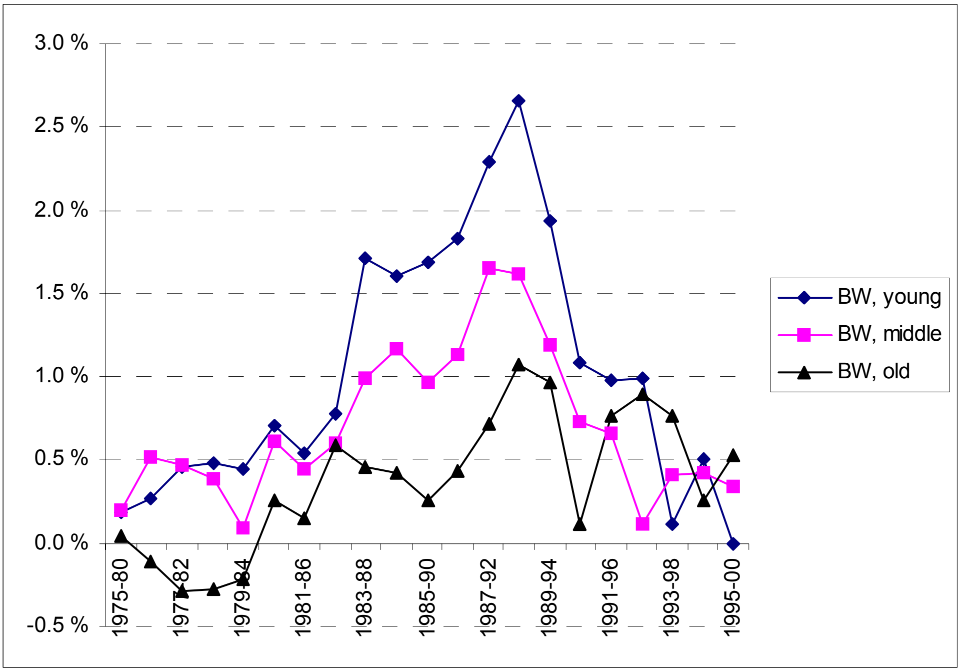
[64] A plant's input usage is measured by the average input usage in the initial and final year.
[65] The average labour productivity level of the young plants was 97.3 percent of that of the old plants in the period 1980-2000.
[66] These findings were reported in Section 3.1.3.

categories are used here and no control variables are included, which is likely to explain the difference in the outcomes (see Section 3.1.3).

Graph 5.18 in turn shows that the average employment growth measured by hours worked has been higher among the newer than the older plants. Interestingly, the growth among the newer plants has been particularly strong during recovery periods.

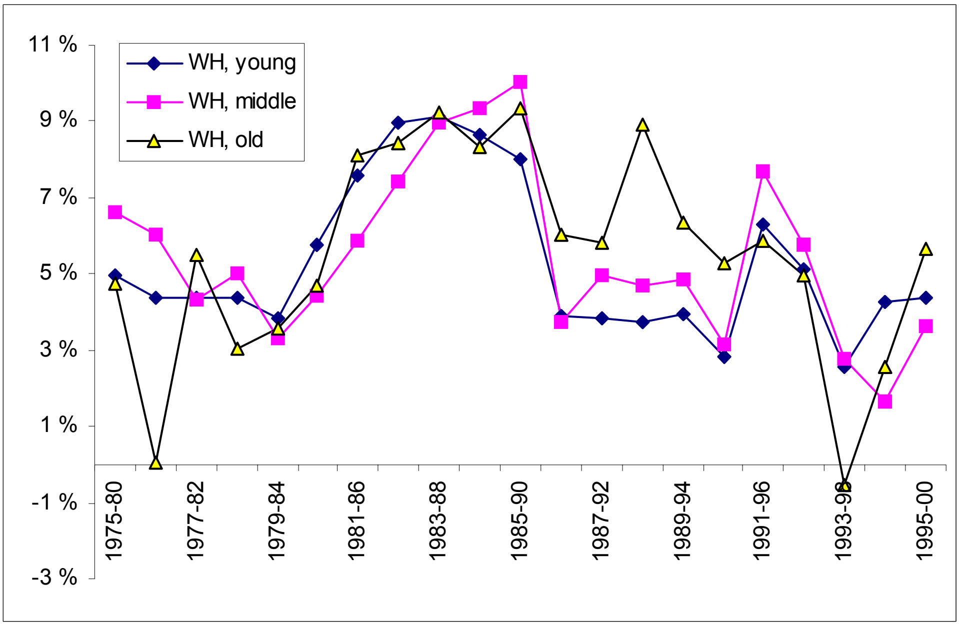
All in all, plant births do seem to have an important role in long-term economic growth despite the negative entry effects found above. A proportion of the new candidates are able to achieve a high productivity level and resources flow to them from the young and old low productivity plants over time.

Graph 5.16 The between component of labour productivity growth split by plant cohorts



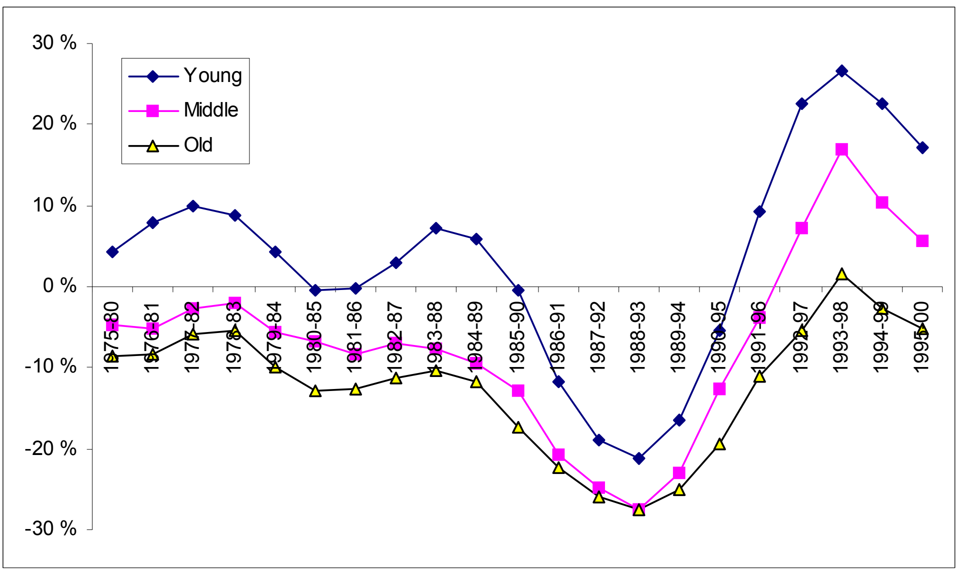
Note: Decomposition is carried out by the GR method with the input-index weights and applied to the continuing plants only. Output is measured by value added.

Graph 5.17 The within component of labour productivity growth split by plant cohorts



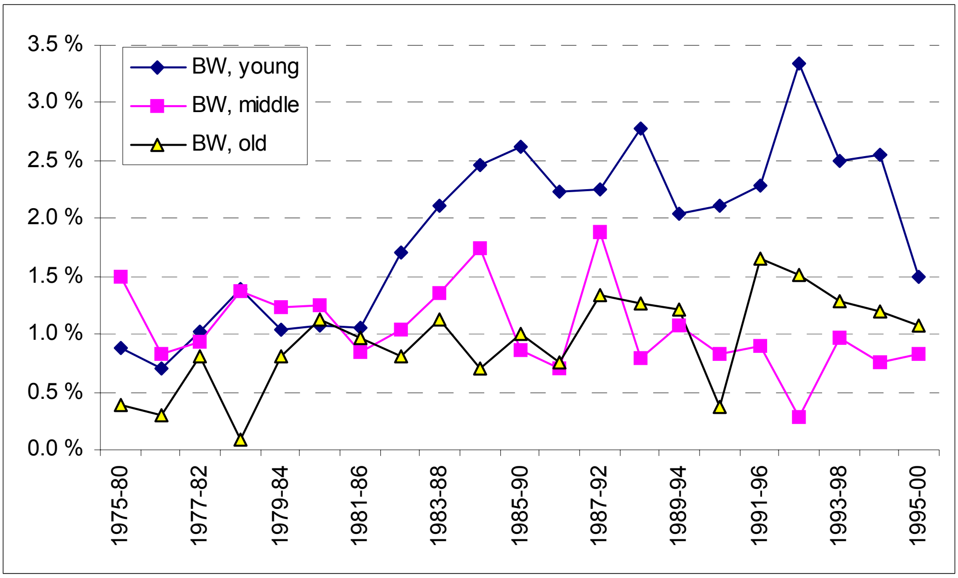
Note: Decomposition is carried out by the GR method with the input-index weights and applied to the continuing plants only. Output is measured by value added.

Graph 5.18 The growth of hours worked in plants of different ages



I have performed similar computations with the TFP indicator (Graph 5.19). We observe that the young plants now make an even more important contribution to the between component. In fact, the increase in TFP-enhancing restructuring can almost entirely be attributed to the young plants defined by the broad categories. Again, I was unable to find any evidence that the relatively new plants have an abnormally high rate of productivity growth (the results are not reported here, see Maliranta (2001, p. 38)).

Graph 5.19 The between component of TFP growth split by plant cohorts



Note: Decomposition is carried out by the GR method with the input-index weights and applied to the continuing plants only. Output is measured by value added.

5.3.3.2 High R&D intensity plants

Maliranta (2001) has made a similar kind of analysis by classifying plants by R&D intensity or by export intensity. The R&D intensity (R&D expenditures per nominal gross output) of a plant is defined by the R&D intensity of the owner firm.[67] This

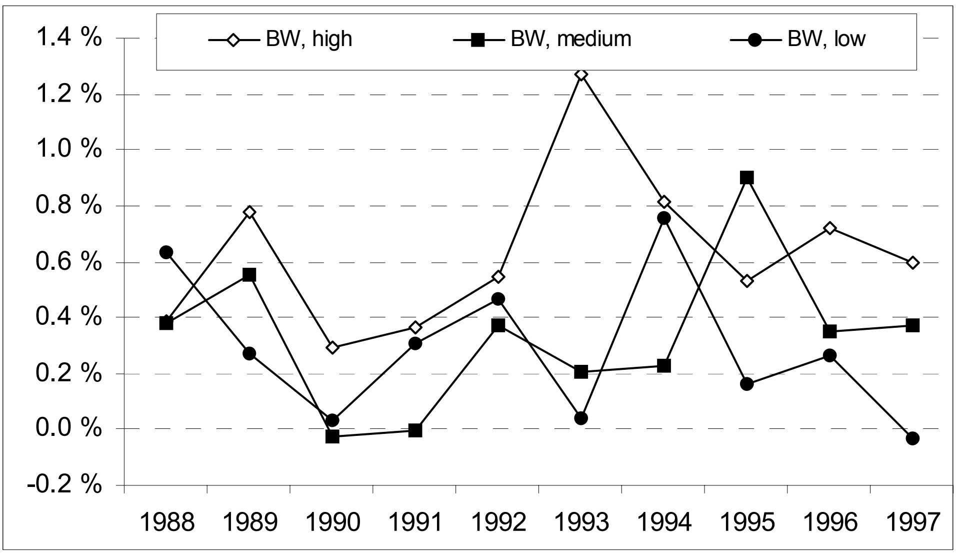
[67] Information on the owner firm's R&D intensity (R&D expenditures per sales in nominal terms) is obtained from R&D survey data that include all large firms and samples of smaller firms. The sample size varies to some extent over time. The classification is done on the basis of the average R&D intensity in the initial and final year. By this means it is possible to achieve more robust indicators of R&D intensity and improve the coverage of the plants owned by smaller firms. More information about the R&D data is given in Maliranta (2000b).

approach can be motivated by the assumption that technological knowledge flows without any friction within the same firm.

Perhaps somewhat surprisingly, the within component of TFP does not seem to vary systematically with R&D intensity (the results are not reported here). Maliranta (2000b) obtains similar findings with a different approach and with partly different data sets. Thus it appears that firms cannot generate extra productivity growth among their incumbent plants by investing in the creation of technological knowledge. Maliranta (2001) has also found that, on average, there is no significant difference in total factor productivity levels between low and high R&D intensity plants either.

However, Maliranta (2001) found that the plants with high R&D intensity significantly contribute to aggregate productivity through the between component (see also Graph 5.20).

Graph 5.20 The between component of TFP growth split by the plants' R&D intensity group



Note: Decomposition is carried out by the GR method with the input-index weights and applied to the continuing plants only. Output is measured by value added. See also the text.

5.3.3.3 High export intensity plants

Maliranta (2001) has investigated to what extent export-oriented plants contribute to the between and within components of TFP growth. Again, hardly any difference in the within component between low and high export intensity (exports per total deliveries) plants could be found. However, the results indicate that export intensity is positively linked to the size of the between component especially from the mid-1980s. This should be no surprise when recalling the theoretical considerations made in Section 2.4.3. Exposure to global markets can be expected to stimulate plant-level restructuring in a productivity-enhancing manner. Moreover, global markets give a lot of room for plants with a high value-added-to-input ratio to expand. It is also likely that R&D (and possibly plant age) and export orientation are mutually inter-linked characteristics at the plant level.

5.4 The components in manufacturing industries

So far the analysis has focused on micro-structural change and other factors within the manufacturing sector as a whole. This helps us to understand the micro-level sources of the developments highlighted in Graphs 1.2-1.5 in Chapter 1. Some proportion of plant level structural change takes the form of changes in industry structures and the remaining is restructuring within industries. In order to capture the restructuring within industries the decompositions are performed at a certain industry level (2 or 3 digit) and then the components are aggregated to the total manufacturing level. The aggregation is made by using industry input shares as weights.[68]

The results for the between component of labour productivity are depicted in Graph 5.21. A couple of conclusions can be drawn from the graph. First, it turns out that a significant proportion of the increase in the aggregate labour productivity growth can be attributed to changes in the industry structures (i.e. the component computed at the aggregate level is higher than the ones computed at the industry levels). The growth effect arising from changes in industry structures was particularly high at the turn of the 1980s and 1990s. However, it should be noted that productivity-enhancing restructuring within industry was usually equally important. The industry-level measures share a rather similar time-pattern to the aggregate level gauge.

Similar computations are made for the catching up and within components as well (the results are not depicted here). The catching up component has quite simi-

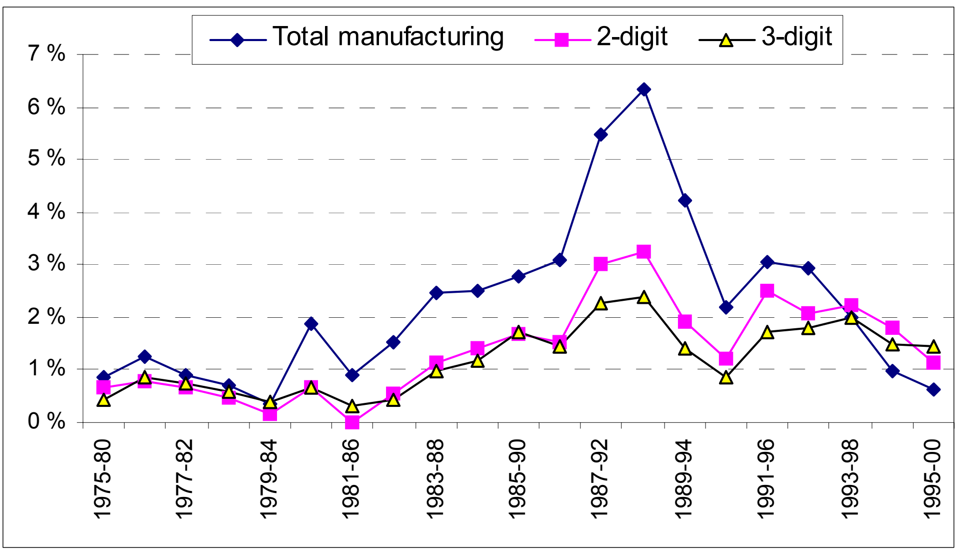
[68] Baily, Hulten and Campbell (1992) and Foster, Haltiwanger and Krizan (2001) have used nominal output shares in this kind of aggregation.

lar patterns over time irrespective of the level at which the computations are made. However, the catching up component is usually slightly higher at the higher level of aggregation. Concerning the within component, the results are naturally identical at all levels of aggregation.

The decomposition results for 2-digit industries are reported in Table 5.1. A look at the contribution of the between component of labour productivity growth reveals some interesting differences between industries. The effect seems to have been modest or negative in food products and wearing apparel. Also in non-metallic minerals (stone, clay and glass products) the between component has been relatively low. The between component increased in the latter part of the 1980s in many industries. These include office and electrical machinery and communication equipment. Also the paper industry, basic metals, non-metallic minerals and the textile industry experienced a significant increase in productivity-enhancing restructuring from the period 1981-86 to the period 1988-93.

All in all, there seem to be many differences in the between components across industries concerning magnitudes and time patterns. These variations in the industry-level results invite us to seek the determinants of the "creative destruction" process with econometric tools. This will be done in Chapter 8.

Graph 5.21 The between component of labour productivity at the different levels of aggregation



Note: Output is measured by value added. Decompositions are made with the MBJ/INP-method.

Table 5.1 The components of aggregate labour productivity growth among continuing plants by 2-digit industries, 5-year moving windows

	Between			Catching up			Within		
Industry	1981-1986	1988-1993	1995-2000	1981-1986	1988-1993	1995-2000	1981-1986	1988-1993	1995-2000
Food & beverages	-1.0	-1.1	-4.1	3.8	2.4	-3.4	23.2	27.6	9.7
Tobacco	5.3	3.2	0.0	-0.3	-5.7	0.0	26.0	-0.5	-66.4
Textiles	0.2	4.9	3.3	0.5	-1.3	1.7	4.9	6.4	17.9
Apparel	-0.8	-2.7	-0.2	-1.7	8.3	-0.3	10.2	19.5	3.7
Leather	0.5	2.3	4.1	6.3	3.4	4.3	-9.2	15.8	11.2
Wood	-1.6	2.4	-2.3	4.7	5.1	0.6	23.9	32.8	25.1
Paper and pulp	1.8	6.2	4.8	-2.1	-0.9	1.2	34.3	21.4	12.6
Printing	3.4	-0.1	2.1	-6.1	0.9	-2.3	5.7	5.7	6.8
Petroleum	-0.9	-18.2	23.8	0.3	-3.2	5.3	83.6	74.0	-33.8
Chemicals	-1.2	3.8	0.9	9.3	-7.5	0.9	26.3	15.4	12.5
Rubber & plastics	0.0	4.0	1.0	-0.5	-1.9	5.2	26.2	17.6	11.0
Non-metallic minerals	-2.2	2.4	-1.8	3.9	-1.2	1.3	13.8	2.9	16.1
Basic metals	2.7	8.2	1.9	-6.5	7.0	7.4	48.9	9.0	7.7
Metal products	0.8	1.3	0.8	2.7	6.9	-1.9	9.9	9.0	4.9
Machinery	1.5	4.4	-1.4	2.4	-0.6	5.3	11.2	0.5	8.8
Office machinery	-1.9	58.8	-6.8	5.4	-42.3	6.2	79.9	-15.3	-15.6
Electrical machinery	-4.9	12.6	0.2	3.6	10.2	6.6	28.0	23.3	14.5
Communication equipment	-9.0	11.9	10.9	4.2	0.4	10.1	43.2	44.9	52.6
Professional goods	4.6	4.8	4.7	-3.1	5.3	-0.3	39.4	32.2	13.8
Motor vehicles	1.3	-4.8	4.5	3.7	1.7	-0.2	26.7	6.6	7.2
Other transport	-1.2	0.9	5.9	2.7	0.8	-3.7	8.9	29.9	13.6
Furniture and other	0.8	3.5	-1.9	1.7	1.3	-0.3	9.1	-0.3	4.7

Note: Decomposition is carried out with the MBJ/INP method. Output is measured by value added.

5.5 Non-manufacturing sectors

Studies on the role of micro-level dynamics for aggregate productivity growth in the non-manufacturing sectors are scarce.[69] Now I use the Business Register on Plants as the source of information. It includes sales and the number of persons, which can be used in generating a gauge for labour productivity. Obtaining appropriate deflators is a generic obstacle to obtaining reasonable productivity growth esti-

[69] An analysis of the productivity components in US automotive repair shops by Foster, Haltiwanger and Krizan (2001) and in Dutch business services by Wiel (1999) are the two of them.

mates. If it is impossible to split the change in nominal output to a change in volume and a change in price, it is naturally impossible to measure the rate of productivity growth within plants as well. I have constructed the deflators for the service sectors by calculating sector (or industry) specific implicit price indexes from the Finnish National Accounts.

However, it should be noted that this type of measurement problem does not affect the results for the between, entry and exit components very much; especially if a rolling-base-year strategy is used. What we need to assume is that the plants share the same prices for the same products. If there are differences in unit prices, they should reflect differences in quality. Of course, establishments may have different output prices reflecting some degree of market power. This can be expected to hold true especially for manufacturing plants operating mainly in domestic markets and for plants in retail trade or services. On the other hand, decisions concerning employment adjustments are made largely on the basis of nominal productivity levels that appear in the decomposition equations, as outputs are expressed in final year prices.

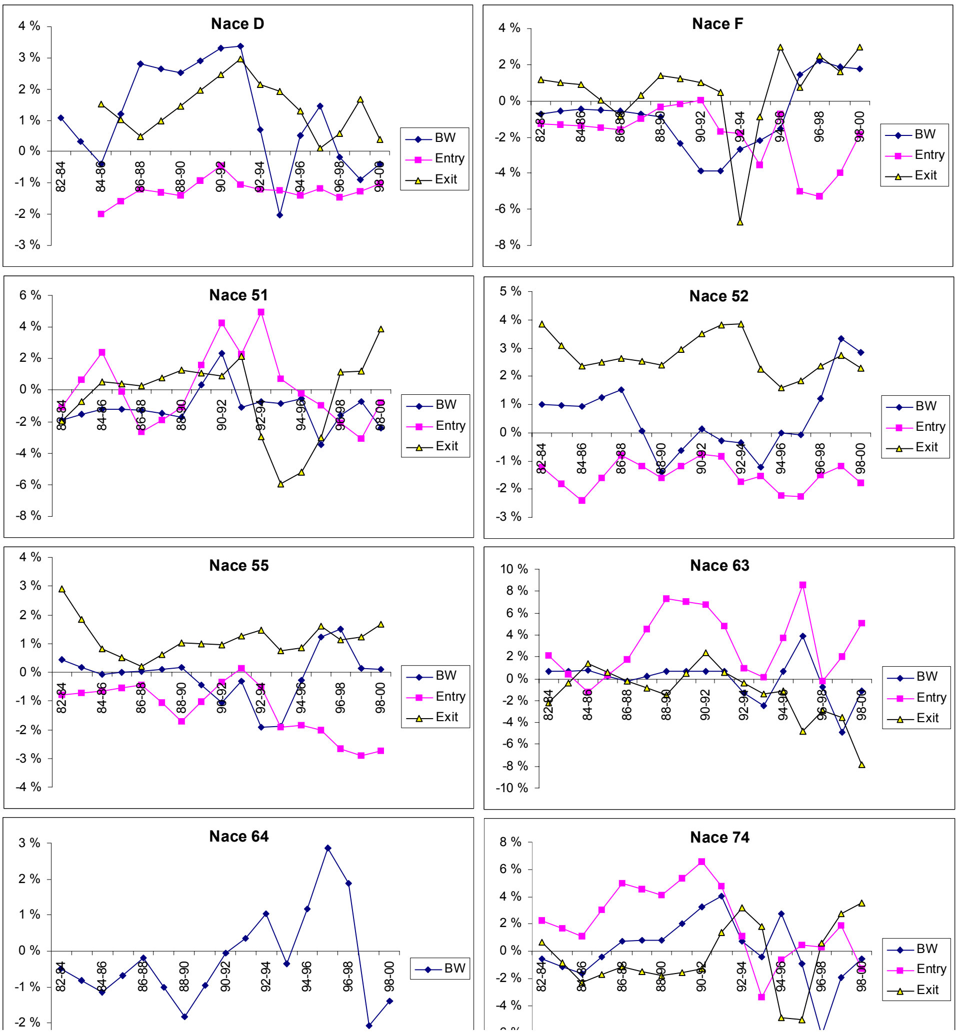
I have found that the results for manufacturing obtained by using the Business Register database are quite closely in line with those obtained by using the Industrial Statistics data source, the main difference being that the between component is slightly higher with the Business Register data than with the Industrial Survey data (comparisons of the results obtained from the alternative data sources are not reported here). Also Maliranta (2001, p. 34) finds that the Business Register and Industry Survey data sets yield quite similar results. The fact that the results are quite insensitive to the choice of data source in manufacturing naturally increases the confidence in the results that are generated for service industries.

The results on the “creative destruction” components (on some occasions entry and exit effects are dropped when they are very unstable or unreliable) for selected sectors including manufacturing, trade and some service industries are reported in Graph 5.22.

We see that the between component has been the largest in the manufacturing sector. Evidence for substantial productivity-enhancing restructuring among continuing plants can also be found in business activities (Nace 74) and post and telecommunications (Nace 64). This effect has been quite low in the wholesale (Nace 51) and retail trade (Nace 52) and in hotels and restaurants (Nace 55).[70] The exit effect, on the other hand, has been quite high in hotels and restaurants and in the retail trade in particular. In contrast with the manufacturing sector, for example,

[70] The between component seems to have increased in the retail trade in recent years.

Graph 5.22 The "creative destruction" components of labour productivity in selected sectors, 2-years moving windows, Business Register data



Note: The following abbreviations are used in the Graph: Nace D is manufacturing, Nace F is construction, Nace 51 is wholesale trade, Nace 52 is retail trade, Nace 55 is hotels and restaurants, Nace 63 is supporting and auxiliary transport activities, Nace 64 is post and telecommunications and Nace 74 is other business activities (legal, accounting, book-keeping etc.). Labour productivity is measured by output per employment. Output is measured by sales deflated by an industry-specific price index. Decomposition is carried out by the MBJ method. Data for the years 1983, 1985, 1987 and 1989 are lacking and therefore the results for the periods 1983-85, 1985-87, 1987-89 and 1989-1991 are interpolated.

productivity-enhancing structural change seems to consist of more "once-and-for-all" events in these two industries. Once a firm has established a production unit by constructing or renting a building, it may be difficult to expand its operations without losses in terms of productivity. It is also possible that local markets, especially typical of the retail trade and hotel sectors, determine the optimal scale of operations more strictly than in manufacturing.

5.6 Cross-country comparisons

In Section 2.4 we considered some factors that give us reason to expect that the restructuring component has stimulated aggregate productivity growth particularly strongly in Finland. One reason is that the trade unions aim to compress wage dispersion between industries (and plants) through centralised wage bargaining. Secondly, firing costs have been relatively low in Finland. Thirdly, small markets that were heavily protected in many industries may have caused micro-structural inefficiencies over time, which began to be corrected through restructuring in the wake of various deregulation steps taken from the mid-1980s.

We have seen an extensive amount of evidence that the decomposition results may be highly sensitive to the choice of method, in the entry effect in particular. This is one of the reasons why the results obtained from the different studies should be compared and interpreted with extreme care. The differences found in the results across countries may be sensitive to the quality of longitudinal linkages especially when the components are computed by the conventional FHK or GR methods. This deserves to be regarded with suspicion, especially when the computations are made with firm-level data.[71]

Within the so-called "OECD firm-level project" attempts were made to yield results that are as comparable across countries as possible. These efforts included adoption of the same methods and codes for computations, for example (see more details on the project in Bartelsman, Scarpetta and Schivardi (2002)). The computation were made by using input weights and thus from this point of view the results should be comparable.[72]

[71] Ahn (2001) provides a very comprehensive review of the literature of productivity decomposition in different countries.

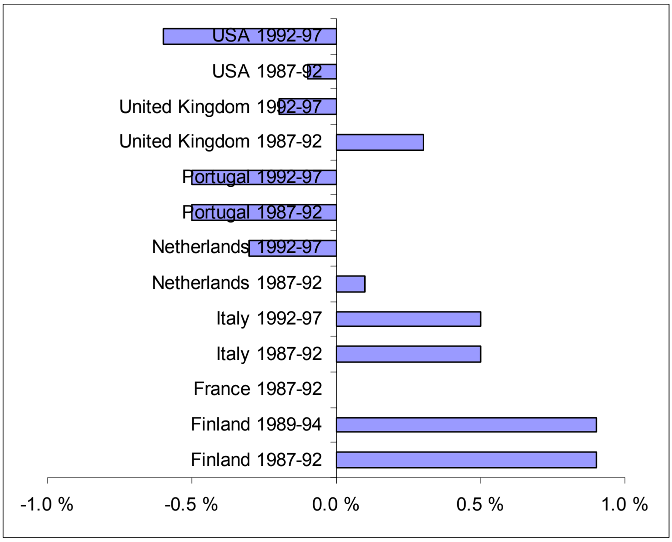
[72] Scarpetta, Hemmings, Tressel and Woo (2002) claim erroneously that the between component reflects output reallocation among existing firms in those results. However, in reality the computations were not made by using output weights (final confirmation of this was obtained by correspondence with Eric Bartelsman, who was responsible for the codes in that project). If Scarpetta et al. were right, the between component would probably be negative and the cross term positive for Finland and other countries, if computations are made with the FHK method (see Tables A3.3-A3.5 in Appendix 3).

Yet, many problems remained without a careful check at this time. For example, the appropriateness of the price deflators in different countries is not necessarily quite certain. Therefore the within component may be unreliable for cross-country comparisons. On the other hand, as has been noted earlier, the between component is not very sensitive to the inaccuracy of the price index when the moving base year strategy is used, as was the case in the project. Next I will focus on the between components obtained by the GR method, because they are probably the least unreliable estimates. However, as the computations did not focus on the continuing plants or firms only, the differences in the quality of longitudinal linkages may reduce the comparability (see examples in Table 3.2). If there are artificial deaths and birth due to problems in longitudinal links, the between component will be biased toward zero. To take an example, job destruction through plant shutdowns, and job creation through plant openings, appear to be surprisingly widespread in UK manufacturing. According to the numbers given by Barnes and Haskel (2001) about 35 percent of job creation was due to entries and about 39 percent of job destruction can be attributed to plant shutdowns. Remember that according to Davis, Haltiwanger and Schuh (1996) the corresponding numbers in US manufacturing are 16 and 23 percent respectively. In Finnish manufacturing these numbers are even smaller. Differences in the numbers across countries of this magnitude may raise some concerns about the quality of longitudinal linkages (see also Oulton (2000)).

Graph 5.23 gives strong support to the hypothesis that productivity-enhancing restructuring has been particularly intensive in Finnish manufacturing. In fact, Italy and Finland are the only countries that have had sustained productivity-enhancing restructuring at the micro-level. Moreover, the positive impact has been clearly bigger in Finland than in Italy. The UK case is quite interesting. To some extent the between component may be biased towards zero in the UK numbers because of possible problems in longitudinal linkages. Especially with this in mind the evidence suggests that productivity-enhancing restructuring was quite intensive in the late 1980s and early 1990s. However, since the early 1990s the between component has been strongly negative. This change in the micro-level dynamics of UK productivity development invites us to look at how its aggregate labour productivity level relative to the international frontier has evolved, which is shown in Graph 4.1 in Chapter 4. The graph suggests that the period from 1980 to 1992 is characterised by a relatively strong catching up process, with a new departure visible in the post-Thatcherian period.

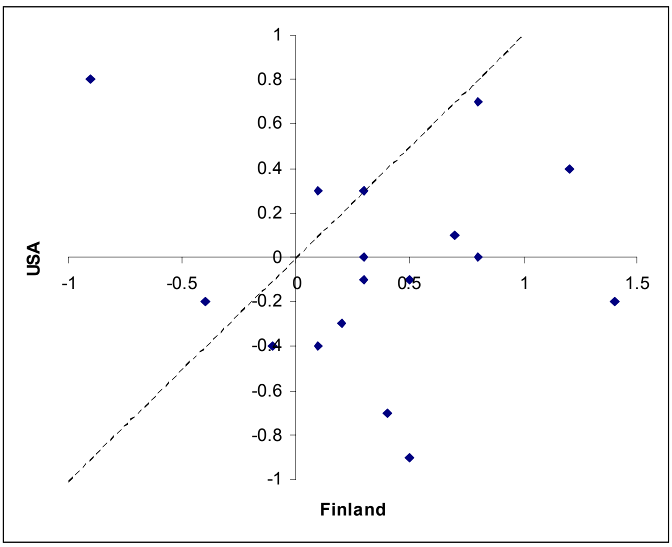
Graph 5.24 shows the annual average of the between components in Finland and the United States by industry in the period 1987-92. We see that nearly all industries (14 out of 17) had a positive between component in Finland (located on the right-hand side of the vertical axis). This graph also indicates that productivity-enhancing restructuring has been milder in the United States than in Finland, since only 3 industries are located above the dashed line.

Graph 5.23 The between component of labour productivity growth, annual %-change in the 5-year periods



Note. Calculations performed in the OECD firm-level growth project (see Scarpetta, Hemmings, Tressel and Woo (2002)). Decompositions are carried out with the GR method.

Graph 5.24 The between component of labour productivity by industries, average annual % change in the period 1987-92



Note. Calculations performed in the OECD firm-level growth project (see Scarpetta, Hemmings, Tressel and Woo (2002)). Decompositions are carried out with the GR method.

5.7 Cyclical variation and the restructuring components of aggregate productivity

Micro-structural factors can be expected to be related to the intensity of competition and cyclical turns. This hypothesis comes from the idea that recessions do the job of cleansing low productivity technologies or recessions bear an element of "creative destruction" (see, for example, Caballero and Hammour 1994). I have provided here empirical support for this hypothesis by estimating simple OLS regressions, where the micro-structural components are explained by the employment growth rate. I have also included a time trend that should capture long-term changes in the economic environment in which the firms operate. The estimates are given in Table 5.2.

The statistical evidence lends support to the view that "creative destruction" components vary counter-cyclically. The coefficient estimate of employment growth change is negative and statistically highly significant (t-value 5.0), when the be-

Table 5.2 Cyclical variation and trends in the micro-structural factors of the aggregate productivity growth rate in Finnish manufacturing

Dependent variable	(1) *BWLP*	(2) *EXITLP*	(3) *BWTFP*
Intercept	-.03 %	.36 %**	.91 %***
	(.18 %)	(.13 %)	(.22 %)
Trend	.05 %***	.02 %**	.02 %
	(.01 %)	(.01 %)	(.01 %)
ΔlnL(t)	-11.39 %***	-2.77 %	2.91 %
	(2.28 %)	(1.73 %)	(3.59 %)
ΔlnL(t-1)			-9.01 %**
			(3.62 %)
Adj. R^2	.582	.189	.201
N	25	25	24

Note: Standard errors are reported in parenthesis. *BWLP* and *BWTFP* denote the between components of aggregate labour and total factor productivity growth rates (the INP method) respectively, *EXIT* the exit component of aggregate labour productivity growth rate, dlnL log-difference of employment. *BWLP*, *BWTFP* and *EXITLP* are computed by using the Industrial Survey panel data, while the employment change in log terms (Δ*lnL)* is from the Finnish National Accounts.
* significant at 10%
** significant at 5%
*** significant at 1% level

tween component of labour productivity growth is the dependent variable. A negative but not statistically significant coefficient estimate is obtained for employment growth when the exit component is explained. Downturns seem to stimulate plant-level restructuring in a TFP-enhancing way, but my regression estimates seem to suggest that the impact comes with a one-year lag.

All in all, although aggregate productivity has usually been found to vary procyclically (see Basu and Fernald 2001; Baily, Bartelsman and Haltiwanger 2001), some components turn out to have evolved in the opposite direction in Finnish manufacturing. Micro-structural factors may, occasionally, even dominate the variation in aggregate productivity growth in very deep and prolonged recessions. The results indicate that there is a positive trend in the micro-structural components in the period from 1975 to 2000, which lends support to the view that the economic landscape has become more dynamic over time at the micro-level (the coefficient of the trend variable is not statistically significant in Model (3)).

5.8 Discussion on the components of aggregate productivity growth

In the period 1976-2000 the average annual within component of labour productivity is 3.0 per cent, which is 65.7 percent of the aggregate productivity growth rate, when the computations are made with the MBJ/INP method and output is measured by value added. It is frequently pointed out in the literature that the between plants component (and other "creative destruction" components) is substantially smaller than the within plants component of the aggregate labour or total factor productivity growth rate. The annual averages of the between and exit components of labour productivity growth are 0.68 and 0.67 per cent respectively. Together these two components account for 29.6 per cent of aggregate productivity growth.

So the within component seems to be the more important of the "creative destruction" components. However, that type of remark arguably misses the point. It is worth noting that, in myriad macro models or empirical growth analysis based on the idea of a representative agent, it is assumed implicitly or explicitly that *all* productivity growth comes through the within plants (or firms) component. Against that perspective the discrepancy between the within plants component and the aggregate productivity growth rate amounting to 20 or 30 percent can be regarded as outstanding and should push theoretical work on economic growth more extensively beyond the representative firm models (e.g. Greenwood and Jovanovic (2001) or Melitz (2002)).

We observed that the acceleration of labour productivity growth in Finnish manufacturing in the mid-1980s can be attributed entirely to other components than the within plants component, mainly to the between and exit components (see Graph 5.14, for example). So the identification of the so-called "creative destruction" components is indispensable when trying to understand the development of productivity performance in Finnish manufacturing. Another case in point is the UK manufacturing sector. A look at micro-level sources of productivity growth gives us an explanation as to why a favourable trend in the manufacturing labour productivity level relative to the international frontier turned to decline in the early 1990s.

In a sense the "creative destruction" components are more interesting sources of productivity growth in industries or sectors because they involve job creation and destruction. External adjustment is more painful for workers and more challenging for capital and labour market institutions. Moreover, we observed that the annual within plants component has wild short-run variations that are probably dominated by changes in utilisation rates, etc. The between component, on the other hand, exhibits much smoother patterns over time. It is possible that the between component is more directly related to its underlying factors than the within component. The signal in the within component numbers is likely to include so much noise that the interesting underlying factors are disguised and difficult to disentangle.

The analysis made in this chapter shows that micro-level restructuring has been substantially more important for aggregate total factor productivity growth than for labour productivity growth. In fact, my computations for annual total factor productivity rates in the period 1976-2000 indicate that the between plants component has been somewhat larger than the within plants component. One interpretation of this result is that productivity development in Finnish manufacturing has involved a lot of substitution of modern capital in young plants for obsolete capital in old plants (see Graph 5.19, in particular).

My final comments concern the cyclical behaviour of the between component. We saw evidence that short-term variation in the between component is negatively related to employment growth, which is consistent with the view that recessions boost productivity growth through plant-level restructuring. It is worth noting that there seems to have been a positive trend in at least the between component of labour productivity that cannot be attributed to cyclical variation. One might suspect that the between component increases during recessions because low skilled workers in low productivity plants are laid off during downturns. This hypothesis will be investigated, and rejected, in the next chapter.

6 The roles of skills in internal and external adjustment

Education has often been seen as an important determinant of the competitiveness and wealth of nations. However, formal schooling is not the only way to increase human capital and skills. Productive knowledge may be gained in various ways such as learning by doing or learning from co-workers. In fact, the average Finnish manufacturing worker finished his or her schooling about two decades ago. Since then some knowledge may have depreciated, i.e. sunk into oblivion, or become obsolete.

Cross-country comparisons show a strong correlation between the income and educational levels of countries. At the individual level, education is positively related to wages, suggesting that education is indeed positively associated with a worker's skills and productivity. Asplund (1999) surveys Finnish studies of earnings and human capital. The returns for an additional year of schooling are slightly over 8 %. According to many wage studies other labour characteristics are also important for productivity. Age appears to have an important effect especially in the early stage of a career. The age effect is inverted U-shaped with a peak in the age group 40-44 in 1980 and in the group 45-49 in 1990 (Eriksson and Jäntti 1997). So it seems that general experience has become increasingly important for a person's productivity over time.

There are some concerns, however, about causal relationships. Education may have elements of association with luxury-good consumption that may bring about a positive correlation at the country level. Furthermore, there may be a spurious relationship between education and wages or productivity due to the fact that ability is likely to affect schooling decisions. Productivity analysis does not unambiguously support the view that education increases the productivity of labour either. Most studies using country data fail to establish a positive correlation between productivity growth and increase in schooling (see Barro and Sala-i-Martin 1995; Benhabib and Spiegel 1994 and Wolff 2000).[73] Largely similar findings have been made with plant level data by Haltiwanger, Lane, and Spletzer 1999), Ilmakunnas, Maliranta, and Vainiomäki (2003b) and Maliranta (2000b).

It does seem obvious that education and skills have important roles to play in economic growth (see Aghion and Howitt 1998). The traditional human capital approach treats skills as an ordinary input in production (see Lucas 1988). Then an

[73] However, some studies do find empirical support for the view that an increase in education leads to a higher productivity growth rate (see Krueger and Lindahl (2001) and Engelbrecht (2001)).

increase in workers' skills should immediately be reflected in the productivity growth rate (when labour is measured with a raw gauge, such as hours worked).

However, there are alternative views that suggest that the productivity effects of skills need not be automatic or immediate. High skills may be needed in order to efficiently utilise the production possibilities afforded by modern technology. Skilled workers may be able to make efficient use of capital which embodies advanced technology. If this is the case, then technological development leads to a greater demand for skills, which is to say that technological change is skill-biased. But with less modern technology, low skilled workers might be as productive as skilled workers.

Nelson and Phelps (1966) in turn emphasised the idea that skills are important in innovation activities. High skilled workers are needed when new technologies are being created by R&D efforts or when new technologies created by others are being implemented. Technical or entrepreneurial skills can be expected to be particularly crucial here. This is related to the idea presented by Murphy, Shleifer and Vishny (1991) that a country's most talented people organise production by others and by this means they spread their ability advantage over a larger scale. They innovate and build new high productivity firms and factories. The challenge of the restructuring process is to allocate other people to those firms and factories where production is organised best, i.e. where the productivity of other people in production is highest (see also Bartel and Lichtenberg 1987). In other words, an external adjustment through reallocation of labour between plants may be called for.

As we saw in the previous chapter and as documented earlier by Maliranta (1997a, 1997d and 2001) an important part of the acceleration in productivity growth can be attributed to micro-level restructuring in Finnish manufacturing. The (input) weighted average plant productivity has increased due to the fact that low productivity plants have become smaller or disappeared and high productivity plants have captured their input shares. In these computations all worked hours were regarded alike, ignoring the fact that education, experience and other potentially important labour characteristics vary between plants.

If the traditional human capital approach is adopted where the skills acquired by schooling or experience affect the efficiency of labour with the current technology, the between component of the productivity decomposition can be expected to be "skill-biased" upwardly. Perhaps the average productivity has increased because low skilled workers in the low productivity plants have lost their jobs? Consequently the average labour efficiency has improved, so that the productivity indicators measured with raw gauges of labour indicate a significant improvement. Moreover, we would expect that an increase in skills in a plant would be reflected in an extra high productivity growth rate at the plant.

The alternative approach emphasising the role of skills in innovation and the implementation of technology yields different predictions. In particular, the expectation is that an increase in skills will not immediately be reflected in a plant's productivity growth, but more likely with a lag. If this approach captures the essence of the role of skills, skill upgrading would be more likely to lead to productivity-enhancing restructuring than productivity growth within plants.

In this chapter I will investigate the role of education and age (that should approximate general experience) in productivity development by using plant-level information on productivity and individual-level information on education and other skill characteristics, as well as wages.[74] More specifically, I will address the following three main questions:

1. Do the empirics support the idea that plant level restructuring has contributed positively to aggregate productivity growth through the cleansing of plants that use low skilled and low productivity workers?

2. How do education and skills translate into higher productivity at the plant level and at the aggregate level? Is there a time lag between the cause and the effect?

3. Are the roles of "technical" and "non-technical" education different from the standpoint of productivity development?

The first question involves the idea that the boost in the productivity growth rate may have been to some extent artificial and unsustainable (the unemployment rate of low skilled workers cannot increase endlessly). According to this view, the growth in productivity may have been based on the rapidly increased average skill level that was a consequence of laying off a lot of low skilled employees during the recession. The second question is important as the government has invested a lot of hope and money in education in order to improve the nation's competitiveness and support growth in the future. The third question relates to the debate on the kind of education that is the most useful from the standpoint of economic development.

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[74] As for earlier related work with the Finnish data Vainiomäki (1999) and Huttunen (2002) have investigated skill upgrading within plants and through plant-level restructuring. The former focused on education and the latter on age (in addition to education).

6.1 The two views on the role of skills in the determination of productivity

6.1.1 Human capital as an input of production

The traditional human capital approach interprets the role of skills as one of improving the efficiency of worked hours and thus augmenting the labour input. The labour input measured by efficiency units L^* can be expressed as follows:

$$L^* = eL, \qquad (6.1)$$

where L is a raw measure of labour input and e is an index of labour efficiency.[75] The labour efficiency e can be viewed as a function of schooling S and other labour characteristics. For example, an equation of the following form might be useful:

$$\ln(e) = a_o + a_1 \cdot S + \eta' X + \varepsilon, \qquad (6.2)$$

where ln(e) is the natural logarithm of the labour efficiency index, S is the number of schooling years, X is a vector of other efficiency-enhancing labour characteristics and e is a random effect. One of the problems is to determine the parameters of the relevant labour characteristics.

6.1.1.1 Micro human capital earnings functions

There is a huge amount of econometric evidence on the positive correlation between wages and schooling at the individual level. This strand of literature makes a good case for the view that schooling is a good indicator of labour input efficiency. The rate of return on investment in schooling is usually estimated by means of the Mincerian wage equation, such as

$$\ln(W_i / L_i) = a_0 + a_1^{'} \cdot S_i + \eta_1 X_{1i} + \eta_2 X_{1i}^2 + \varepsilon, \qquad (6.3)$$

where $\ln(W_i/L_i)$ is the natural logarithm of the hourly wage for individual i, S_i is the years of schooling, X_{1i} is experience, X_{1i}^2 is experience squared, and ε_i is the disturbance term. If the wage measure correctly indicates the efficiency of the labour input, this equation can be used to measure the effect of schooling on labour input efficiency as then $a_1 = a_1^{'}$.

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[75] In this context it is possible to use the expressions labour input quality and labour input efficiency interchangeably.

Of course, this relationship does not need to indicate a causal relationship from education to labour efficiency. Spence (1973) notes that education could be a signal of inherent characteristics (intelligence, motivation etc.) by which an employer can evaluate a person's productivity in a cost-efficient way. In this case, Equation (6.3) can still be used to measure labour efficiency, but this does not imply that an increase in the general educational level should increase a country's income, for instance.

There is, however, overwhelming evidence obtained from econometric analysis with instruments based on natural experiments in support of the view that education indeed has a positive effect on wages. So, if the usual assumptions about profit maximising firms hold true, it seems that education improves a person's productivity.[76]

6.1.1.2 The efficiency of labour input in production

Numerous cross-country regression studies have thrown light on the importance of education from the standpoint of production. The Cobb-Douglas production function with the constant returns-to-scale assumption provides a natural starting point for the analysis of the role of labour efficiency in production. Let us assume that labour efficiency (e) affects output (Y) through augmenting raw labour input (L). This leads to the following equation:

$$Y_i = AK_i^{\,b}\left(e_i L_i\right)^{1-b}\exp(\varepsilon_i), \tag{6.4}$$

where i stands for the plant and b is capital input elasticity with respect to output. Taking natural logs of the variables and rearranging the terms yields the following formulation:

$$\ln\left(Y_i/L_i\right) = \ln A + (1-b)\cdot\ln e_i + b\cdot\ln\left(K_i/L_i\right) + \varepsilon_i\,. \tag{6.5}$$

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[76] On the other hand, high education may improve not only a person's ability to produce more output but also his or her ability to appropriate quasi-rents from irreversible investments (see for example the discussion in Murphy, Schleifer and Vishny (1991) and Wolff (2000)). Secondly, let us assume that managers do not maximise firms' profits but try to dissipate rents in some pleasure-producing ways (see discussion in Borenstein and Farrel 2000, for example). One might believe that managers are inclined to hire highly-educated persons, because social life with them is more satisfying, for example. This hypothesis predicts a positive correlation between a firm's productivity (and profitability) and its wage levels, while high productivity plants can afford expensive highly educated labour input. We would expect that highly educated persons do not run their own businesses, but are usually hired by a large firm that is profitable and whose ownership is dispersed.

For now, the efficiency of labour is assumed to be a function of schooling in the following way:

$$\ln(e_i) = a_0 + a_1 \cdot S_i \,. \tag{6.6}$$

Inserting this into (6.5) yields

$$\ln(Y_i/L_i) = \ln A' + \theta \cdot S_i + b \cdot \ln(K_i/L_i) + \varepsilon_i \,, \tag{6.7}$$

where $\theta = (1-b) \cdot a_1$.

The labour efficiency effect of schooling can be derived from the parameter estimate of the schooling variable as follows:

$$a_1 = \theta/(1-b) \,. \tag{6.8}$$

On the other hand, we might assume that an increase in labour quality improves the efficiency of both raw labour and tangible capital.[77] Then an upgrade in skills augments output with a given amount of raw labour and tangible capital and with a given technology *A*. The production function takes the following forms:

$$\begin{aligned} &Y_i = A(K_i e_i)^b (e_i L_i)^{1-b} = A \cdot e_i \cdot (K_i)^b (L_i)^{1-b} \\ &\Leftrightarrow Y_i/e_i = A \cdot (K_i)^b (L_i)^{1-b} \end{aligned} \tag{6.9}$$

Of course, in this case the effect of schooling on labour efficiency is obtained from equation (6.7) directly as $a_1 = \theta$.

If Equation (6.7) is assumed to have a trend, differencing Equation (6.7) leads us to the following estimation model that is used in the growth analysis:

$$\ln\left(\frac{Y_{it}/L_{it}}{Y_{is}/L_{is}}\right) = a_0 + a_1(S_{it} - S_{is}) + b \cdot \ln\left(\frac{K_{it}/L_{it}}{K_{is}/L_{is}}\right) + \varepsilon_{it} \,, \tag{6.10}$$

[77] It seems reasonable to assume that capital productivity is dependent on the quality of labour as well. Educated workers may be able to use machines (like computers) efficiently.

where t denotes the final year and s the initial year. So this specification is in accordance with the human capital approach, according to which schooling improves productivity through making raw labour input more efficient.

As mentioned in the beginning of this chapter empirical findings obtained from aggregate national data sets by using these types of specifications are mixed and somewhat bewildering. In most cases the studies fail to find a positive relationship between the change in human capital and productivity growth. A number of explanations have been offered:

1. The signal in the education data may be poor, especially after differencing (see Krueger and Lindahl 2001).

2. The timing of the education variable may be critical, as the possible positive effect of increased education may materialise with a lag for various reasons (see Haltiwanger, Lane and Spletzer 1999).

3. Educational and technological characteristics may form a match. If a firm or plant is stuck with some particular technology, it is possible that an increase in education will not alone increase output. A skill upgrade may need to be accompanied by a technology advance, which may be time-consuming. We will come back to this issue later.

The field of education may play an important role here. Interestingly, Maliranta (2000b) finds that an increase in education in fields other than natural sciences and engineering is positively correlated with a productivity increase at the firm level, when various other relevant factors such as tangible capital, size, etc. are controlled. The positive relationship appears to be particularly pronounced in the service sector. On the other hand, an increase in technical skills seems to be negatively correlated with productivity growth.[78]

6.1.1.3 Plant level Mincer wage equation

If value added Y is replaced by payroll W, we obtain the following model that can be estimated with a plant-level panel data set:

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[78] Quite consistently with the evidence obtained by Maliranta (2000b), Ilmakunnas and Maliranta (2003b) find with fixed plant effects that technical and scientific skills obtained at the university level are negatively associated with productivity in Finnish manufacturing, whereas non-technical skills obtained at the same level have a significantly positive relationship with productivity. This analysis also shows (with or without fixed plant effects) that employers definitely value technical university education very highly in terms of the wage level.

$$\ln\left(\frac{W_{it}/L_{it}}{W_{is}/L_{is}}\right) = a_0 + a_1\left(S_{it} - S_{is}\right) + b\ln\left(\frac{K_{it}/L_{it}}{K_{is}/L_{is}}\right) + \varepsilon_{it}\,. \qquad (6.11)$$

A couple of points are worth noting when this model is compared with Equation (6.10). Equation (6.11) can be interpreted as a plant-level counterpart to the micro-Mincer equation, with experience variables dropped and capital intensity included. Of course, it is straightforward to include experience variables in all the equations shown above. Moreover, it is potentially useful to include a capital intensity variable in the wage Equation (6.3). Although the wages of individuals in the competitive labour markets are determined by labour characteristics, a plant's (or an industry's) capital intensity may have a positive effect for at least two reasons. Firstly, capital intensity may serve as a proxy of labour conditions that are compensated in the competitive labour markets. Secondly, capital intensity may be positively correlated with some relevant labour characteristics because of sorting among individuals and plants. A spurious correlation may be obtained if some of these relevant characteristics are unobservable to the econometricians but not to the employers.

There may be some other explanations for this positive correlation, if the assumption of competitive labour markets is dropped. For example, insiders may be able to appropriate quasi-rents pertaining to capital stock built with irreversible investments (Caballero and Hammour 1996). Some efficiency wage models suggest that firms may want to pay above the market clearing level in order to reduce the turnover of the workforce. Labour turnover may be especially costly for those firms that have high capital intensity, for example.

The effect of schooling on wages and productivity can be also examined from the standpoint of the determination of labour's factor share. For example, if schooling increases wages more than productivity, then, when other factors are kept constant, there is a positive correlation between labour's income share and schooling.[79] Determination of factor income shares in micro-level restructuring is examined in Chapter 9.

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[79] Krueger (1999) has recently considered how human capital has contributed to labour's share of the US National Income in the post-war period. He has adopted an approach in which workers' earnings are assumed to consist of two additive components, raw labour and human capital. In some sense the former corresponds to raw labour (or bodies) and the latter to labour quality. He has estimated that raw labour's share of the National Income declined from 13 % in 1959 to 5 % in 1996. During the same period, human capital's share of the National Income increased from 63 % to 72 %. So human capital has taken over the proportion of raw labour in recent decades.

6.1.1.4 Growth accounting methodology

Growth accounting tradition provides a convenient and useful approach to quantifying the output growth effect of schooling and other relevant labour characteristics when they augment raw labour input by making it more efficient in production (see Jorgenson, Gollop and Fraumeni 1987). The method of measuring changes in the efficiency of labour input (or other inputs) with aggregate data sets is described in Section 2.2.2).

In Section 2.2.2 it is implicitly assumed that a certain type of labour input *m* is equally efficient in all plants (or industries). Alternatively it is possible to assume that the efficiency of labour is dependent on its type *m* and on the plant that has employed it. If this is the case, the efficiency of an individual unit of labour may change when it moves from one plant to another plant, and plant-level restructuring may then have a role to play. Now Equation 2.17 takes the following form:

$$\Delta \ln e_{st} = \sum_i \sum_{m=1}^{M} \bar{S}_{imt} \cdot \ln\left(\frac{L_{imt}}{L_{ims}}\right) - \ln\left(\frac{\sum_i \sum_{m=1}^{M} L_{imt}}{\sum_i \sum_{m=1}^{M} L_{ist}}\right), \qquad (6.12)$$

where $\bar{S}_{imt} = \left(\frac{p_{imt} L_{imt}}{\sum_i \sum_m p_{imt} L_{imt}} + \frac{p_{ims} L_{ims}}{\sum_i \sum_m p_{ms} L_{ms}}\right) \Big/ 2$.

Let us consider another formula for measuring the labour input efficiency growth rate:

$$\Delta \ln e_{st} = \sum_i \sum_{m=1}^{M} \bar{S}_{imt} \cdot \ln\left(\frac{L_{imt}}{L_{ims}}\right) - \sum_i \sum_{m=1}^{M} \overline{SN}_{imt} \cdot \ln\left(\frac{L_{imt}}{L_{ims}}\right), \qquad (6.13)$$

where $\bar{S}_{imt}$ is as in (6.12) and $\overline{SN}_{imt} = \left(\frac{L_{imt}}{\sum_i \sum_m L_{imt}} + \frac{L_{ims}}{\sum_i \sum_m L_{ms}}\right) \Big/ 2$

In Equation (6.13) the quality-adjusted and quality-unadjusted labour input growth rates are computed in an analogous manner and the only difference is that the wage differences are taken into account in the former term. I will use both formulations (6.12) and (6.13). As is demonstrated below, the last terms on the right-hand side of Equations (6.12) and (6.13) are normally quite similar. However, when we use extremely detailed classifications in which labour groups are distinguished by labour characteristics and employer, the difference may not necessarily be irrelevant.

6.1.2 Skills as a factor in technological development

Skills may not only improve the efficiency of raw labour and tangible capital with current technology but may be an important factor in technological change. The level of education may affect steady-state productivity growth positively because it may enable the workforce to continuously create, adopt and implement new technologies, which is the view emphasised by Nelson and Phelps (1966). Thus the growth rate of labour productivity can be a function of the skill level as well. Then we would have an extended version of equation (6.10):

$$\ln\left(\frac{Y_{it}/L_{it}}{Y_{is}/L_{is}}\right) = a_0 + a_1\left(S_{it} - S_{is}\right) + a_2 \cdot S_{is} + b\ln\left(\frac{K_{it}/L_{it}}{K_{is}/L_{is}}\right) + \varepsilon_{it}\,, \qquad (6.14)$$

which includes the initial level of schooling S_{is} in addition to the difference of schooling (see Wolff 2000). The timing of the schooling level variable is not quite obvious, especially when long differences are used, e.g. *t-s* is large, say 10 years or so.

Of course, it can be argued that various other factors affect productivity growth. It is quite usual to include the initial productivity level in the equation (see Benhabib and Spiegel 1994). Then the labour productivity equation can be written as follows:

$$\ln\left(\frac{Y_{it}/L_{it}}{Y_{is}/L_{is}}\right) = a_0 + \beta \cdot \ln\left(\frac{Y_{is}}{L_{is}}\right) + a_1\left(S_{it} - S_{is}\right) + a_2 \cdot S_{is} + b \cdot \ln\left(\frac{K_{it}/L_{it}}{K_{is}/L_{is}}\right) + \varepsilon_{it} \qquad (6.15)$$

A negative β indicates that plants with low initial productivity levels tend to have achieved productivity growth rates. This result is commonly used as an indicator of the so-called beta convergence (see discussion in Barro and Sala-i-Martin 1995 and critical points on the interpretation of convergence by Friedman 1992).

6.2 Growth accounting computations

The data provide an opportunity to apply the growth accounting approach to the estimation of the labour efficiency growth rate pretty exhaustively. Plant-level data on employee characteristics and monthly earnings are constructed by using the Employment Statistics data files. These files are originally constructed by using various registers and in principle they cover the whole working age population. The employees can be matched to plants based on information about their primary employer in the last week of the year. Although some individuals are dropped in the matching process, on the basis of the National Accounts this sample covers about 70 percent of total employment in manufacturing up to the year 1995 and 80 percent since 1996. The data cover the manufacturing sector and most of the other business sectors[80] from 1988 to 1998. More detailed information on the process of matching employees and plants is presented in Ilmakunnas, Maliranta, and Vainiomäki (2001) (see also Appendix 2).

Employment is classified into 70 groups according to gender (2 groups), age (5 groups), and educational level and field (7 groups). The data have information on the number of persons in each group in each plant and the average monthly wages,

Table 6.1 Distribution of labour and monthly wages by labour characteristics in manufacturing

	Labour shares, %			Monthly wage, EUR		
Year	1990	1994	1998	1990	1994	1998
Sex						
Male	66.4	69.2	70.9	1 763	1 992	2 343
Female	33.6	30.8	29.1	1 291	1 503	1 809
Age						
15-24	9.4	6.3	7.8	1 211	1 317	1 574
25-34	27.1	25.7	26.3	1 539	1 696	2 035
35-44	34.2	32.4	28.8	1 689	1 913	2 287
45-54	22.2	28.7	29.6	1 712	1 990	2 338
55-64	7.0	6.8	7.5	1 635	1 913	2 388
Education						
Basic	38.8	33.2	26.6	1 441	1 673	1 985
Vocational, technical	33.4	35.5	36.9	1 507	1 728	2 064
Vocational, non-technical	9.2	9.5	11.1	1 405	1 588	1 832
Polytechnic or lower university, technical	12.5	14.4	16.4	2 062	2 229	2 550
Post secondary non-tertiary or lower university, non-technical	2.8	3.1	3.5	1 870	1 987	2 152
University, technical	2.6	3.4	4.4	3 132	3 287	3 733
University, non-technical	0.8	1.0	1.1	2 868	3 003	3 259

Note: The 'technical' field includes engineering and natural science. The data are obtained from the Employment Statistics.

[80] The agriculture, construction and transportation sectors are excluded because of problems in the accurate delineation of plants in the primary data sources.

the average schooling years and the average age, for example. The classification scheme of employees is shown in Table 6.1, which also includes information on the labour shares and average wages in manufacturing in three selected years (1990, 1994 and 1998).

The results based on Equations (2.16) and (2.17) with the use of a detailed classification of labour (70 groups) are shown in Graph 6.1. Lack of information about the hours worked is one deficiency of the Employment Statistics data. We need to assume that workers with different levels of education work the same average number of hours.[81]

The graph suggests a sustained improvement in labour efficiency or quality. The rate of quality-upgrading has been somewhat lower in the manufacturing than in the non-manufacturing sectors.[82] The average annual growth rate has been 0.67 % (in log-percent terms) in manufacturing and 1.01 % in non-manufacturing. An interesting finding from the standpoint of this study is that labour efficiency seems to vary counter-cyclically (the correlation between (raw) employment growth and labour efficiency growth in manufacturing and in non-manufacturing is -0.81 and -0.80, respectively). This is illustrated in Graph 6.1 by including the growth rate of employment according to the Finnish National Accounts side by side with the labour efficiency growth measure (note that the scales for employment growth on the right-hand side are reversed). The labour efficiency growth rate has come down after the recession; in manufacturing earlier than in non-manufacturing, which is in keeping with the fact that the recovery started earlier in manufacturing. It is, however, worth noting that the labour efficiency increase was reasonably high in the pre-recession years as well.

Due to lack of good data, the growth accounting method is quite commonly applied by using a much less detailed classification of labour than here (see e.g. Jalava 2002). For the sake of checking the sensitivity of the results with the classification and in order to assess the separate roles of education and age, I have repeated the calculations by classifying labour by education (7 groups) or by age (5 groups) only.[83]

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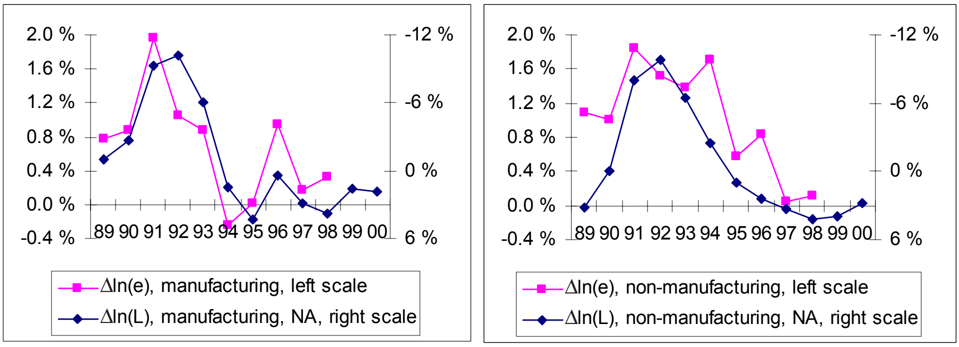
[81] The Employment Statistics data do not include information on social security payments. Their share of total compensation is, however, reasonably constant across different labour groups and thus wage shares constitute appropriate weights for these computations.
[82] Here the non-manufacturing sector consists of business sector industries outside of manufacturing. See also footnote 80.
[83] Fosgerau, Jensen, and Sørensen (2002) investigate the magnitude of measurement bias when a few education categories are used instead of a very detailed grouping of persons by education. They find that the error is quite small. They do not, however, provide us with statistics about the extent of error that is caused by ignoring labour characteristics other than education, such as age. In this study a lot of attention is paid to the role of general experience as well.

Graph 6.1 The change of labour input efficiency and employment growth in manufacturing and in non-manufacturing



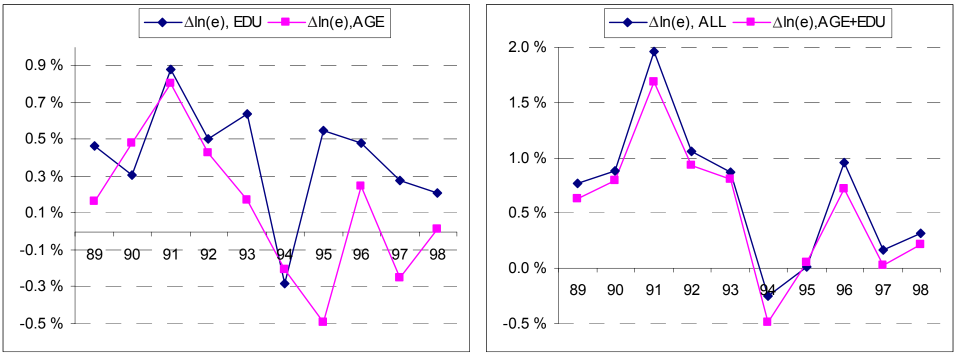
Note: The labour efficiency change rate, dln(e), is calculated by the growth accounting method. The log-difference of employment, dln(L), is obtained from the Finnish National Accounts (NA). Right scales are reversed.

The results from these computations are shown in Graph 6.2. Changes in the educational composition seem to have contributed positively to labour efficiency in all years except 1994, which can be seen in the left diagram. It is interesting to see that, at the turn of the 1980s and 1990s, the changes in education and age composition seem to have contributed about equally as much to up-skilling. Changes in age composition seem to have resulted in labour efficiency increases up to the year 1993, but thereafter the effect has been mostly negative. My results for the contribution of the compositional changes by education groups are broadly consistent with those of Jalava (2002). He found that labour efficiency has upgraded annually by 0.2-0.3 percent in the years 1990-99, when labour input is broken down solely by education.

So if we believe that this methodology is an appropriate way to capture the role of skills in economic growth, we may conclude that both education and age have played important roles in skill-biased employment growth in Finnish manufacturing. This appears to be the case during downturns in particular. The right-hand diagram indicates that the sum of these two measures quite closely predicts the gauge based on the more detailed classification of labour input. So the findings do not conflict badly with the assumption that education and age (general experience) are two additive main elements of labour efficiency.

So far it is assumed that all plants are similar and that the marginal product of a given labour input type is the same in each and every plant. This assumption may be too restrictive, however. Different plants may have different technologies, which is likely to affect the productivity of a certain labour input type. If the mobility of labour is imperfect, the marginal product and hence the wage level of a certain

Graph 6.2 The roles of education and age for labour input efficiency change in manufacturing



Note: *EDU* indicates that labour efficiency has been measured by using the educational classification (7 groups), while *AGE* indicates the use of the age classification (5 groups) and *ALL* the use of the detailed classification (70 groups).

labour input may be abnormally high in some plants, which are equipped with a more advanced technology, for example. High wages can then serve as a tool to encourage the inflow of labour to high productivity plants (see Acemoglu and Shimer 2000).

Because of the above considerations, I have used Equations (6.12) and (6.13) and thus allowed the marginal product of a given labour input to vary between plants. Consequently, an extremely detailed classification is used, where labour is differentiated by labour characteristics (70 groups) and by plant.[84] So this labour efficiency measure should capture the effect arising from the changes in plant structures. This effect would be positive if labour is reallocated to plants with a higher marginal product and higher wages. I report the results obtained by (6.13), where raw labour input growth is measured by using the number of persons as weights (instead of payroll shares as when computing labour service growth).[85]

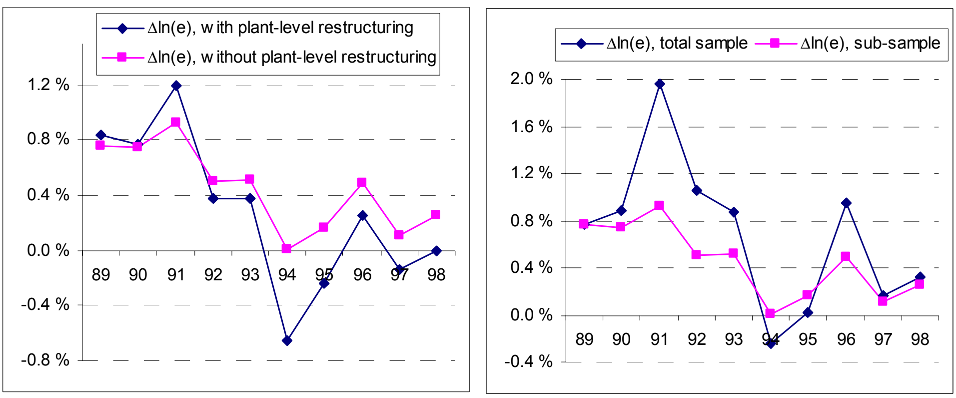
[84] For example, in the period 1988-89 there were some 65,000 groups in manufacturing that had non-zero employment in both the initial and final years.

[85] In more usual cases, where the number of groups is a hundred or so, this is practically equal to the results obtained by (6.12). However, when labour is differentiated by both socio-economic characteristics and by plants, the difference between (6.12) and (6.13) is not totally negligible. When the plant dimension is included, the average difference in the whole period is only 0.11 %, but the standard deviation of the difference is 0.23 %. When plant delineation is not included (70 groups) the average difference between these two ways of measuring raw labour growth is 0.0007 % and the standard deviation is 0.0039 %. So the earlier results shown in Graphs 6.1 and 6.2 are practically the same as Equation (6.12) and (6.13), where the plant subscript *i* is dropped.

A drawback of the following analysis is that it is possible to focus only on those plants that appear in both the initial and final years and only on those worker groups among incumbent plants that have non-zero employment in both years. The coverage of this new sub-sample is 85 percent of the original total sample used above. To check for possible selection bias I have drawn corresponding labour efficiency increase measures obtained from the total sample and the sub-sample side by side in the right-hand diagram of Graph 6.3. The average labour efficiency growth in the sub-sample is 0.45 % compared to 0.67 % for the total sample. The difference comes solely from the recession years 1991-93 and from the "mini-recession" year 1996. The average labour efficiency growth rates in the non-recession years for the total sample and the sub-sample are 0.32 % and 0.34 % respectively. So we do not find any indication of the sub-sample being badly unrepresentative, at least during normal times. But it should be noted that this sub-sample consisting of the continuing groups only gives an under-rated picture of labour efficiency growth during the recessions.

Somewhat surprisingly, perhaps, these computations do not provide us with the evidence that plant-level restructuring among continuing plants has contributed positively to labour efficiency change (except in 1991). The labour efficiency growth rate is normally *higher* when the plant dimension is not included. The problem is likely to lie in the methodology that assumes that each input is paid according to its

Graph 6.3 Labour efficiency increase with and without plant-level restructuring



Note: Calculations are made by the growth accounting methodology. A sub-sample refers to those individuals that are employed by a plant that appears in both the initial and final years and that belongs to a group within a plant having workers in both years. A sub-sample is used for computing the series that are given in the left-hand side diagram. Note that the line labelled by 'dln(e), without plant-level restructuring' in the left-hand diagram is the same as the one labelled by 'dln(e), sub-sample' in the right-hand diagram.

current marginal product. Wages may be determined in the labour markets so that the law of one price holds true. In that case high productivity plants pay a below marginal product during the process of reallocating labour between plants. If this is the case, the growth accounting method fails particularly badly in times of such technological shocks that bring about intensive plant-level restructuring.

Maliranta (2002a) found that plant-level restructuring accounted for very little of the aggregate hourly wage growth in Finnish manufacturing, which is in keeping with the message obtained from the left-hand diagram of Graph 6.3. So there does not seem to have been a systematic reallocation of labour input towards high wage plants. The effects of plant level restructuring for the components of aggregate wage growth are investigated in more detail when studying the determination of factor income shares in Chapter 9 (see for example Graph 9.6).

6.3 Labour efficiency and productivity

In Graph 6.1 we saw that a change in labour efficiency is negatively related to employment growth. In Section 5.7 we noted that the "creative destruction" components of manufacturing productivity are also negatively correlated with employment growth. These findings seem to suggest that high values of the between components during downturns reflect more or less the fact that low productivity jobs occupied by low skilled workers are destroyed, and thus average labour efficiency and average labour productivity are improved. To put it another way, the estimates of the micro-structural factors presented in Chapter 5 might be "skill-biased" because of the fact that differences in skill levels between plants are not controlled.

6.3.1 Deriving labour efficiency indexes for plants

The analysis of this question is started by first estimating how labour efficiency is related to labour characteristics, i.e. we try to determine Equation (6.2). For that purpose I link the Industrial Statistics database with the Employment Statistics database by plant codes. Then I have information on the plants' output, worked hours, capital and hourly wages, supplemented with information on average labour characteristics. This allows me to make corrections for labour efficiency for each plant by using information on the average labour characteristics of the employees in the plant and the coefficient estimates on the relationship between labour efficiency and labour characteristics.

Labour efficiency is assumed to be reflected in labour productivity or, alternatively, in the hourly wages of the plants measured in natural logarithms. The labour characteristics of the interest include the average years of schooling and the average age of the employees. The results are reported in Table 6.2.[86] All the models suggest that schooling improves labour input efficiency. One extra year of schooling increases labour productivity by 7.8 log-percent according to Model (1) and 5.6 log-percent according to Model (2). The wage models suggest a somewhat bigger role for schooling. Model (3), which corresponds to labour productivity Model (1), tells us that one year of schooling increases wages by 10.7 log-percent and Model (4) suggests a 7.9 log-percent increase. It should be noted that the results for wages are close to individual-level estimates (see Asplund 1999).

The relationship between age and labour efficiency seems to be concave. Labour efficiency peaks at 43.7 years in Model (1), at 30.8 years in Model (2), at 47.6 years in Model (3), and at 47.1 in Model (4). Again, these wage estimates are reasonably close to individual-level estimates. In comparing the results of these models we may conclude that the wage models show employees to be in the prime of their careers in terms of labour input efficiency at a later age than do the productivity models.

Table 6.2 OLS estimates of productivity and hourly wage levels. Dependent variable: log of labour productivity and hourly wage

Model Dependent variable	(1) ln(LP)	(2) ln(LP)	(3) Ln(W/L)	(4) ln(W/L)
S	.0788***	.0553***	.1068***	.0786***
	(.0031)	(.0034)	(.0011)	(.0010)
AGE	.0713***	.0130*	.0945***	.0652***
	(.0087)	(.0084)	(.0029)	(.0025)
AGE^2	-.0008***	-.0002*	-.0010***	-.0007***
	(.0001)	(.0001)	(.0000)	(.0000)
R^2	.1147	.3298	.5292	.7110
N	46 850	39 793	46 848	39 791

Note: All models include dummies for years and an intercept that are not reported. The sample covers the years 1988-98. Standard errors in parenthesis. Models (2) and (4) also include dummies for two-digit industries and log of capital intensity interacted with the two-digit industry dummies. Plants are weighted by worked hours.
* significant at 10%
** significant at 5%
*** significant at 1% level

[86] In the regression estimations I have dropped some outliers. An observation is deemed as an outlier if its log labour productivity (or log of hourly wage) differs from the 3-digit industry average more than 4.4 standard deviations. This method is adopted from the study by Mairesse and Kremp (1993).

I have computed indexes of labour input efficiency by using the coefficient estimates of the variables *S*, *AGE*, and *AGE* squared reported in Table 6.2 (see Equation (6.6)). The efficiency index calculated by using Model (1) is called *e1*, using Model (2) *e2*, and so forth. These are exponents of the logged indexes obtained by formulas of Equation (6.2) type.[87]

6.3.2 Analysis with labour efficiency indexes

In the previous section 6.3.1 different labour efficiency indexes were derived. Next they are utilised in the productivity analysis. As the computation of these indexes is broadly based on the same theory as growth accounting computations, e.g. standard human capital theory, we should not observe a significant difference in the results, especially when the labour efficiency indexes are computed by using regression Models (3) or (4) for wages documented in Table 6.2. This is checked below.

The aggregate labour productivity growth rates are calculated by using equation (3.4) (Section 3.2.1) five times with the same plant sample. First computations are made, as usual, with raw labour input measures (hours worked) and then using four versions of efficiency-adjusted labour input measures. The efficiency-adjusted computations are performed by multiplying raw labour *L* by labour efficiency indexes (*e1*-*e4*). Then I have computed measures of the labour efficiency change rate by taking the difference of the labour efficiency unadjusted and the labour efficiency adjusted aggregate labour productivity growth rate. So this procedure provides us with four aggregate measures of the labour efficiency growth rate that are alternatives to those obtained by the growth accounting methodology. These indicators are depicted in Graph 6.4.

The graph reveals a number of important points:

1. All the indicators of labour efficiency change show generally positive values and usually the variation over time appears to be reasonably similar. The only exception is the one made with *e2* that suggests that the labour efficiency upgrade was relatively low during the recession and increased during the recovery years. All labour efficiency indicators except that made by using *e2* are mutually positively correlated in a statistically significant way in this short time period.

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[87] The index is normalised so that labour quality is 1.00 in those plants where the average years of schooling is 9 and the average age is 20. Then, for example, the labour quality index of the first model is obtained as follows; $e1=\exp(-1.809+0.0788*S+0.0713*AGE - 0.0008*AGE^2)$. The standard deviation of ln(*e1*) is 8.95 % and the interquartile range is 9.6 %.

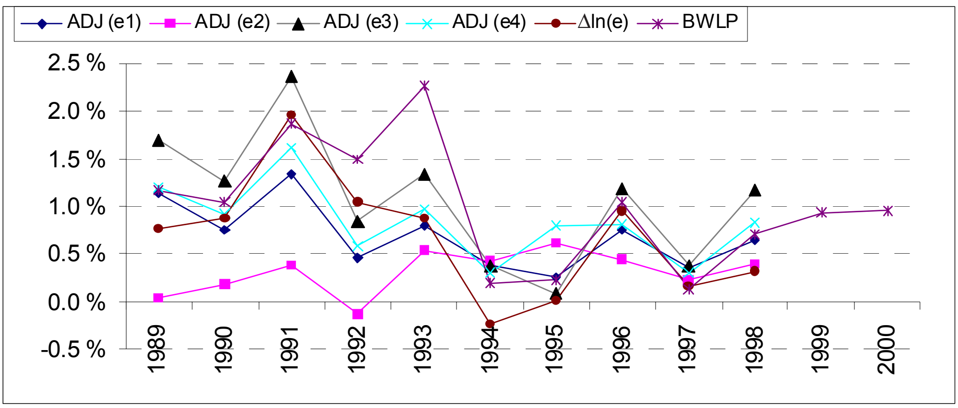
2. Labour efficiency change seems to be larger when it is measured by wages instead of productivity, i.e. efficiency change computed by *e3* is bigger than that computed by *e1* and the one computed by *e4* is bigger than the one computed by *e2*.

3. Controlling for industry and capital intensity usually lowers labour efficiency change, i.e. efficiency change computed by *e1* is bigger than that by *e2,* and when it is computed by *e3* it is bigger than that computed by *e4*.

4. All the labour efficiency indexes utilised here, except *e2,* generally yield a picture of the development of labour input efficiency that is reasonably similar to the growth accounting estimates in Graph 6.2, which is reproduced in Graph 6.4.

5. The between component of the aggregate labour productivity growth rate (*BWLP*) seems to be correlated with the various indicators of labour efficiency.[88]

Graph 6.4 Labour efficiency increase and productivity improving restructuring



Note: *ADJ* denotes that labour efficiency change is measured by adjusting labour efficiency with a labour efficiency indicator. Labour efficiency indicators *e1-e4* are computed by using the coefficient estimates of Models (1) – (4) in Table 6.2. An estimate of the labour efficiency growth rate, obtained by the growth accounting methodology, is denoted by *dln(e)*. *BWLP* refers to the between component of raw labour productivity growth obtained by the MBJ/INP method.

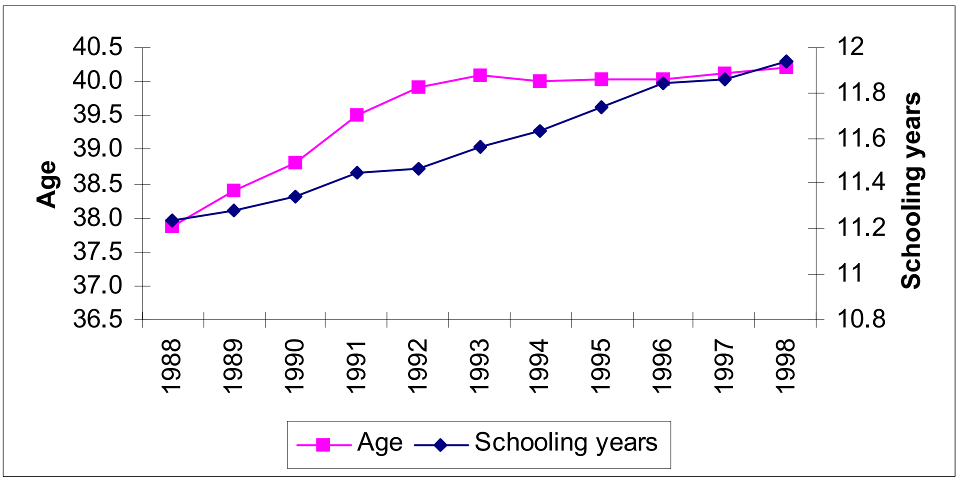
[88] It should be noted that the labour quality computations with *e1-e4* differ from the growth accounting computations in several respects. The growth accounting computations are based solely on the Employment Statistics data source whereas, for the computations with *e1-e4*, the information on hourly wages and labour productivity is from a sub-sample that is obtained by matching the Industrial Statistics and the Employment Statistics data by plant codes. The computations of the *BWLP* variable are done by using the Industrial Statistics data source that is not matched with Employment Statistics data. So the plant samples behind the *BWLP*, *ADJ* and *dln(e)* estimates are different.

Looking more carefully, the between component (*BWLP*) is positively correlated with all labour efficiency change indicators, except with that generated by using the *e2* index.

The fact that the use of *e2* estimates leads to a discrepancy in this analysis deserves some further comments. The OLS estimates behind this indicator suggest that relatively young workers are productive when plant characteristics such as industry and capital intensity are controlled.[89] Graph 6.5 shows that the development of labour characteristics in Finnish manufacturing in the period 1988-92 is characterised by an increase in the average age from 38 to 40 years. This increase is towards the optimum of all the other models except (2). The average years of schooling, in turn, has upgraded at a reasonably stable rate during the whole period under consideration.

The estimates of the labour efficiency change rate presented above are supposed to gauge the contribution of skill upgrading to the aggregate productivity growth rate. The methods of decomposing the aggregate productivity growth rate render a way to identify the micro-level sources of productivity-enhancing skill upgrading. The role of skills in the between component, for example, can be evaluated by taking the difference of the between components obtained with and without the labour efficiency indicators *e1* – *e4*. The "skill-bias" of the other components

Graph 6.5 Average labour characteristics in Finnish manufacturing



Note: The data are from the Employment Statistics.

[89] It is the capital intensity variable that is especially important here.

of aggregate productivity growth can be gauged in an analogous way. The MBJ/INP method is used here. It is worth remembering that we still assume that the standard human capital approach provides us with a suitable method for disentangling the role of skills.

The magnitudes of the "skill-bias" of the labour productivity components are shown in Graph 6.6. The between and exit components appear to have a minor role here. Again the labour efficiency index *e2* stands out. The between component obtained by the efficiency-unadjusted labour input measure is on average slightly upward biased when the labour input adjustment is based on Model (2), but more clearly downward biased when the other three models are used. Moreover, when Model (2) is used in the labour efficiency measurement, the upward bias in the between component does not seem to be particularly prevalent during the downturn years (1991-92).

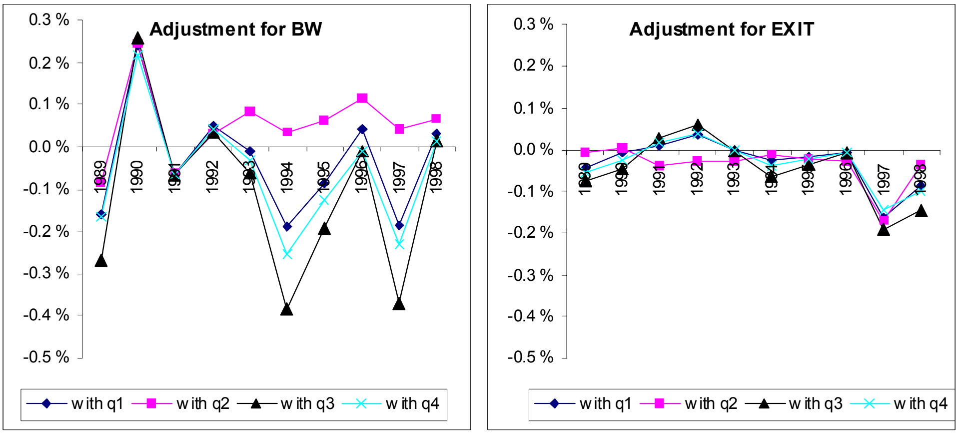
These computations suggest that skill upgrading contributes to the aggregate productivity growth rate mainly through the within plants component. So assuming that this way to gauge labour efficiency is appropriate, two conclusions can be drawn:

1. The productivity decomposition exercise usually tends to *undervalue* the relative importance of plant-level restructuring for aggregate productivity growth, especially in the post-recession years. It is worth noting that this is consistent with the message that can be concluded from Graph 6.3. We noticed there that the inclusion of plant-level restructuring tends to mitigate the labour efficiency growth rate estimate except during the boom years preceding the deep recession of the early 1990s. To put it another way, in general these computations suggest that restructuring itself actually *diminished* the labour efficiency growth rate during the recovery period, which seems surprising. The exception is the signal obtained by using the efficiency indicator *e2,* which indicates that productivity-enhancing restructuring has a positive skill-upgrading element, albeit very small (usually some 0.1 percentage points per year). It might be the case that *e2,* which is based on the relationship between labour characteristics and productivity, gives a more correct message. It should be noted, however, that it yields a picture of skill upgrading that is quite different from the growth accounting exercise, for example.

2. The analysis made from the usual premises suggests that skill upgrading should turn into improved productivity within plants through immediate *internal adjustment*. To put it another way, the within component of raw labour productivity growth appears to be "skill-biased" upwardly. The average annual bias is 1.9 percentage points in 1989-91 and 0.9 percentage points in 1992-98 when the labour efficiency adjustment is made with *e3*.[90]

[90] When the *e2* index is used the respective numbers are 0.1 and 0.2 percentage points.

Graph 6.6 Labour skill-upgrading through the between and the exit component of aggregate productivity growth



Note: The results are obtained by using decomposition of the aggregate productivity growth rate and by using efficiency indicators derived from the regression Models (1) – (4) in Table 6.3. See the text.

So if the premises of the growth accounting method and the labour efficiency growth decomposition method are valid, we would expect to find those plants that have had the greatest increase in skills to have experienced the highest raw labour productivity growth rate.

6.4 Skill upgrading and productivity growth at plants

We noticed in Graph 6.4 that the aggregate productivity growth rates computed with the efficiency-unadjusted labour input measures are generally upwardly biased. The bias comes essentially from the within component of aggregate raw productivity growth that should gauge the weighted average productivity growth rate of the plants. In other words, the within component obtained from the productivity growth decomposition clearly *over-rates* the average productivity growth rate among the incumbent plants when labour efficiency is ignored. Vainiomäki (1999) shows that, for the main part, skill upgrading has indeed taken place within plants, which is in keeping with the findings made above. According to his analysis the between plants component of skill upgrading was generally quite low, but highest before the recession. Huttunen (2002) documents that the increase in age (and general experience) has taken place within plants as well.

I have estimated OLS regression models where the dependent variable is now the labour productivity growth rate measured by the log difference. The results are shown in Tables 6.3 and 6.4. Models (1)-(4) of Table 6.3 show a negative correlation between an increase in schooling (denoted by ΔS) and labour productivity growth, which is in sharp contrast with the findings obtained from the estimations with the levels above. Moreover, according to Model (2) the level of the initial schooling (in year t-1) does not positively affect the subsequent productivity growth. However, a comparison with Model (3) reveals that it is important to check the initial productivity level as stated by Benhabib and Spiegel (1994) and Maliranta (2000b), for example.[91]

After inclusion of the initial productivity level $\ln(Y_{t-2}/L_{t-2})$, the coefficient estimate of schooling level S_{t-1} becomes positive and is statistically significant at the 95 % confidence level. These results indicate that education has a positive effect in the long run, even though the immediate effect may be negative. Model (5), which includes lagged changes in schooling years, lends further support to this view. According to Model (5) it takes four or five years before an increase in the average schooling level of the employees is reflected in the labour productivity growth rate. One interpretation of these findings is that schooling is not predominantly an input in production, as assumed earlier, but an input contributing to a long-run productivity increase through creating or absorbing better technologies (see Leiponen 2000).

The field of education can be expected to play a role here. "Technical education" (engineering and natural sciences, *TECH*) is distinguished from "non-technical education" (commercial science, humanities, etc., *NTECH*). The amount of education is now measured as the proportion of employees having a lower or higher university degree. Model (1) in Table 6.4 suggests that an increase in education (see variables $\Delta TECH$ and $\Delta NTECH$) affects productivity growth negatively irrespective of the field of education, which is perfectly consistent with the earlier findings. Neither does Model (2) of Table 6.4 provide evidence that the initial level of education (see variables *TECH* and *NTECH)* is important for subsequent productivity growth. Again, checking the initial productivity level changes the results in an important way (see Model (3) of Table 6.4). Although we now find that the initial level of technical skills in the plant has a significant positive effect on the subsequent productivity growth, empirical support for a positive effect of "non-technical" skills is still not obtained. One problem with the latter case is that the standard error estimate is quite large. The results obtained by Model (5) of Table 6.4 are consistent with the other findings. An increase in "technical" skills affects productivity growth first negatively, but then positively, with a lag of four or five years. Lagged changes in "non-technical" skills have positive coefficient estimates as well, but large standard errors make them still statistically insignificant.

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[91] I have measured the initial productivity level in the year *t-2* in order to avoid a spurious correlation that might emerge if the same variable appears in both sides of the equation, as is the case if the initial productivity is measured in the year *t-1*.

Table 6.3 OLS estimates of productivity growth. Dependent variable: the log-difference of labour productivity

	(1)	(2)	(3)	(4)	(5)
$\ln(Y_{t-2}/L_{t-2})$			$-.129^{***}$	$-.121^{***}$	$-.120^{***}$
			(.005)	(.005)	(.009)
$\Delta\ln(K_t/L_t)$	$.057^{***}$	$.058^{***}$	$.060^{***}$	$.093^{***}$	$.059^{***}$
	(.008)	(.008)	(.010)	(.007)	(.018)
ΔS_t	$-.019^{***}$	$-.021^{***}$	$-.015^{***}$	$-.013^{***}$	-.019
	(.005)	(.005)	(.006)	(.005)	(.014)
S_{t-1}		-.004	$.012^{***}$	.003	
		(.003)	(.004)	(.003)	
ΔS_{t-1}					-.007
					(.015)
ΔS_{t-2}					-.014
					(.014)
ΔS_{t-3}					.001
					(.013)
ΔS_{t-4}					$.030^{***}$
					(.012)
ΔS_{t-5}					$.025^{***}$
					(.009)
ΔAGE_t	$-.003^{**}$	-.002	-.002	$-.003^{***}$	
	(.001)	(.001)	(.002)	(.001)	
AGE_{t-1}		$.001^{*}$	.001	$.002^{***}$	
		(.001)	(.001)	(.001)	
ΔFEM_t	$-.156^{***}$	$-.139^{***}$	$-.181^{***}$	-.038	
	(.032)	(.033)	(.038)	(.029)	
FEM_{t-1}		$.028^{*}$	-.026	$-.032^{**}$	
		(.015)	(.017)	(.014)	
R^2	0.062	0.063	0.092	0.059	0.083
N	31497	31497	25828	25828	7797

Notes: Standard errors in parentheses. The data coverage varies between models depending on the variables that are included. For example, the data behind Models (1) and (5) cover the years 1989-98 and 1994-98 respectively. All models include year dummies interacted with 2- or 3-digit industries (13 manufacturing industries). Intercept terms are not reported either. All models except (4) are weighted by labour input.

* significant at 10%

** significant at 5%

*** significant at 1% level

Table 6.4 OLS estimates of productivity growth. Dependent variable: log difference of labour productivity

	(1)	(2)	(3)	(4)	(5)
$\ln(Y_{t-2}/L_{t-2})$			$-.128^{***}$	$-.119^{***}$	$-.120^{***}$
			(.005)	(.005)	(.009)
$\Delta\ln(K_t/L_t)$	$.058^{***}$	$.058^{***}$	$.060^{***}$	$.093^{***}$	$.056^{***}$
	(.008)	(.008)	(.010)	(.007)	(.018)
$\Delta TECH_t$	$-.158^{***}$	$-.189^{***}$	$-.122^{***}$	$-.069^{**}$	$-.193^{**}$
	(.027)	(.029)	(.032)	(.028)	(.078)
$TECH_{t-1}$		$-.064^{***}$	$.072^{***}$	.015	
		(.022)	(.025)	(.021)	
$\Delta TECH_{t-1}$					-.049
					(.083)
$\Delta TECH_{t-2}$					-.034
					(.081)
$\Delta TECH_{t-3}$					-.006
					(.078)
$\Delta TECH_{t-4}$					$.169^{**}$
					(.069)
$\Delta TECH_{t-5}$					$.126^{**}$
					(.054)
$\Delta NTECH_t$	$-.164^{***}$	$-.159^{**}$	$-.174^{**}$	-.055	-.077
	(.063)	(.065)	(.076)	(.049)	(.161)
$NTECH_{t-1}$		.024	.050	.028	
		(.040)	(.044)	(.031)	
$\Delta NTECH_{t-1}$					-.128
					(.188)
$\Delta NTECH_{t-2}$					-.014
					(.175)
$\Delta NTECH_{t-3}$					.105
					(.167)
$\Delta NTECH_{t-4}$					.223
					(.158)
$\Delta NTECH_{t-5}$					.182
					(.128)
ΔAGE_t	-.002	-.002	-.002	-.003	.004
	(.001)	(.001)	(.001)	(.001)	(.003)
ΔFEM_t	$-.165^{***}$	$-.165^{***}$	$-.176^{***}$	-.021	$-.198^{***}$
	(.033)	(.033)	(.037)	(.028)	(.066)
R^2	0.063	0.063	0.092	0.059	0.085
N	31497	31497	25828	25828	7797

Notes: Standard errors in parentheses. The data coverage varies between models depending on the variables that are included. For example, the data behind Models (1) and (5) cover the years 1989-98 and 1994-98 respectively. All models include year dummies interacted with 2- or 3-digit industries (13 manufacturing industries). Intercept terms are not reported either. All models except (4) are weighted by labour input.

* significant at 10%; ** significant at 5%; *** significant at 1% level

The conclusions concerning the effect of age are similar to those of schooling in many respects. The immediate consequence of an increase in the average age for the productivity growth rate is negative rather than positive. In all models reported in Tables 6.3 and 6.4, I have also checked the effects of changes in the sex composition; the *FEM* variable indicates the proportion of female workers and ΔFEM the change in this proportion. However, the results commented on above are not sensitive to the control of this labour characteristic.

6.5 Discussion on skill upgrading and productivity-enhancing restructuring

In Chapter 5 we saw that the acceleration of aggregate labour and total factor productivity in the latter part of the 1980s can be ascribed almost entirely to increased productivity-enhancing restructuring at the plant level. In this chapter it is asked whether this happened because low productivity technologies were cleansed from the production system, or because low productivity workers were cleansed from manufacturing employment. In the latter case, the process should hardly be described as "creative destruction".

The view that productivity has improved because of intensive destruction of the jobs of low-skilled workers and the creation of new jobs mainly for high-skilled workers can be challenged on several grounds:

1. Productivity enhancing-restructuring started to become more intensive long before the great depression and continued during the recovery period.

2. If skill upgrading was behind the aggregate productivity growth acceleration then the skill upgrading rate should have increased. However, the rate at which average schooling years increased was reasonably stable at least over the period from 1989 to 1998. Instead, the average age had risen sharply from 38 to 40 by the end of the recession. So relatively high age should characterise efficient workers.

3. We saw in Table 5.1 that productivity-enhancing restructuring has been strong in the manufacture of communications equipment, which has expanded very strongly in recent years. So productivity-enhancing restructuring does not necessarily seem to require slow-down in industry.

Growth-accounting computations made by using a detailed classification of labour into 70 groups suggest that the rate of labour efficiency increase varies counter-cyclically (see also Section 5.7). This observation seems to support the view that skill upgrading through plant-level restructuring has a role to play in recessions. Likewise, a comparison of the aggregate labour productivity growth rates computed with efficiency-unadjusted and with efficiency-adjusted labour input suggests that labour quality varies counter-cyclically.

However, a more detailed analysis making use of aggregate labour productivity decomposition reveals that the skill upgrading effect on aggregate productivity should have come from the within plant component, not from the "creative destruction" components. The between and exit components of aggregate raw labour productivity growth seem to be *downward* biased when labour quality is not taken into account.

A positive within component of labour efficiency change implies, and growth accounting methodology assumes, that an increase in skills within plants is immediately reflected in greater productivity growth rates. Regression results obtained with plant level data suggest, however, something quite opposite. These findings cast some doubt on the assumption that skills augment raw labour input by making it immediately more efficient with current technology. The validity of the growth accounting method in quantifying labour efficiency growth can be questioned, especially during intensive micro-level restructuring.

My results indicate that the role of formal education is likely to be essentially of different kind. Skills can be expected to improve a plant's ability to create, adopt and implement new technologies. It is then no surprise that the results show that an increase in a plant's skill level boosts productivity growth with a considerable lag. This seems to apply especially to education obtained in the fields of engineering and natural sciences. In this respect, the results confirm the conclusions made by Leiponen (2000). Further, it seems to take time to build a new technology and implement it efficiently at plants.

A worker needs to be equipped with a proper technology in order to utilise his or her skills in a productive way. As a consequence, in order to turn higher skills into higher aggregate productivity, new technologies must be created. Then labour input must be reallocated to those plants that have managed to implement high productivity technologies successfully. So skill upgrading needs to be accompanied by incessant plant level restructuring through simultaneous job destruction and creation.

On the other hand, skill upgrading can be expected to stimulate productivity-enhancing restructuring in the future. Higher skills (especially in "technical" fields) make it possible to build new plants equipped with modern high productivity technology that need new workers when the new technologies have been implemented and passed the market test. New workers need not be as skilled as the creators of technology (see Bartel and Lichtenberg 1987). Thesmar and Thoenig (2000) are on the same track in arguing that an increasing supply of skills stimulates "creative destruction". Skilled workers participate in innovation activities which leads to more intensive renewal of technologies. So we might expect that R&D intensity and labour skills are related to productivity-enhancing restructuring in a similar way. The effect of R&D on the between component of aggregate productivity growth is investigated in Chapter 8.

7 Job and worker flows

7.1 Introduction

An analysis of job turnover[92] should help to put some detail on the overall picture of external adjustment involved in aggregate technical progress. Moreover, in this section the investigation is extended to worker flows.

Empirical analysis of worker turnover has long traditions. Recent research has examined these two types of turnover, i.e. job and worker flows, together in order to obtain more information on the dynamics of the labour market. Ideally, the analysis is based on data sets that include information on both firms or plants and their employees. This gives us an opportunity to investigate both external and internal adjustment, or restructuring and the matching process, in a coherent way. Finally, an analysis of worker flows to and from a state of unemployment sheds some light on the most painful part of the adjustment to technical change.

In this chapter I use a linked employer-employee data set. The job and worker flows of the plants are computed by using a register-based Employment Statistics database, which covers practically the whole working age population in Finland. The data are such that it is possible to discover the identity of all the employees in each plant at the end of the year. Thus, by this data source, it is possible to gauge the worker flows by discrete measures that are based on a comparison of employees at the end of two consecutive years. This data source is also used to calculate the number of employees, the average monthly wage level and the wage dispersion within plants. Information about plants' labour productivity (value adder per hours worked) and capital intensity (capital stock per hours worked) is obtained from the LDPM (Industrial Statistics) data set. R&D intensity (R&D expenditures per sales) is derived from the Research and Development Statistics data set. The R&D Statistics database contains firm-level data, which I have linked to plant-level data on job and worker flows by the firm code. In other words, the same R&D intensity is used for all plants owned by the same firm in a particular year.[93]

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[92] The seminal work is Davis, Haltiwanger, and Schuh (1996). The more recent work is surveyed in Davis and Haltiwanger (1999).

[93] I have calculated R&D intensity by taking the average intensity in the current and previous years. This has two advantages. Firstly, the estimates of innovation activity are likely to be more reliable. Secondly, the number of observations can be increased in this way, especially for small firms that are randomly included in the annual R&D surveys. We then obtain an estimate for the intensity of innovation activity if a firm has been in the R&D sample in either the current or the previous year. A similar method was also applied in Section 5.3.3.2, when the R&D intensity of a plant was defined for productivity decomposition.

Linking information from the three data sources provide me with a data set that covers the years from 1990 to 1997.[94] The focus is on the continuing plants. This restriction can be justified in the same way as the decision to focus on the between component of productivity decomposition made with the MBJ or INP methods. The great majority of annual restructuring takes place among the continuing plants. Moreover, this share of job and worker flows can probably be gauged much more reliably than the one taking place through plant births and deaths. The data include some 1700 plant observations per year that cover roughly one half of total manufacturing employment.[95]

7.2 Definitions and variables of interest

Worker inflow or hiring is defined as the sum of new employees in the plant in question. Dividing the worker inflow in period t by the average employment in years t and t-1, yields the worker inflow rate or hiring rate $WIF_{it} = H_{it}/((E_{it}+E_{i,t-1})/2)$, where H_{it} is the number of hirings and E_{it} employment in plant i in year t. Correspondingly, worker outflow or separation is the sum of employees that have left their place of employment. The worker outflow rate or separation rate $WOF_{it} = S_{it}/((E_{it}+E_{i,t-1})/2)$, where S_{it} is the number of workers that have left plant i in year t. The difference of the inflow and outflow rates is the net rate of change of employment, $NET_{it} = WIF_{it} - WOF_{it}$. In addition to these measures, it is also possible to calculate worker flows by source and destination. In this section, we will have a look at the inflow of workers to plants from unemployment, $WIFU_{it}$, and the outflow from plants to unemployment, $WOFU_{it}$. The so-called "churning flow rate", which is denoted by CF, is an indicator of the "excessive" worker turnover in a plant. It is the difference of the plant's worker turnover and the absolute value of net growth, $CF_{it} = WIF_{it} + WOF_{it} - |NET_{it}|$(Burgess, Lane, and Stevens 2000).[96] This measure provides us with an indicator of the worker turnover within plants due to the matching process that can be expected to accompany an internal adjustment to technology upgrading. Job creation is defined as the positive employment change of the plant. The corresponding job creation rate is obtained by dividing this figure by the average number of employees, $JC_{it} = \Delta E_{it}^{+}/((E_{it}+E_{i,t-1})/2)$, where the superscript "+" refers to positive changes. The job destruction rate is defined as absolute value of negative employment change, divided by the average number of employees, $JD_{it} = |\Delta E_{it}^{-}|/((E_{it}+E_{i,t-1})/2)$, where the superscript "-" refers to negative

[94] The first year for which I have flow measures is 1991.

[95] Leaving R&D intensity information aside, the data set would cover about 60 percent of manufacturing employment.

[96] A measure that equals CF/2 is called a replacement rate by Albæk and Sorensen (1998) and excess turnover by Barth and Dale-Olsen (1999).

changes. The net rate of change of employment is the difference of these values, $NET_t = JC_t - JD_t$. Of course, at the plant level $NET=JC$ ($NET=JD$), when the plant has increased (decreased) employment.

In the following descriptive analysis the job and worker flows, i.e. NET_{it}, WIF_{it}, WOF_{it}, CF_{it}, $WIFU_{it}$ and $WOFU_{it}$, are explained by various characteristics of the plants and their personnel. I have also estimated models where the dependent variable is the job creation rate (*JC*) or job destruction rate (*JD*).[97] These models are not, however, reported in the tables, but some findings are commented on briefly.

Most of the models are estimated using weighting by plant employment (average of two years). This is justified on the grounds that we are interested in estimating effects that describe turnover in total employment. Unweighted estimation would give equal weight to large plants with low flow rates and to small plants with high flow rates, but would account for a small proportion of total employment. Another justification for using weights is that the errors may be heteroscedastic with standard deviations inversely proportional to plant size.

A few words about the distributions of dependent variables and the use of alternative econometric estimation methods are in order at this point. As the focus is on the continuing plants only, there is no truncation in variable *NET*. Other flow rate measures, however, have positive probability mass at zero point. There are a large number of plants that have no worker inflow or worker outflow (or churning for that matter). The share of those plants with no hirings during the year varies from 7 to 29 percent, depending on the year (29 percent in 1992 and 7 percent in 1997). Usually the plants with zero flows are small and thus have a minor weight in the estimations. For example, those plants that had no hirings during the year accounted for 2 to 7 percent of manufacturing employment in 1990-97.

It should be noted that there is no "censoring" here and thus there is no need for a "censored regression model" (cf. for example Bauer and Bender 2002). All observations can be genuine realisations of the decisions made by employers or employees. Sometimes they may arrive at a corner solution outcome, such as no hirings or no layoffs/separations. There is clearly potentially substantial nonlinearity here. It is important to notice that the standard Tobit model, which is relatively

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[97] The analysis of this chapter very much resembles that of Ilmakunnas and Maliranta (2003d). There are some differences in the explanatory variables. For example, that study lacks R&D intensity, which is included here. In contrast to this descriptive analysis, that study uses somewhat more sophisticated econometric methods (see text). Finally, this study focuses on manufacturing sectors, whereas the study by Ilmakunnas and Maliranta (2003d) covers many non-manufacturing industries as well.

frequently applied in this kind of situation, may be highly inappropriate here. For example, plant characteristics may differently affect decisions to hire and decisions on the hiring rate. To take an example, a small plant may have a higher probability to exhibit zero worker inflow rates than a larger plant. Then, an examination only of the separate effect of size on worker inflow rate, conditional on a flow rate being positive, will be fallacious. An alternative approach is to allow, for example, the initial decision of *JC*=0 versus *JC*>0 to be separate from the decision as to what is the *JC* given that *JC*>0. This approach is used in Ilmakunnas and Maliranta (2003d). They estimated type 2 Tobit models which include a discrete part (a probit model for non-zero flow rates) and a continuous part (a truncated model for positive flow rates).

Anyhow, for the current purpose a simpler approach is preferable and therefore OLS seems attractive. OLS estimates can be justified on the grounds that they approximate the conditional means of the flow rates when the explanatory variables are close to their mean values (Wooldridge 2002, p. 525). Moreover, the interpretations of the results are quite intuitive. For instance, it is possible to distinguish consistently how a certain factor, say high productivity, affects a plant's net employment growth through increasing hirings on one hand, and through decreasing separations on the other hand.

It should be mentioned, however, that the OLS estimates are inconsistent. The OLS model may also predict negative flow rates even when they are impossible by definition. Furthermore, the assumption of homoscedasticity is likely to be seriously violated (see Wooldridge 2002). On the other hand, while weighted estimations are preferable, in the current context the problem of zero flow rates is quite inconsequential. The experience gained by Ilmakunnas and Maliranta (2003d) shows that the weighted OLS gives practically the same results as the continuous part of the Tobit 2 model estimated with weighted maximum likelihood.

Most of the explanatory variables are categorical, so that for example plant size is defined by five groups, from the smallest (group 1) to the largest (group 5). The classification is always from the lowest/smallest/youngest to the highest/largest/oldest. The reference group in the categorical variables is group 1. The groups are defined at the two-digit industry level (23 manufacturing industries) for each industry separately in each year, so that the labour input shares of the groups are 20 percent.

However, R&D intensity groups are constructed slightly differently. The R&D intensity of the plant is defined in the same way as in Maliranta (2000a):

Group 1 (reference group):	0 % ≤ R&D intensity < 1 %
Group 2:	1 % < R&D intensity ≤ 3 %
Group 3:	3 % < R&D intensity ≤ 50 %

The reason for using categorical rather than continuous variables is that in this way industry differences in plant size distributions can be taken into account. The categorical variables can also track possible non-linearities in the relationships. Note that a plant can be classified in different groups in different years, although in many cases the classifications are fairly stable (plant age, in particular, that is dropped from the fixed effects estimations). I first report results obtained from the pooled data that do not include fixed plant effects. Estimations made by including fixed plant effects are reported in a distinct sub-section below. In some important respects they will confirm the conclusion made from the pooled OLS estimations, but, on the other hand, they will contain some interesting discrepancies as well.

To reduce problems with the simultaneity of the variables (e.g. the simultaneity of wage, tenure and quits), the classifications are based on year *t*-1 values, whereas the flow rates are flows from year *t*-1 to year *t*.[98] All models include year dummies to account for macroeconomic developments and most models include two-digit industry dummies.

I use the following 5-group categorical explanatory variables to describe plant characteristics: plant productivity, R&D intensity, plant capital intensity, plant age**,** plant size (measured by average of employment in years *t*-1 and *t* as recommended by Davis, Haltiwanger and Schuh 1996), average wage level and the dispersion of wages within the plant (measured by the coefficient of variation). As to employee characteristics, I have 5-group categorical variables that measure the average age of employees, average education years, average years of plant-specific seniority, the share of women among employees, and the share of employees that own their own house or apartment. To account for regional differences in labour markets, the unemployment rate of the region where the plant is situated (83 regions) is included as a continuous variable.[99]

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[98] It should be noted that as labour productivity, i.e. value added per labour input, is measured in year *t*-1, a sharp reader may think that these computations are subject to a bias that is analogous to the one in the productivity decompositions when the FHK or (M)BBH methods are used. However, one should note that a different labour concept for labour productivity and job (and worker) flows is used here. The hours worked are used in the former case and the number of employees in the latter. Secondly, the information is obtained from different data sources – from the Industrial Statistics in the case of hours worked and from the Employment Statistics in the case of employment. This should eliminate the possibility of a spurious relationship between the initial productivity level and the subsequent employment growth due to measurement error in the labour input numbers. We have replicated the analyses by using the average labour productivity in the initial and final years and found inconsequential changes in the results.

[99] Regional unemployment rates are obtained from the Labour Force Surveys (Statistics Finland).

7.3 Empirical analysis

7.3.1 Job flows

Estimation results for the net employment growth rates are given in Table 7.1. I shall focus on those results of the greatest interest to this study. Many of the explanatory variables can be regarded as controls. Model (1) includes all the variables and the estimation is made with employment weights. Model (2) is similar to Model (1), except that it is estimated without employment weights. As there are reasons to expect a high positive correlation between plant age and the tenure of the personnel, as a check we have dropped the tenure variables from Model (3). Model (4) is similar to Model (1), except that industry dummies are dropped.

The results for labour productivity levels are perfectly in agreement with the earlier conclusions that there has been a reallocation of labour shares from low productivity plants to higher productivity ones.[100] An interesting new finding is that the relationship does not seem to be quite linear. Rather, the results give support to the view that there is a reallocation of labour shares from the low productivity plants (first two groups) to the medium and high productivity plants.[101] So these results suggest that cleansing is concentrated in the left-hand tail of the productivity distribution, and as the restructuring is of this kind, it can be expected to compress the productivity dispersion between plants and diminish industry inefficiency.

At first glance, R&D intensity does not seem to have an independent significant effect on employment growth. However, a comparison of the results obtained by Model (4) with the other models reveals that industry effects soak up the contribution of R&D intensity. There is a large variation in R&D intensity levels between industries, as we will see in Chapter 8. According to Model (4) there is a substantial reallocation of labour shares towards the high R&D intensity plants, when industry effects are not controlled. The results for labour productivity, on the other hand, are insensitive to the inclusion of industry dummies. Capital intensive plants (groups 4 and 5) appear to have higher employment growth than the less capital intensive

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[100] Consistently with these results Nurmi (2002a) finds with more sophisticated econometric methods that the relative labour productivity of the plant affects employment growth positively. She uses essentially the same data as I do. Her result does not seem to be sensitive to the selection bias. Further, Nurmi (2002b) finds with the same data that a high labour productivity level increases the plant's survival probability.

[101] The results documented by Ilmakunnas and Maliranta (2000a, see p. 112) and (2002c, see p. 37) are reasonably similar. They found that employment growth was particularly low among the very low productivity or the very unprofitable plants or firms. This was essentially caused by high job destruction and worker outflow rates among them.

plants, except for those having the lowest capital intensity. The growth of the latter group is about equal to that of the groups with high capital intensity.

Plant age does not seem have a significant negative relationship with employment growth. Of course, one should bear in mind that the productivity levels are controlled. Besides, two partly mutually related aspects are worth noting. The appropriate definition and the accurate measurement of plant age (vintage) is difficult. Secondly, plant age is likely to be tightly related to various other plant characteristics, the average tenure of the personnel in particular. We see that there is a very strong negative relationship between the average tenure and the subsequent growth. It may be the case that the modernity of an organisation is more relevant than the date of a plant's appearance or, alternatively, the average tenure of the personnel may be measured more accurately than the age of the plant and therefore the tenure variables may capture the plant vintage effects. When the tenure variables are dropped, we obtain evidence that the very oldest plants have the lowest employment growth that is consistent with various life cycle models.[102]

The results reported in Table 7.1 for wage effects are in line with the expectation that high wages reduce labour demand.[103] To put it another way, according to these estimates there has been a reallocation of labour shares from high wage plants to lower wage plants. Sometimes it is argued that high wages in a plant or firm reflect the so-called "unobservable skills" among the plant's staff. An alternative view, raised in this study at times, is that high wages may be a symptom of ex post bargaining over quasi-rents. This can be expected to curb labour demand in the future, as is found here.[104] The effect of wage dispersion within plants has no clear pattern except that those plants having the very lowest wage dispersion (group 1) have the highest employment growth.

As for education, there does not appear to be any statistically significant relationship between the amount of formal schooling and net employment growth. The same holds true for regional unemployment.

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[102] When plant size and the average age and wage of the staff are dropped, a very clear negative relationship between plant age and employment growth is obtained (results are not reported here).

[103] The results obtained by Nurmi (2002a and 2000b) are to some extent different from mine. She finds that high wages increase survival probability and employment growth. Labour characteristics are not, however, controlled in that study, which might explain the difference in the results. Furthermore, the effect of wages on survival probability is not statistically significant when such factors as ownership change of the plant is controlled.

[104] Later I will examine the effect of wage dispersion between plants on the between component of productivity growth with industry panels.

Table 7.1 OLS estimates of job flows

Dependent variable		(1) NET	(2) NET	(3) NET	(4) NET
Labour productivity	2	0.009	0.034***	0.010	0.008
		(0.012)	(0.010)	(0.013)	(0.013)
	3	0.026*	0.057***	0.026*	0.025*
		(0.014)	(0.010)	(0.014)	(0.014)
	4	0.017	0.052***	0.017	0.016
		(0.015)	(0.010)	(0.015)	(0.015)
	5	0.034**	0.064***	0.034**	0.033**
		(0.014)	(0.010)	(0.014)	(0.015)
R&D intensity	2	-0.004	0.003	-0.004	0.004
		(0.009)	(0.009)	(0.010)	(0.010)
	3	0.006	-0.018	0.004	0.038***
		(0.014)	(0.012)	(0.014)	(0.014)
Capital intensity	2	-0.022*	-0.025***	-0.023**	-0.019
		(0.012)	(0.009)	(0.012)	(0.012)
	3	-0.031**	-0.030***	-0.033***	-0.028**
		(0.013)	(0.011)	(0.012)	(0.013)
	4	0.016	-0.009	0.015	0.017
		(0.013)	(0.011)	(0.013)	(0.013)
	5	-0.016	-0.010	-0.019*	-0.011
		(0.011)	(0.010)	(0.011)	(0.011)
Plant age	2	0.004	0.001	0.001	0.002
		(0.012)	(0.009)	(0.012)	(0.012)
	3	0.004	0.008	0.001	0.003
		(0.013)	(0.010)	(0.013)	(0.013)
	4	-0.012	-0.012	-0.017	-0.011
		(0.014)	(0.011)	(0.014)	(0.015)
	5	-0.018	-0.014	-0.026**	-0.021
		(0.013)	(0.013)	(0.013)	(0.013)
Plant size	2	0.029***	0.047***	0.025**	0.027**
		(0.011)	(0.009)	(0.011)	(0.011)
	3	0.064***	0.080***	0.059***	0.059***
		(0.012)	(0.010)	(0.012)	(0.012)
	4	0.058***	0.082***	0.051***	0.054***
		(0.014)	(0.012)	(0.014)	(0.014)
	5	0.091***	0.116***	0.084***	0.084***
		(0.017)	(0.013)	(0.016)	(0.017)
Wage level	2	-0.016	-0.009	-0.018	-0.017
		(0.013)	(0.009)	(0.013)	(0.013)
	3	-0.018	-0.002	-0.021	-0.017
		(0.014)	(0.010)	(0.014)	(0.014)
	4	-0.026*	-0.008	-0.030*	-0.027*
		(0.016)	(0.011)	(0.016)	(0.016)

	5	-0.024	-0.008	-0.028*	-0.023
		(0.015)	(0.012)	(0.015)	(0.015)
Wage dispersion	2	-0.049***	-0.028***	-0.050***	-0.051***
		(0.014)	(0.010)	(0.014)	(0.014)
	3	-0.061***	-0.041***	-0.060***	-0.063***
		(0.015)	(0.010)	(0.015)	(0.015)
	4	-0.051***	-0.033***	-0.051***	-0.051***
		(0.015)	(0.010)	(0.015)	(0.015)
	5	-0.046***	-0.029***	-0.046***	-0.047***
		(0.014)	(0.010)	(0.014)	(0.014)
Average education	2	-0.016	-0.011	-0.013	-0.019
		(0.014)	(0.010)	(0.014)	(0.014)
	3	-0.004	-0.013	0.001	-0.002
		(0.013)	(0.010)	(0.013)	(0.013)
	4	0.006	0.001	0.012	0.005
		(0.014)	(0.010)	(0.014)	(0.014)
	5	0.014	0.005	0.020	0.008
		(0.016)	(0.011)	(0.016)	(0.016)
Average tenure	2	-0.016	-0.013		-0.018
		(0.015)	(0.010)		(0.015)
	3	-0.039**	-0.044***		-0.041***
		(0.016)	(0.011)		(0.016)
	4	-0.047***	-0.060***		-0.051***
		(0.018)	(0.013)		(0.018)
	5	-0.046**	-0.075***		-0.047**
		(0.019)	(0.014)		(0.019)
Average age	2	-0.014	-0.015	-0.026*	-0.013
		(0.016)	(0.010)	(0.014)	(0.016)
	3	-0.020	-0.026**	-0.041***	-0.019
		(0.017)	(0.011)	(0.015)	(0.017)
	4	-0.010	-0.026**	-0.034**	-0.009
		(0.017)	(0.012)	(0.014)	(0.017)
	5	-0.006	-0.008	-0.032**	-0.005
		(0.018)	(0.012)	(0.014)	(0.019)
Female share	2	-0.004	-0.011	-0.006	-0.004
		(0.011)	(0.010)	(0.011)	(0.011)
	3	-0.038***	-0.032***	-0.039***	-0.037***
		(0.014)	(0.010)	(0.014)	(0.014)
	4	-0.023*	0.001	-0.023*	-0.024*
		(0.012)	(0.010)	(0.012)	(0.012)
	5	-0.009	-0.004	-0.007	-0.006
		(0.013)	(0.010)	(0.013)	(0.013)
Home owners	2	-0.028**	-0.024**	-0.031**	-0.025*
		(0.014)	(0.010)	(0.014)	(0.014)
	3	-0.006	-0.001	-0.008	-0.005
		(0.013)	(0.010)	(0.013)	(0.013)

4	-0.014	0.011	-0.019	-0.010
	(0.014)	(0.010)	(0.013)	(0.014)
5	0.004	0.014	-0.002	0.009
	(0.014)	(0.010)	(0.014)	(0.014)
Unemployment	0.147	0.136	0.093	0.094
	(0.148)	(0.099)	(0.150)	(0.132)
Year 1992	-0.081***	-0.164***	-0.089***	-0.094***
	(0.028)	(0.019)	(0.028)	(0.026)
Year 1993	-0.084***	-0.154***	-0.089***	-0.093***
	(0.020)	(0.014)	(0.020)	(0.019)
Year 1994	-0.065***	-0.120***	-0.066***	-0.069***
	(0.016)	(0.012)	(0.016)	(0.016)
Year 1995	0.008	0.004	0.010	0.008
	(0.016)	(0.011)	(0.015)	(0.016)
Year 1996	-0.002	-0.043***	-0.001	-0.002
	(0.016)	(0.009)	(0.016)	(0.017)
Year 1997	-0.039**	-0.062***	-0.039**	-0.039**
	(0.017)	(0.010)	(0.017)	(0.016)
Industry dummies	yes	yes	yes	no
Weighting	employment	no	employment	employment
Observations	12 159	12 159	12 159	12 159
Adjusted R^2	0.06	0.06	0.06	0.05

Robust standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1% level

7.3.2 Worker flows

Table 7.2 shows estimation results for worker flows and churning. Model (5), which explains the worker inflow rates, and Model (6), which explains the worker outflow rates, both have the same set of explanatory variables as Model (1). As the net employment growth rate is the worker inflow rate minus the worker outflow rate by definition, the parameter estimates of Model (1) can be derived from the estimates of Models (5) and (6). For example, the coefficient estimate of labour productivity of group 3 in Model (1) is -0.023 - (-0.049) = 0.026.

Churning is explained in Models (7) and (8). These two models have the same explanatory variables as Models (1), (5) and (6), except that education is dropped from Model (8).

The results of Models (5) and (6) for labour productivity reveal that low productivity plants have low employment growth mainly because their worker outflow is much higher than in medium and high productivity plants, but on the other hand the differences in worker inflow rates between the productivity categories are relatively small. In fact, the worker inflow rates seem to be highest among the plants having the lowest (!) or the highest productivity level. According to Model (7) and (8), churning is most intensive in both tails of the productivity dispersion (churning is the most intensive in the left-hand tail).

There are no significant differences in worker flows by R&D intensity. This holds true for both inflow and outflow. According to Model (7) there are no differences in churning either, which is at odds with the findings made by Maliranta (2000a). High R&D intensity may bring about a need for the matching of new workers with the new tasks. Thus a positive relationship between R&D intensity and churning can be expected. This would also be consistent with the findings by Bellmann and Boeri (1998) that upgrading of technology is positively associated with churning. Evidence obtained by Bauer and Bender (2002) suggests that new information technologies increase churning rates among professionals and engineers.

Here it turns out that the coefficient estimates of R&D intensity groups are sensitive to the inclusion of education. According to Model (7) there is a very strong positive relationship between the average educational level of the personnel and churning. One possible interpretation of these results is that high skills need to be matched with a suitable technology in order to be useful.[105] We note that when the education variables are removed from the model, the coefficient estimate for the high R&D intensity group becomes strongly positive (see Model (8)). High formal education and the development of new technologies are certainly mutually related, and we find evidence that they are positively related to the matching process. All in all, this analysis indicates that efforts to stimulate technological progress within the plant involve internal adjustment that may take the form of renewal of the work force composition.

We obtain evidence that very low capital intensity (group 1) is typically associated with high worker inflow and high churning. Worker outflow, instead, exhibits no relationship with capital intensity here.

New vintage plants have higher worker inflow rates than the middle-aged or old plants. According to Model (6) the worker outflow rates are highest at the beginning and end of a plant's life-cycle. This fits well with the conjecture that high

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[105] Another interpretation is that repeated bargaining with new employers is particularly useful for high-skilled workers. An employee with a higher initial wage has a better starting point in bargaining over rents than in the previous round. High skilled workers are likely to be good rent seekers (see e.g. Murhphy, Shleifer and Vishny 1991). It is also possible that some high skilled workers are needed in the plant only for a short time, e.g. during a development project.

Table 7.2 OLS estimates of worker flows

Dependent variable		(5) *WIF*	(6) *WOF*	(7) *CH*	(8) *CH*
Labour productivity	2	-0.023***	-0.031***	-0.019**	-0.024***
		(0.009)	(0.009)	(0.009)	(0.009)
	3	-0.023**	-0.049***	-0.030***	-0.035***
		(0.010)	(0.010)	(0.009)	(0.009)
	4	-0.024**	-0.041***	-0.016	-0.020**
		(0.011)	(0.010)	(0.010)	(0.010)
	5	-0.013	-0.047***	-0.016	-0.019**
		(0.010)	(0.010)	(0.010)	(0.010)
R&D intensity	2	0.006	0.010	0.009	0.011
		(0.006)	(0.008)	(0.007)	(0.007)
	3	0.012	0.005	0.011	0.021***
		(0.008)	(0.011)	(0.008)	(0.008)
Capital intensity	2	-0.020**	0.001	-0.027***	-0.028***
		(0.008)	(0.009)	(0.009)	(0.009)
	3	-0.021**	0.010	-0.029***	-0.028***
		(0.008)	(0.010)	(0.010)	(0.010)
	4	0.002	-0.014	-0.033***	-0.034***
		(0.010)	(0.009)	(0.009)	(0.009)
	5	-0.022***	-0.006	-0.029***	-0.027***
		(0.008)	(0.009)	(0.010)	(0.010)
Plant age	2	-0.011	-0.015	-0.011	-0.015
		(0.009)	(0.009)	(0.010)	(0.010)
	3	-0.021**	-0.025***	-0.021**	-0.030***
		(0.009)	(0.010)	(0.009)	(0.009)
	4	-0.027***	-0.015	-0.026***	-0.035***
		(0.010)	(0.010)	(0.008)	(0.008)
	5	-0.026***	-0.007	-0.014	-0.017*
		(0.009)	(0.010)	(0.009)	(0.009)
Plant size	2	-0.000	-0.029***	-0.004	-0.003
		(0.007)	(0.009)	(0.010)	(0.010)
	3	-0.003	-0.067***	-0.018*	-0.016*
		(0.009)	(0.010)	(0.009)	(0.009)
	4	-0.010	-0.068***	-0.020**	-0.017*
		(0.009)	(0.011)	(0.010)	(0.010)
	5	-0.000	-0.092***	-0.017	-0.012
		(0.012)	(0.012)	(0.011)	(0.011)
Wage level	2	-0.005	0.011	0.003	0.005
		(0.009)	(0.009)	(0.008)	(0.008)
	3	-0.003	0.016	0.007	0.013
		(0.010)	(0.010)	(0.009)	(0.009)
	4	-0.016*	0.010	-0.013	-0.003
		(0.009)	(0.012)	(0.008)	(0.008)

	5	-0.016	0.008	-0.012	0.005
		(0.010)	(0.011)	(0.009)	(0.008)
Wage dispersion	2	-0.041***	0.008	-0.013	-0.011
		(0.011)	(0.009)	(0.010)	(0.010)
	3	-0.049***	0.012	-0.020**	-0.013
		(0.012)	(0.010)	(0.009)	(0.009)
	4	-0.049***	0.002	-0.009	0.002
		(0.012)	(0.010)	(0.010)	(0.009)
	5	-0.036***	0.010	0.004	0.018*
		(0.012)	(0.008)	(0.010)	(0.010)
Average education	2	-0.007	0.009	0.003	
		(0.009)	(0.011)	(0.008)	
	3	0.007	0.011	0.021***	
		(0.009)	(0.010)	(0.008)	
	4	0.021**	0.015	0.031***	
		(0.009)	(0.011)	(0.009)	
	5	0.045***	0.031***	0.057***	
		(0.012)	(0.010)	(0.010)	
Average tenure	2	0.000	0.016*	0.009	0.009
		(0.012)	(0.009)	(0.009)	(0.009)
	3	-0.007	0.032***	0.006	0.002
		(0.011)	(0.010)	(0.009)	(0.008)
	4	-0.019*	0.028**	-0.014*	-0.020**
		(0.011)	(0.013)	(0.008)	(0.008)
	5	-0.014	0.032***	-0.003	-0.012
		(0.014)	(0.012)	(0.010)	(0.010)
Average age	2	-0.012	0.001	0.013	0.011
		(0.011)	(0.011)	(0.009)	(0.009)
	3	-0.010	0.010	0.021**	0.015
		(0.011)	(0.013)	(0.010)	(0.009)
	4	-0.012	-0.003	0.013	0.006
		(0.011)	(0.013)	(0.009)	(0.009)
	5	-0.012	-0.006	0.002	-0.008
		(0.012)	(0.013)	(0.009)	(0.009)
Female share	2	-0.004	0.000	0.018*	0.020*
		(0.009)	(0.008)	(0.010)	(0.010)
	3	-0.008	0.030***	0.005	0.006
		(0.009)	(0.010)	(0.009)	(0.009)
	4	-0.011	0.012	0.003	0.005
		(0.009)	(0.009)	(0.009)	(0.009)
	5	0.005	0.014	0.013	0.011
		(0.010)	(0.009)	(0.009)	(0.009)
Home owners	2	-0.019**	0.010	-0.002	0.002
		(0.009)	(0.010)	(0.008)	(0.008)
	3	-0.018**	-0.013	-0.014*	-0.007
		(0.009)	(0.009)	(0.007)	(0.007)

4	-0.018**	-0.004	-0.012*	-0.004
	(0.009)	(0.010)	(0.007)	(0.007)
5	-0.005	-0.009	-0.017**	-0.007
	(0.010)	(0.010)	(0.008)	(0.008)
Unemployment	-0.105	-0.252**	-0.291***	-0.222***
	(0.097)	(0.104)	(0.079)	(0.079)
Year 1992	-0.045***	0.036*	-0.040***	-0.032**
	(0.017)	(0.020)	(0.015)	(0.015)
Year 1993	-0.047***	0.037**	-0.036***	-0.033***
	(0.012)	(0.015)	(0.011)	(0.011)
Year 1994	-0.036***	0.029**	-0.020**	-0.020**
	(0.009)	(0.013)	(0.009)	(0.009)
Year 1995	0.014	0.006	0.009	0.006
	(0.009)	(0.012)	(0.009)	(0.009)
Year 1996	0.013	0.015	0.020**	0.019**
	(0.011)	(0.010)	(0.009)	(0.009)
Year 1997	-0.018*	0.021*	0.002	0.001
	(0.010)	(0.012)	(0.008)	(0.008)
Industry dummies	yes	yes	yes	yes
Weighting	employment	no	employment	employment
Observations	12 159	12 159	12 159	12 159
Adjusted R^2	0.15	0.07	0.10	0.09

Robust standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%

worker outflow and job destruction rates characterise the selection process among the new-comers and, furthermore, do the job of cleansing obsolete production activities among the oldest plants.[106] The results for churning from Model (8) indicate that not only worker outflows are chilled in the middle of plants' life cycles but the same holds true for churning, i.e. internal adjustment, as well.

Differentiating the two distinct components of net employment growth, i.e. worker inflow and worker outflow rates, reveals that the high average employment growth of the large plants in the period 1991-1997, shown in the models of Table 7.1, is mainly due to the low worker outflow rate that can be seen in Model (6). We also see that, like middle-aged plants, the medium sized plants are the least dynamic in terms of the renewal of workforce, gauged by the churning rate.

[106] Unreported results obtained from the analysis of job creation and job destruction rates indicate that both rates are high among young plants (for parallel findings see Ilmakunnas and Maliranta 2000, pp. 103-104 and Ilmakunnas and Maliranta 2002c, pp. 33-34).

High wages are negatively related to the worker inflow rate, which conflicts with the view presented by Acemoglu and Shimer (2000) that some firms pay high wages in order to attract workers. We will come back to this issue with some more carefully elaborated interpretations, when I discuss the findings from the fixed effects models. We cannot see solid evidence that higher wages decrease the "excessive" worker turnover, i.e. churning, either. Uusitalo (2002) made a similar finding.

There seems to be a (weak) negative relationship between the average firm-specific experience, i.e. tenure, and the worker inflow rate. Perhaps somewhat surprisingly, the worker outflow rate is highest in those plants in which the firm-specific experience is at a high or medium level. However, it should be noted that the worker outflow rates are likely to reflect not only quits, but layoffs as well. As mentioned earlier, the churning rate probably better gauges the matching process within a plant. Evidence obtained here suggests that organisations that are composed of high tenure workers are not typically revitalised in the future either. It seems reasonable to think that replacement hirings are particularly costly in such organisations, because the ways of doing things may be quite particular (and possibly inefficient). These workers might find it costly to learn the work practises of other firms, for example. Ilmakunnas, Maliranta and Vainiomäki (2003a) find evidence that a high churning rate is associated with high productivity growth when a number of controls are included in the model. Further support for the view that churning nourishes productivity growth is given by OECD (2001). It concludes that low tenure countries have a high productivity growth rate.

Not so surprisingly, owner-occupation is negatively related to churning. The causality may run both ways. Those who own their home may find it more costly to switch jobs, i.e. continue to seek better matches. On the other hand, those who feel that they have a good match with the current employer (and neighbourhood, for example) often find it profitable to buy a home.[107]

The worker inflow rate does not have a significant relationship to regional unemployment, but worker outflow is low (!) in high unemployment regions. One explanation for this is that quits constitute an important proportion of all separations and quits are probably rare in those regions where unemployment is high and labour demand is low. The results suggest that high unemployment leads to chilled renewal of labour force within the plants in that region. Also the year dummies provide us with evidence that worker turnover within plants is chilled during downturns. The churning rates were particularly low during the worst recession years 1992 and 1993 but surged in the recovery years 1995 and 1996.

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[107] I thank Petri Böckerman for useful remarks about this.

7.3.3 Unemployment flows

The relationships between technical progress, plant-level restructuring and unemployment are considered, for example, in a model by Aghion and Howitt (1994). In their search model the source of unemployment is labour reallocation across firms equipped with technologies from different vintages. More specifically, there is flow of workers into unemployment from firms that have obsolete (and low productivity) machines. The flow of workers out of unemployment occurs as a firm with a new machine is matched with an appropriate worker whose skills are adapted to that machine. The pool of unemployed who are seeking a match (i.e. job) increases as a result of the acceleration of technological change. Hence, analysing the worker flows from and into unemployment according to various plant characteristics might give us an idea of the way an economy or a sector that has experienced a technology shock (temporary acceleration of technical progress) re-shuffles employment through a temporary increase in the pool of the unemployed.

A typical feature of various search models is that they assume one worker (and one skill type) per firm (plant). On the other hand, production of new types of products as well as the use of new production techniques typically requires various kinds of tasks where the productivity effect of skills may vary. Kremer and Maskin (1996) incorporate this aspect in their model. Establishing a new modern plant may increase the demand for skilled and perhaps less skilled workers, too. What is particularly important, productivity of the less skilled may also improve without substantial upgrading of skills, the reason being that they are dealing with better techniques.

Table 7.3 presents the estimation results for unemployment flows.[108] There is no significant relationship between the labour productivity level and the subsequent worker inflow from unemployment, i.e. low and high productivity plants have contributed equally to absorbing the unemployed (see Model (9) and (10)). Looking the other end of the unemployment pool, we notice that workers employed by medium or high productivity plants are clearly better secured from unemployment than those working at low productivity plants, which presumably are often equipped with obsolete machines (see Models (11) and (12)). So in net terms the low productivity plants increase the pool of the unemployed, while medium and high productivity plants reduce the pool, which accords with the model by Aghion and Howitt (1994).

According to Model (9) high R&D intensity plants (or firms) have a low demand for the unemployed. However, again, this outcome is sensitive to the inclu-

[108] In a related work Ilmakunnas and Maliranta (2003a) examine plant-level worker flows to unemployment and from unemployment in Finnish business sector.

sion of industry dummies. When industry effects are removed from the model, it turns out that plants with medium or high R&D intensity have *higher* worker inflow rates from unemployment than the low R&D intensity ones (Model (10)). Maliranta (2000a) arrived at the same conclusion. Concerning worker flows to unemployment, workers employed by high R&D intensity plants are relatively well secured from unemployment. This conclusion is not sensitive to the inclusion of industry dummies as one can note by comparing the coefficient estimates of Models (11) and (12).

Capital intensity is not related to unemployment flows by any systematic way. The plant vintage effects do not seem to have clear patterns either. Some suggestive evidence is obtained from Model (12) that old plants have relatively high worker flows to unemployment. On the other hand, the results show that the worker flow to unemployment is relatively high in group 2 (and 3), too.

The results for wage effects indicate that low and high wage plants have similar flows to unemployment, but that high wage plants have somewhat lower worker flows from unemployment. So in net terms high wage plants increase unemployment. Wage dispersion within plants does not seem to be related to unemployment flows according to OLS estimates.

Plants with a lot of highly educated workers hire the unemployed at similar rates to those with less skilled workers. Models (11) and (12) suggest that highly educated workers are well secured from unemployment.

New organisations, defined by the average tenure in the plant, are supplemented by the previously unemployed more often than are organisations composed of high tenure workers. In other words, some workers are reallocated to new organisations via the pool of the unemployed. The worker flows into unemployment, on the other hand, are distributed reasonably evenly between plants according to the average tenure.

We do not find any support for the view stated by Oswald (1996) that owner-occupation is related to unemployment, at least when examined by unemployment flows. Nor do we find any association between plants' share of female workers and unemployment flow.

Finally, we note that worker flows both into and from unemployment are high in regions where the unemployment rate is high. This is consistent with the finding made by Böckerman and Maliranta (2001) that in those regions where the worker inflow rate from unemployment is high the outflow rate to unemployment is also high, or vice versa. Böckerman and Maliranta provide three explanations for this finding. The first is that the active labour market measures that are commonly used

Table 7.3 OLS estimates of unemployment flows

Dependent variable		(9) *WIFU*	(10) *WIFU*	(11) *WOFU*	(12) *WOFU*
Labour productivity	2	0.003	0.002	-0.009***	-0.010***
		(0.002)	(0.002)	(0.003)	(0.003)
	3	0.001	0.000	-0.013***	-0.014***
		(0.002)	(0.002)	(0.003)	(0.003)
	4	-0.001	-0.003	-0.015***	-0.016***
		(0.002)	(0.002)	(0.003)	(0.003)
	5	0.002	0.001	-0.015***	-0.016***
		(0.002)	(0.002)	(0.003)	(0.003)
R&D intensity	2	-0.001	0.003*	-0.003	-0.003
		(0.002)	(0.002)	(0.003)	(0.004)
	3	-0.004**	0.003**	-0.010***	-0.015***
		(0.002)	(0.002)	(0.003)	(0.002)
Capital intensity	2	-0.000	0.001	0.004	0.004
		(0.002)	(0.002)	(0.003)	(0.003)
	3	-0.001	-0.002	0.002	0.001
		(0.002)	(0.002)	(0.003)	(0.003)
	4	-0.000	-0.001	-0.000	-0.002
		(0.002)	(0.002)	(0.003)	(0.003)
	5	-0.003	-0.001	-0.000	-0.001
		(0.002)	(0.002)	(0.003)	(0.003)
Plant age	2	0.002	0.003	0.002	0.004*
		(0.002)	(0.003)	(0.002)	(0.002)
	3	0.000	-0.000	0.005	0.005
		(0.002)	(0.002)	(0.004)	(0.004)
	4	-0.000	-0.000	0.001	-0.000
		(0.002)	(0.002)	(0.002)	(0.002)
	5	-0.002	-0.002	0.004	0.005**
		(0.002)	(0.002)	(0.002)	(0.002)
Plant size	2	-0.006***	-0.006***	-0.012***	-0.011***
		(0.002)	(0.002)	(0.003)	(0.003)
	3	-0.010***	-0.011***	-0.017***	-0.015***
		(0.002)	(0.002)	(0.003)	(0.003)
	4	-0.013***	-0.012***	-0.021***	-0.018***
		(0.002)	(0.002)	(0.003)	(0.003)
	5	-0.010***	-0.011***	-0.023***	-0.020***
		(0.002)	(0.002)	(0.003)	(0.003)
Wage level	2	-0.002	-0.002	0.003	0.003
		(0.002)	(0.002)	(0.002)	(0.002)
	3	-0.004**	-0.003	0.003	0.004
		(0.002)	(0.002)	(0.003)	(0.003)
	4	-0.007***	-0.007***	0.006	0.006
		(0.002)	(0.002)	(0.004)	(0.005)

	5	-0.010***	-0.010***	-0.001	-0.001
		(0.002)	(0.002)	(0.003)	(0.003)
Wage dispersion	2	-0.002	-0.004*	0.001	-0.001
		(0.002)	(0.002)	(0.002)	(0.003)
	3	-0.001	-0.002	-0.002	-0.002
		(0.002)	(0.002)	(0.002)	(0.002)
	4	-0.000	-0.001	0.002	0.001
		(0.002)	(0.002)	(0.004)	(0.004)
	5	0.002	0.002	-0.003	-0.003
		(0.003)	(0.003)	(0.003)	(0.003)
Average education	2	0.001	-0.000	-0.003	-0.003
		(0.002)	(0.002)	(0.004)	(0.004)
	3	0.000	0.002	-0.006**	-0.004
		(0.002)	(0.002)	(0.003)	(0.003)
	4	0.002	0.001	-0.005*	-0.005
		(0.002)	(0.002)	(0.003)	(0.003)
	5	0.002	0.001	-0.008***	-0.007**
		(0.002)	(0.002)	(0.003)	(0.003)
Average tenure	2	-0.006***	-0.006***	-0.001	-0.000
		(0.002)	(0.002)	(0.002)	(0.003)
	3	-0.008***	-0.008***	0.000	0.002
		(0.002)	(0.002)	(0.004)	(0.004)
	4	-0.010***	-0.009***	0.002	0.005
		(0.003)	(0.003)	(0.004)	(0.004)
	5	-0.014***	-0.013***	-0.001	0.002
		(0.003)	(0.003)	(0.004)	(0.004)
Average age	2	0.001	0.000	0.004	0.003
		(0.002)	(0.002)	(0.004)	(0.004)
	3	-0.004*	-0.004*	0.000	-0.001
		(0.002)	(0.002)	(0.005)	(0.005)
	4	-0.001	-0.002	0.002	-0.000
		(0.002)	(0.003)	(0.005)	(0.005)
	5	0.000	-0.001	0.003	0.000
		(0.003)	(0.003)	(0.005)	(0.005)
Female share	2	-0.001	0.000	-0.004**	-0.004
		(0.002)	(0.002)	(0.002)	(0.002)
	3	-0.002	-0.001	-0.004*	-0.003
		(0.002)	(0.002)	(0.002)	(0.002)
	4	-0.002	-0.003	-0.004	-0.004
		(0.002)	(0.002)	(0.003)	(0.003)
	5	-0.003	-0.001	-0.004	-0.002
		(0.002)	(0.002)	(0.004)	(0.004)
Home owners	2	-0.002	-0.001	0.004	0.004
		(0.002)	(0.002)	(0.003)	(0.004)
	3	-0.000	-0.000	-0.001	-0.001
		(0.002)	(0.002)	(0.003)	(0.003)

4	0.001	0.002	-0.002	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
5	-0.001	0.000	-0.002	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)
Unemployment	0.126***	0.063***	0.050**	-0.007
	(0.028)	(0.024)	(0.026)	(0.022)
Year 1992	-0.014***	-0.024***	0.009**	0.002
	(0.004)	(0.003)	(0.004)	(0.003)
Year 1993	-0.017***	-0.022***	0.009***	0.007***
	(0.002)	(0.002)	(0.003)	(0.003)
Year 1994	-0.008***	-0.009***	0.034***	0.034***
	(0.002)	(0.002)	(0.006)	(0.006)
Year 1995	0.013***	0.015***	-0.007***	-0.005**
	(0.003)	(0.003)	(0.002)	(0.002)
Year 1996	-0.011***	-0.010***	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Year 1997	-0.025***	-0.024***	0.019***	0.019***
	(0.002)	(0.002)	(0.003)	(0.003)
Industry dummies	yes	no	yes	no
Weighting	employment	employment	employment	employment
Observations	12 159	12 159	12 159	12 159
Adjusted R^2	0.19	0.14	0.09	0.05

Robust standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%

in high unemployment regions can displace other employees into the pool of unemployed persons. The second is that, in those regions where economic activity is depressed and unemployment is high, firms may prefer short-term contracts to permanent contracts that in turn may lead to more frequent unemployment spells. The third possible explanation is that during the 1990s it was possible to use active labour market measures to renew unemployment benefits that are tied to past wages.

7.3.4 Fixed effects models

OLS estimates give us some characterisations of the directions of labour share reallocation between different kinds of plants. To investigate the process of job and worker flows slightly more carefully, various fixed effects models are estimated, too. In some important respects, they give additional confirmation for the earlier conclusions, even if in some other respects they throw up interesting discrepancies that make us elaborate our conclusions and interpretations. In Table 7.4 one basic model for each of the 6 flow indicators *NET*, *WIF*, *WOF*, *CF*, *WIFU* and *WOFU* is reported (Models (13)-(18)).[109] Although I have estimated random effects models too, Hausman's (1978) specification tests clearly reject the assumption that plants' effects are uncorrelated with the regressors. Therefore those estimations are not reported or commented on.

Quite a bit of additional consistent evidence about the role of plant productivity in labour reallocation is found. High labour productivity indeed boosts subsequent employment growth, keeps personnel in the current plant and secures them against unemployment. Unreported results for job creation and job destruction rates indicate a significant negative connection between productivity and job destruction, but an insignificant relationship between productivity and job creation. Very low productivity seems to lead to high churning of workers within plants. The evidence is not very solid, however.

Within plants variation in the data does not suggest any independent statistically significant role for R&D intensity. The results for capital intensity are changed in an interesting way, when the fixed plant effects are included. Now we observe that a very high capital-to-labour input ratio, which can be expected to occur after a major investment project, leads to high employment growth, high worker inflow from other plants (*WIF – WIFU*) and unemployment, as well as to low worker outflow to other plants (*WOF – WOFU*). In addition, the unreported results indicate that job creation is high and job destruction low. Capital intensity does not seem to affect churning.

Another more important change in the results after the inclusion of fixed plant effects appertains to wage effects. Now we discover that a wage increase is related to increased employment growth. Furthermore, this appears to be due rather to increased worker inflow than to depressed worker outflow. In contrast to OLS estimates, these results are consistent with the view that higher wages are used to induce labour reallocation à la Acemoglu and Shimer (2000). High wages seem to stimulate worker flows from unemployment as well. It should be noted, however, that these findings are not necessarily in conflict with the view that wage increases due to ex post bargaining will reduce plants' labour demand in the future. Centralised or industry-level wage agreements fix the minimum wage increase. Nevertheless, employers can increase wages more if they find it profitable. Thus wages are flexible upward in the Scandinavian wage determination model. This is reflected in wage drifts. Wage dispersion between plants may reflect the consequence of both ex post bargaining or efficiency wage type considerations among a proportion of

[109] I have estimated similar models by allowing first-order serial correlation, but the results are mostly similar. In those estimations, a lot of observations are lost (12159 observations in the reported models vs. 8560 observations in the AR models).

Table 7.4 Fixed effect models of job and worker flows

Dependent variable		(13) *NET*	(14) *WIF*	(15) *WOF*	(16) *CHURN*	(17) *WIFU*	(18) *WOFU*
Labour productivity	2	0.018	-0.008	-0.025	-0.010	-0.001	-0.013
		(0.011)	(0.007)	(0.009)***	(0.007)	(0.003)	(0.004)***
	3	0.027**	-0.008	-0.035	-0.017	-0.000	-0.017
		(0.013)	(0.007)	(0.009)***	(0.008)**	(0.003)	(0.004)***
	4	0.027**	-0.010	-0.038	-0.012	-0.001	-0.019
		(0.014)	(0.008)	(0.010)***	(0.009)	(0.003)	(0.005)***
	5	0.035**	-0.013	-0.048	-0.028	-0.004	-0.021
		(0.015)	(0.009)	(0.011)***	(0.010)***	(0.003)	(0.005)***
R&D intensity	2	-0.005	-0.002	0.003	0.016	-0.000	-0.000
		(0.014)	(0.008)	(0.011)	(0.009)*	(0.003)	(0.005)
	3	-0.003	-0.020	-0.017	-0.000	-0.001	-0.004
		(0.022)	(0.012)	(0.016)	(0.014)	(0.005)	(0.007)
Capital intensity	2	-0.010	-0.006	0.005	-0.020	0.005	0.006
		(0.017)	(0.010)	(0.012)	(0.011)*	(0.004)	(0.006)
	3	0.013	0.007	-0.005	-0.015	0.005	0.004
		(0.021)	(0.012)	(0.016)	(0.014)	(0.005)	(0.007)
	4	0.036	0.016	-0.021	-0.018	0.005	0.003
		(0.023)	(0.013)	(0.017)	(0.016)	(0.005)	(0.008)
	5	0.090***	0.041	-0.049	-0.006	0.018	-0.007
		(0.025)	(0.014)***	(0.019)**	(0.017)	(0.006)***	(0.009)
Plant size	2	0.088***	-0.015	-0.103	-0.016	-0.010	-0.038
		(0.016)	(0.009)*	(0.012)***	(0.010)	(0.004)***	(0.005)***
	3	0.160***	-0.015	-0.176	-0.014	-0.016	-0.062
		(0.022)	(0.013)	(0.016)***	(0.015)	(0.005)***	(0.007)***
	4	0.174***	-0.039	-0.213	-0.017	-0.020	-0.078
		(0.029)	(0.017)**	(0.022)***	(0.020)	(0.007)***	(0.010)***
	5	0.248***	-0.051	-0.299	-0.032	-0.020	-0.083
		(0.040)	(0.023)**	(0.030)***	(0.026)	(0.009)**	(0.014)***
Wage level	2	-0.003	-0.002	0.001	0.004	0.005	-0.000
		(0.013)	(0.007)	(0.010)	(0.008)	(0.003)*	(0.004)
	3	0.026	0.009	-0.017	0.004	0.012	-0.010
		(0.016)	(0.009)	(0.012)	(0.010)	(0.004)***	(0.005)*
	4	0.031*	0.023	-0.009	0.012	0.016	-0.010
		(0.018)	(0.010)**	(0.013)	(0.011)	(0.004)***	(0.006)
	5	0.053**	0.032	-0.021	0.012	0.024	-0.010
		(0.021)	(0.012)***	(0.016)	(0.014)	(0.005)***	(0.007)
Wage dispersion	2	-0.083***	-0.056	0.027	-0.009	-0.008	0.000
		(0.013)	(0.007)***	(0.010)***	(0.008)	(0.003)***	(0.004)
	3	-0.129***	-0.069	0.060	-0.006	-0.010	0.001
		(0.015)	(0.008)***	(0.011)***	(0.009)	(0.003)***	(0.005)
	4	-0.139***	-0.072	0.067	-0.008	-0.010	0.004
		(0.016)	(0.009)***	(0.012)***	(0.010)	(0.004)***	(0.005)

	5	-0.148***	-0.073	0.075	0.002	-0.009	0.000
		(0.017)	(0.010)***	(0.013)***	(0.011)	(0.004)**	(0.006)
Average education	2	-0.028*	-0.023	0.004	-0.013	0.007	-0.013
		(0.015)	(0.008)***	(0.011)	(0.009)	(0.003)**	(0.005)**
	3	-0.025	-0.010	0.015	0.005	0.016	-0.010
		(0.018)	(0.010)	(0.013)	(0.011)	(0.004)***	(0.006)*
	4	0.007	0.012	0.006	-0.000	0.022	-0.020
		(0.020)	(0.011)	(0.014)	(0.013)	(0.005)***	(0.007)***
	5	0.070***	0.052	-0.019	0.002	0.039	-0.034
		(0.022)	(0.012)***	(0.016)	(0.014)	(0.005)***	(0.007)***
Average tenure	2	0.017	0.019	0.002	0.024	0.010	-0.009
		(0.016)	(0.009)**	(0.012)	(0.011)**	(0.004)***	(0.006)*
	3	-0.003	0.012	0.015	0.051	0.014	-0.011
		(0.021)	(0.012)	(0.015)	(0.013)***	(0.005)***	(0.007)
	4	-0.009	-0.002	0.006	0.051	0.013	-0.009
		(0.024)	(0.014)	(0.018)	(0.016)***	(0.006)**	(0.008)
	5	-0.010	0.001	0.011	0.081	0.012	-0.005
		(0.028)	(0.016)	(0.021)	(0.018)***	(0.006)*	(0.009)
Average age	2	0.011	-0.002	-0.013	-0.020	0.003	-0.003
		(0.015)	(0.009)	(0.011)	(0.010)**	(0.004)	(0.005)
	3	-0.003	-0.009	-0.006	-0.026	-0.000	-0.003
		(0.018)	(0.010)	(0.013)	(0.012)**	(0.004)	(0.006)
	4	0.003	-0.013	-0.016	-0.041	0.005	-0.007
		(0.020)	(0.011)	(0.015)	(0.013)***	(0.005)	(0.007)
	5	0.038*	0.013	-0.025	-0.058	0.017	-0.003
		(0.023)	(0.013)	(0.017)	(0.014)***	(0.005)***	(0.008)
Female share	2	-0.019	-0.013	0.006	0.008	0.002	-0.005
		(0.015)	(0.009)	(0.011)	(0.009)	(0.003)	(0.005)
	3	-0.031*	-0.011	0.020	-0.014	0.004	-0.002
		(0.018)	(0.010)	(0.013)	(0.011)	(0.004)	(0.006)
	4	0.008	0.004	-0.004	-0.016	0.010	-0.010
		(0.020)	(0.012)	(0.015)	(0.013)	(0.005)**	(0.007)
	5	0.015	0.019	0.004	-0.012	0.009	-0.007
		(0.024)	(0.013)	(0.018)	(0.016)	(0.006)*	(0.008)
Home owners	2	-0.035***	-0.013	0.022	0.011	0.001	0.008
		(0.014)	(0.008)*	(0.010)**	(0.009)	(0.003)	(0.005)*
	3	-0.012	-0.005	0.007	0.013	0.003	0.003
		(0.015)	(0.009)	(0.011)	(0.010)	(0.004)	(0.005)
	4	0.011	0.010	-0.001	0.006	0.009	0.005
		(0.017)	(0.009)	(0.012)	(0.011)	(0.004)**	(0.006)
	5	0.038**	0.036	-0.002	0.019	0.017	0.006
		(0.018)	(0.010)***	(0.013)	(0.012)	(0.004)***	(0.006)
Unemployment		0.554	0.276	-0.277	0.527	0.421	0.020
		(0.360)	(0.205)	(0.267)	(0.259)**	(0.084)***	(0.122)
Year 1992		0.006	0.014	0.008	-629.827	0.013	0.001
		(0.051)	(0.029)	(0.038)	(602.331)	(0.012)	(0.017)

Year 1993	-0.045	-0.008	0.037	-141.907	-0.003	0.007
	(0.028)	(0.016)	(0.021)*	(135.717)	(0.007)	(0.010)
Year 1994	-0.076***	-0.030	0.046	-31.941	-0.008	0.053
	(0.013)	(0.008)***	(0.010)***	(30.530)	(0.003)**	(0.005)***
Year 1995	0.009	0.015	0.006	-7.159	0.011	-0.005
	(0.016)	(0.009)	(0.012)	(6.816)	(0.004)***	(0.006)
Year 1996	-0.028**	-0.010	0.018	-1.551	-0.027	0.002
	(0.012)	(0.007)	(0.009)**	(1.475)	(0.003)***	(0.004)
Year 1997	-0.051***	-0.032	0.019	-0.302	-0.041	0.024
	(0.012)	(0.007)***	(0.009)**	(0.271)	(0.003)***	(0.004)***
Observations	12 159	12 159	12 159	12 159	12 159	12 159
Plants	3 599	3 599	3 599	3 599	3 599	3 599
R^2	0.048	0.047	0.035	0.014	0.124	0.058

Standard errors in parentheses.
* significant at 10%; ** significant at 5%; *** significant at 1%

plants. The results for churning do not lend support to the view that high wages are used to eliminate “excessive” worker flows; an aspect incorporated into some efficiency models. Higher within-plant dispersion of wages seems to lead to lower employment growth and worker inflow, and higher worker outflow.

High education level turns out to be positively related to subsequent employment growth when plant effects are controlled. A very high education level seems to lead to higher worker inflow from other plants or unemployment, as well as to lower worker outflow to unemployment.

As with the results for wages, the results for tenure also turn out to be sensitive to the inclusion of fixed plant effects. In fact, these findings are quite remarkable. Now we find evidence on a positive effect of tenure on worker inflows from unemployment and, what is particularly interesting, on churning. More precisely, tenure increases with churning (and with *WIFU*) at low tenure levels.

High worker age seems to increase employment growth and, as one may expect, workers advanced in years have low churning. The estimates indicate that when the average age of the staff becomes quite high, the worker flow from unemployment increases. One possible explanation for this is that when workers are retired they are replaced by the unemployed. Some labour market measures encouraged this type of replacement especially during recessions.

Finally, these estimates tell us that an increase in the unemployment rate in a region leads to more intensive worker flow from unemployment in the region’s plants.

7.4 A short summary of the characteristics of job and worker flows

The descriptive analysis of job and worker flows confirms and supplements some earlier findings about the features of restructuring and gives some new insights into the issue:

1. It is found that among continuing plants there is indeed a reallocation of labour shares from low productivity plants to higher productivity plants. This has been earlier inferred from the positive between component of aggregate labour productivity growth. In addition, we noted that the relationship between productivity level and subsequent employment growth is not linear. Job destruction appears to be concentrated in plants with the lowest productivity level. Consequently we may anticipate that plant-level restructuring compresses the productivity dispersion between plants. These conclusions are robust to the inclusion or exclusion of fixed plants' effects.

2. Young plants (defined by the date of the plant's birth) or young organisations (measured by the average tenure of the plant) appear to play a central role in the "creative destruction" process. These plants have high job creation rates, high hiring rates and disproportionately large shares of worker flows from unemployment. It should be noted that these observations are obtained when labour productivity and various other factors are controlled. So these plants create jobs and hire workers more than their current labour productivity and other characteristics imply. Perhaps this is due to positive prospects in the first phases of a plant's life cycle (see for example Graphs 3.3 and 3.4). On the other hand, the results also point to a large variation and selection among the newcomers. Both the worker inflow and outflow rates are high among them. Unreported results indicate that both the job creation and job destruction rates are high as well.

3. A disproportionately high share of jobs is destroyed among the oldest plants and oldest organisations. A low productivity level is one explanation for the depressed labour demand of the oldest plants and organisations. However, their labour demand turns out to be low even when productivity and other factors are controlled, which may be an indication of pessimistic prospects about future performance among them.

4. When industry effects are not controlled, the plant's R&D intensity appears to make an independent positive contribution to subsequent (net) job creation. Those firms and plants that have decided to make innovation efforts probably expect to have high productivity performance in the future and this confidence is likely to be reflected in positive (net) job creation. However, we have also found evidence that efforts to boost technical progress involve "excessive" worker turno-

ver, i.e. churning. R&D is obviously related to high education. We obtain some evidence that high education is positively associated with churning within plants. In Chapter 6 I asserted that high education does not essentially augment labour input in production with the current technology, at least not so much as is usually assumed or believed. Skills can be expected to improve a plant's ability to create, adopt and implement new techniques and by this means improve productivity in the future. And indeed, the fixed effects models indicate that high education usually leads to high employment growth and high worker inflow from other plants and from unemployment. Furthermore, the findings obtained here and earlier by Maliranta (2000a) are in keeping with the conjecture that these efforts entail a lot of reorganisation within plants. In other words, it seems that technological advancement within plants is a time-consuming process which involves internal adjustment.

5. In some sense the results concerning the role of wages in the reallocation of jobs and workers between plants are conflicting. However, the wage level of a plant (or a firm) depends on different factors. High wages may be a reflection of the fact that the personnel has managed to appropriate some quasi-rents derived from some irreversible past investments in the current technology. On the other hand, an employer may have decided to pay higher wages in order to stimulate worker inflow. This is important especially when a plant has just made an irreversible investment in new machines and they need to be occupied by workers soon. We just noted that according to the fixed effects models, high capital intensity leads to high worker inflow and job creation. In some cases firms and plants decide to set wages higher to attract new recruits for the vacancies created by previous investments.

8 Explaining productivity-enhancing restructuring

It was shown in Chapter 5 that productivity-enhancing restructuring was an important factor in the acceleration of productivity growth in the mid-1980s (see Graphs 5.11 and 5.14, for example). Moreover, we noticed from Table 5.1 that there are substantial differences in the magnitudes and time patterns of the between component across different industries. In Chapter 6 we observed that the results concerning the between component do not change much when labour skills are taken into account. Quite typically the between component is *larger* when labour efficiency is controlled by methods that are based on standard human capital theory.

In this chapter the factors of productivity-enhancing restructuring are sought by means of an industry panel. The focus is on the determinants of the between component among continuing plants. This component can be measured more reliably than the entry or exit effects. Remembering that the entries, exits and selection are time-consuming and gradual processes (as illustrated in Graph 3.2), the between component is also arguably a valid indicator of the influence of the "creative destruction" process.[110] Productivity decompositions have become increasingly popular in recent years, but as far as I know, very little research has been done to investigate empirically the stimulants of productivity-enhancing restructuring.

8.1 Factors of productivity growth

8.1.1 The productivity effects of internal adjustment

The effects of R&D and international trade on the aggregate productivity growth of industries or countries have been extensively investigated in the literature.[111] Various other explanatory variables are included in the analysis in addition to R&D. The initial relative productivity level is incorporated into the model to capture the catching-up potential. The use of indicators for human capital in this context has also become more popular in recent years (see, for example, Benhabib and Spiegel 1994, and Krueger and Lindahl 2001).[112] The theoretical framework of these stud-

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[110] At this point it is again worth remembering what we observed in Graph 5.16 and in Graph 5.19 in particular. The between component is largely dominated by relatively young plants.

[111] For the effect of R&D on productivity, see, for example, Gustavsson, Hansson, and Lundberg (1999); Cameron, Proudman, and Redding (1999) and Rouvinen (2002) and numerous other studies listed in Bassanini, Scarpetta, and Hemmings (2001).

[112] Griffith, Redding, and van Reenen (2000), for example, find evidence that R&D and human capital enhance technology transfer and thus stimulate the catching up process. They also study the role of trade and find that it plays a more modest role in productivity growth.

ies is based on Marshall's concept of a representative firm or Viner's concept of the average firm (see Baldwin 1993). Consequently the effects are assumed to come solely from the productivity growth within firms (or plants).

Another strand of literature makes use of micro-level data as in Chapter 6 in this study. These studies also commonly use some aggregate level indicators in addition to various firm or plant characteristics. Aggregate gauges are included to capture spill-over effects, for example.[113] It is still assumed that R&D or some other factors improve industry productivity by making the incumbent firms and plants more productive. The stimulus may originate from their own R&D efforts or those of other firms, but, nonetheless, the effect materialises through internal adjustment within firms.

8.1.2 The productivity effects of external adjustment

Neither of the strands of literature mentioned above have anything to say about the productivity effects that occur through selection and reallocation of the resources between firms or plants. When restructuring is part of the mechanism it cannot be portrayed by aggregate data or by studying the effects at the firms or plants. Nickell (1996, pp. 741-742) was concerned about whether "we are barking up the wrong tree", when we examine how competition affects the efficiency of individual firms. He demanded a method that is suitable for detecting the effects through selection.

As demonstrated in Chapter 3, productivity decomposition methods provide us with a way of identifying the restructuring components of aggregate productivity growth. The effects should be studied at the industry level, not by looking at aggregate growth numbers, but at their relevant components instead. By this means it is possible to analyse how much external adjustment has contributed to productivity growth (see, e.g., Aw, Chung and Roberts 2000; Bernard, Eaton, Jensen and Kortum 2000; Melitz 2002).

8.1.3 The factors of "creative destruction"

I will focus on two factors that can be hypothesised to play a central role in the creative destruction process. One factor is R&D efforts that are a manifestation of purposeful attempts to create new technological knowledge. Because the creation and implementation of knowledge takes time, the R&D efforts of the past should

[113] See Mairesse and Sassenou (1991) who provide a good review of the methodology and empirical findings of studies on productivity and R&D efforts using firm-level data.

be essential. To the extent that R&D stimulates such technological progress that is implemented successfully in only some of the plants, it should be reflected in higher productivity dispersion. In a competitive environment, intra-industry diversity in technological knowledge and productivity levels is a source of selection which, in turn, drives the evolution of industry productivity (see e.g. Llerena and Oltra 2002).

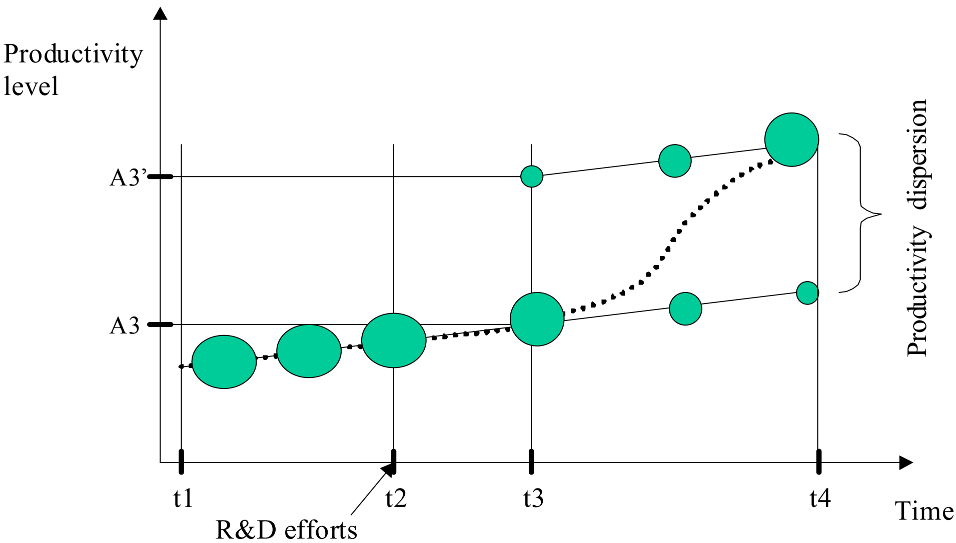
International trade may contribute to the creative destruction process in another way as well. Boone (2000) illustrates that competitive pressure on a firm can be expected to increase when the number of opponents increases or when the efficiency of the competitors improves. This is something that domestic firms face when exposure to global competition is increased by the lowering of trade barriers, for example. Both the opportunity and appropriability of conditions in the Finnish economic environment are likely to have thoroughly changed. Increased competition due to deregulation and higher imports may have made firms "eager" or "struggling" to adopt better technology, which led to internal adjustment, at least among some of the plants (see Boone 2000, p. 551). Or alternatively, increased competitive pressure may have triggered selection and external adjustment that should be reflected in the creative destruction components of industry productivity growth. But it is worth noting the argument of Melitz (2002) mentioned in Section 2.4.3. Mere competitive pressure from import intensity may not be enough. Exports may also be needed.

8.1.4 A framework for empirical analysis

Graph 8.1 presents the framework that outlines the empirical analysis of this chapter (see also Graph 3.2). Productivity within plants evolves over time due to disembodied technological change. This is indicated by the parallel upward sloped solid lines. Initially there is only one technology (and productivity level) at each point of time. R&D efforts are made in the year *t2*. No acceleration in productivity growth can be observed at first. Finally in the year *t3* a new high productivity technology is implemented in one or more plants that account for a small share of total input usage. This is indicated by a small ball located above a larger ball in the year *t3*. There is no extra productivity growth within continuing plants due to (lagged) R&D here, so the slopes of the solid lines remain unchanged.[114] Aggregate productivity (indicated by the thick dashed line) growth accelerates in the year *t3* and is higher than within plants growth until the year *t4*. This can be seen from the slope of the aggregate productivity line that is steeper than that of the within plants productivity growth in the period *t3*-*t4*. The difference in the steepness of the slopes indicates

[114] This is to say that this picture is consistent with the findings by Maliranta (2000b), who found little solid evidence that a firm's R&D intensity is positively related to subsequent productivity growth.

Graph 8.1 A framework for analysing productivity growth through restructuring



the intensity of productivity-enhancing restructuring (i.e. the magnitude of the between component) among continuing plants at a given point of time. In the year *t4* the aggregate productivity growth rate converges to the within plants productivity growth. Plant level restructuring is completed and all fruits of R&D efforts in the industry in the year *t2* are reaped. All inputs are equipped with the new technology, which is more productive than the previous one. The difference in the productivity potential between the old and new technology is |A3'-A3|. We also see that R&D has increased the (input-weighted) productivity dispersion for the period from the year *t3* to *t4*, but productivity-enhancing restructuring trims the dispersion.

The following analysis examines whether the econometric evidence obtained from Finnish manufacturing industries is consistent with this picture. The following questions are addressed:

1. How wide is the distance from *t2* to *t3* before any significant signs of industry productivity acceleration can be observed (see Rouvinen 2002 and Espost ja Pierani 2003)?

2. How long does it take for an R&D stimulus to increase productivity-enhancing restructuring; i.e. what is the distance from *t3* to *t4*?

3. Do R&D efforts generate productivity dispersion within an industry in the coming years, as assumed in Graph 8.1?

4. How is productivity dispersion related to productivity-enhancing restructuring?

5. What are the effects of imports, exports and the initial relative productivity level in the process?

8.2 Data and variables of interest

The following analysis covers 12 manufacturing industries from the mid-1970s up to 1998. The between component of TFP growth is the main dependent variable in the analysis. I have made computations by using a labour productivity indicator, too. These results are reported or commented on briefly.

One of the aims of this analysis is to find a relationship between the reallocation of input shares and productivity dispersion. This is why I prefer to use the input-index-weighted measures of productivity dispersion that are dependent on the allocation of inputs between plants that have varying productivity levels. Furthermore, I use the INP method that also makes use of input-index weights in a quite analogous way (see Section 3.2.2).

The twelve industries analysed here are introduced in Table 8.1.[115]

8.2.1 Between and catching up components by industry

Graph 8.2 depicts the between component of TFP growth in the 12 industries for the years 1975-98.[116] A substantial amount of variation in the levels of the restructuring components, as well as in their patterns over time across industries, can be found. There are some industries, like the food industry, textile and wearing apparel

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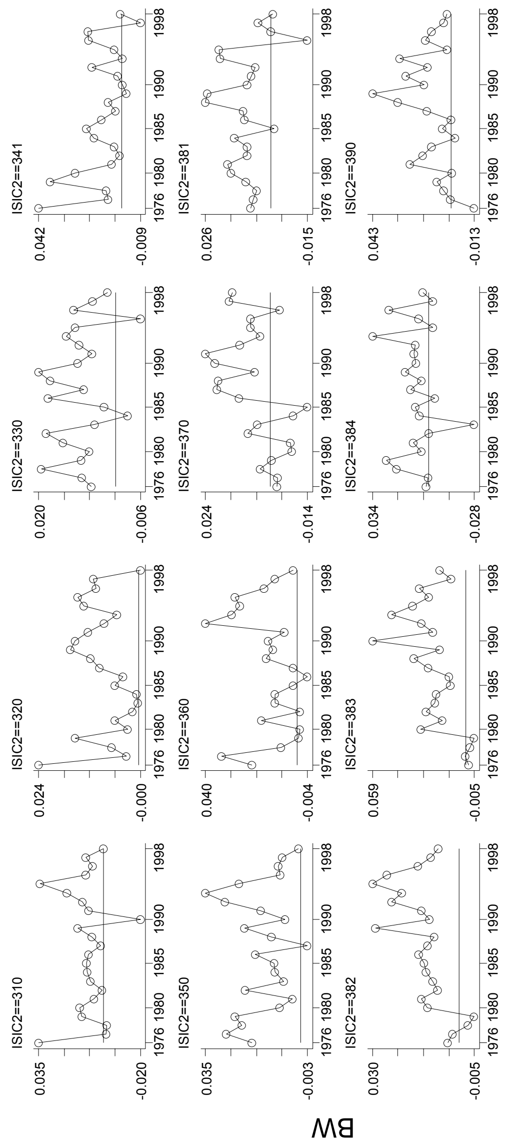
[115] Printing and Publishing is dropped from the analysis. There are two main reasons for this. Firstly, relative productivity level is one of the background variables. But for this industry it was not possible to compute an industry-specific unit value ratio for use in converting outputs into comparable units in the Finland/US productivity comparison. Secondly, R&D intensity, which is one of the main variables in the analysis, is obtained from the OECD's ANBERD database. However, this source has R&D expenditures for the combined Paper, Products & Printing industry only. As the paper industry covers about 80 per cent of the value added and some 90 percent of the R&D expenditures of the 1990s, these numbers indicate reasonably well the development of R&D intensity (R&D expenditure per value added) in Paper & Products, but not necessarily in Printing & Publishing.

[116] These computations were made when the data set covered the years up to 1998. The computations and the following regression analyses have not been updated thereafter. One reason for this is that I have lacked more recent information for some of the other variables anyway.

industry and the manufacture of non-metallic minerals, where the between component was quite insignificant during the first part of the period under consideration. In some industries a notable increase in the restructuring component can be found in the late 1980s or early 1990s. This is the case especially in the food industry, chemical industry, manufacture of non-metallic minerals, non-electrical machinery industry and especially in the electrical machinery industry. The values of the catching up component are given in Graph 8.3. These series are quite volatile and do not seem to have as clear patterns as the between component.

Graph 8.2 The between component of TFP growth by industry

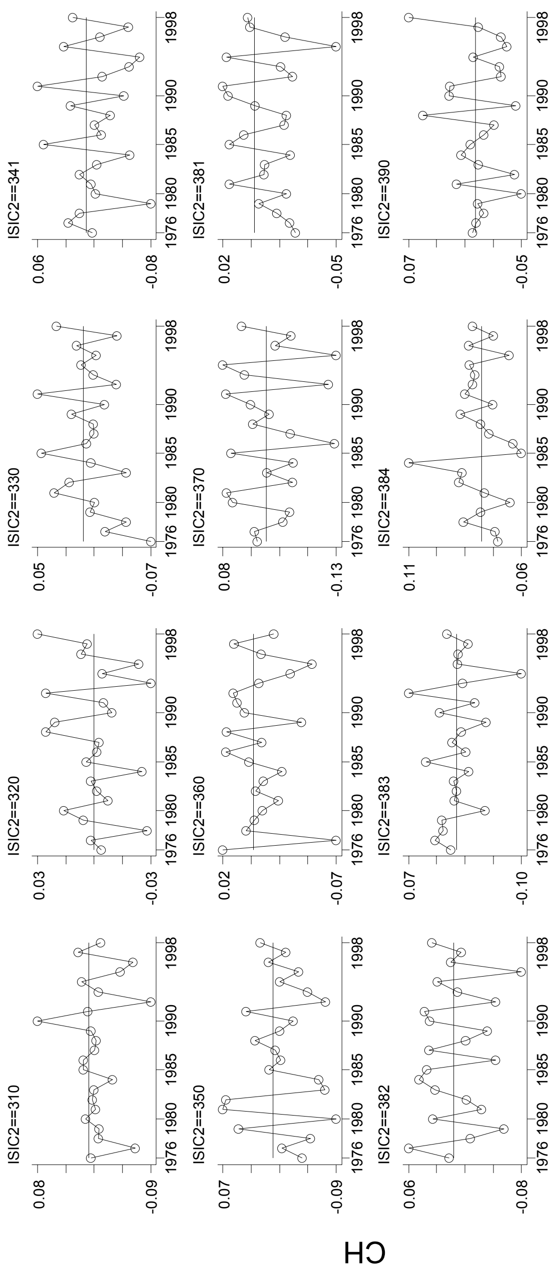


Graphs by ISIC2.

8.2.2 R&D intensity

Graph 8.4 indicates that R&D intensity (the nominal R&D expenditures per value added) has increased markedly in most industries. R&D efforts are long-term activities and thus the abrupt drop in value added, the denominator, in 1991 shows up

Graph 8.3 The catching up component of TFP growth by industry



Graphs by ISIC2.

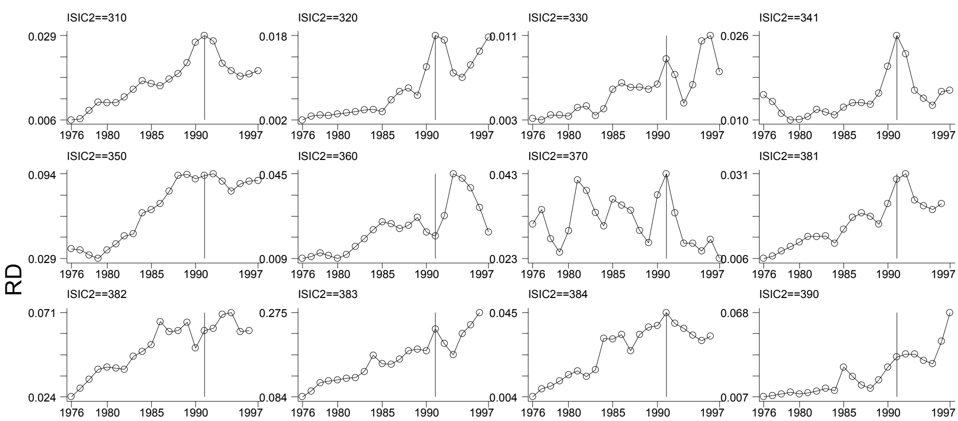
as a peak in R&D intensity in many industries. However, overlooking the short term fluctuations reveals important tendencies in the innovation activity of the 12 industries.

Table 8.1 The 12 manufacturing industries analysed in the panel estimations

Industry	ISIC2
Food, Beverages & Tobacco	310
Textiles, Apparel & Leather	320
Wood Products & Furniture	330
Paper & Products	341
Chemical Products	350
Non-Metallic Mineral Products	360
Basic Metal Industries	370
Metal Products	381
Non-Electrical Machinery*	382
Electrical Machinery**	383
Transport Equipment	384
Other Manufacturing	390

* excludes computers, ** includes computers, instruments and other professional goods.

Graph 8.4 R&D intensity (RD)

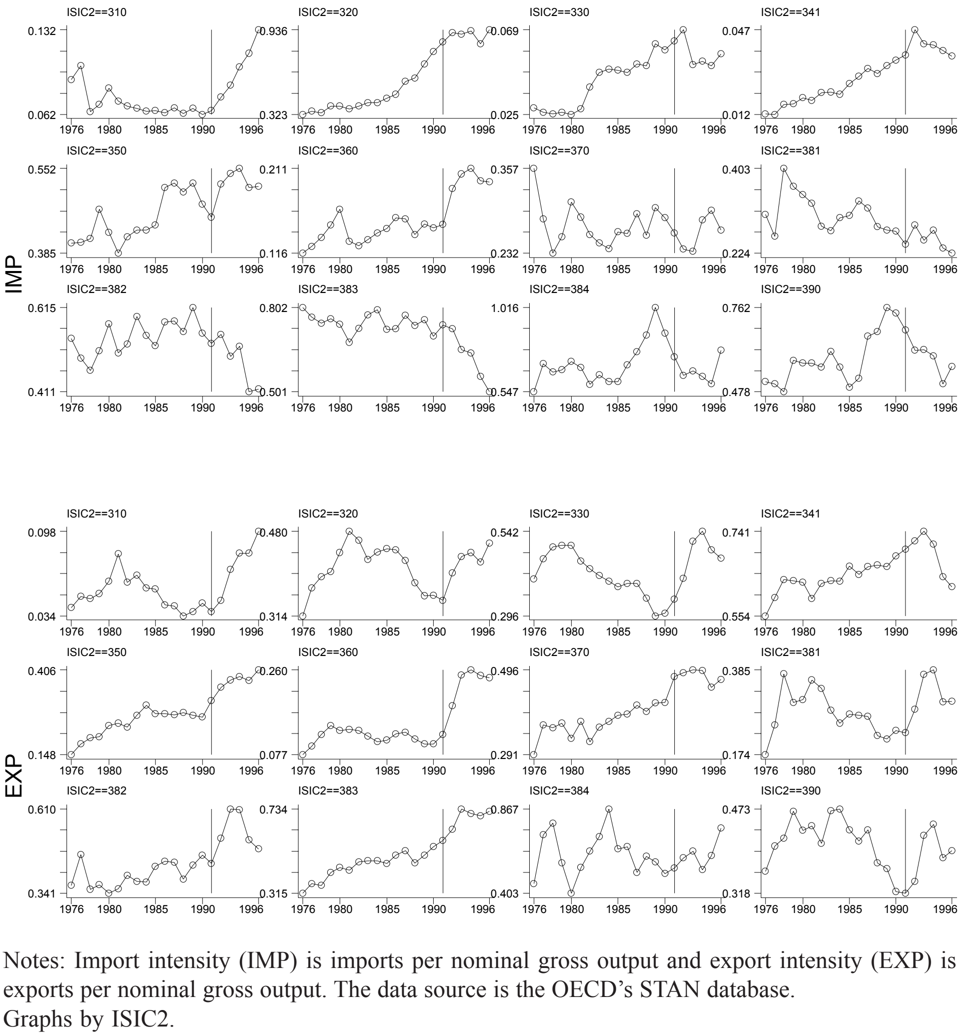


Note: R&D intensity is nominal R&D expenditures per nominal value added. The data sources are the OECD's ANBERD and STAN databases.
Graphs by ISIC2.

8.2.3 *International trade*

In order to examine the influence of exposure to global competition, two more variables are included in the analysis. As discussed above, nominal imports per nominal gross output (*IMP*)[117] can be expected to affect restructuring positively for the reasons discussed above. We see in Graph 8.5 that import intensity has in-

Graph 8.5 Imports share (*IMP*) and exports share (*EXP*)



Notes: Import intensity (IMP) is imports per nominal gross output and export intensity (EXP) is exports per nominal gross output. The data source is the OECD's STAN database.
Graphs by ISIC2.

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[117] Imports sum the value of those imported products that belong to the industry in question. The denominator, gross output, naturally indicates the value of domestic production in that industry.

creased in the 1990s markedly in a number of industries, in the food industry and in the manufacture of non-mineral products in particular.

Nominal exports per nominal gross output (*EXP*) is a variable that is quite commonly used in this kind of context. High export intensity indicates that a substantial share of the production faces direct international competition. As argued by Maliranta (2001), not all foreign markets need be challenging from the standpoint of productivity performance. Because of this concern Maliranta (2001) focused on exports to Western markets (and ignored exports to the former Soviet Union) and found that it was clearly positively associated with the subsequent restructuring component of aggregate productivity. Concerning industry level exports, however, it is not possible to use a detailed enough classification of exports by destinations. Therefore, the exports variable can be argued to be an insufficient indicator of the exposure to hard global competition.

Much of the increased orientation towards Western markets in the mid-1980s may be ascribed to the collapse of trade with the former Soviet Union. It seems natural to think that this shock fuelled reshuffling among firms and plants, as only a proportion of them were able to meet Western standards concerning the quality of products and production processes.[118]

When we deal with industry-level observations, there may be more doubt as to what extent the changes in export intensity reflect such exogenous factors that fuel productivity-enhancing restructuring and to what extent the success in export markets is a consequence of good productivity performance. At this point it may be useful to consider the developments in the Finnish electronics industry. It is now successful to a large extent due to cell phone production that has emerged through restructuring within this industry.

8.2.4 Productivity dispersion

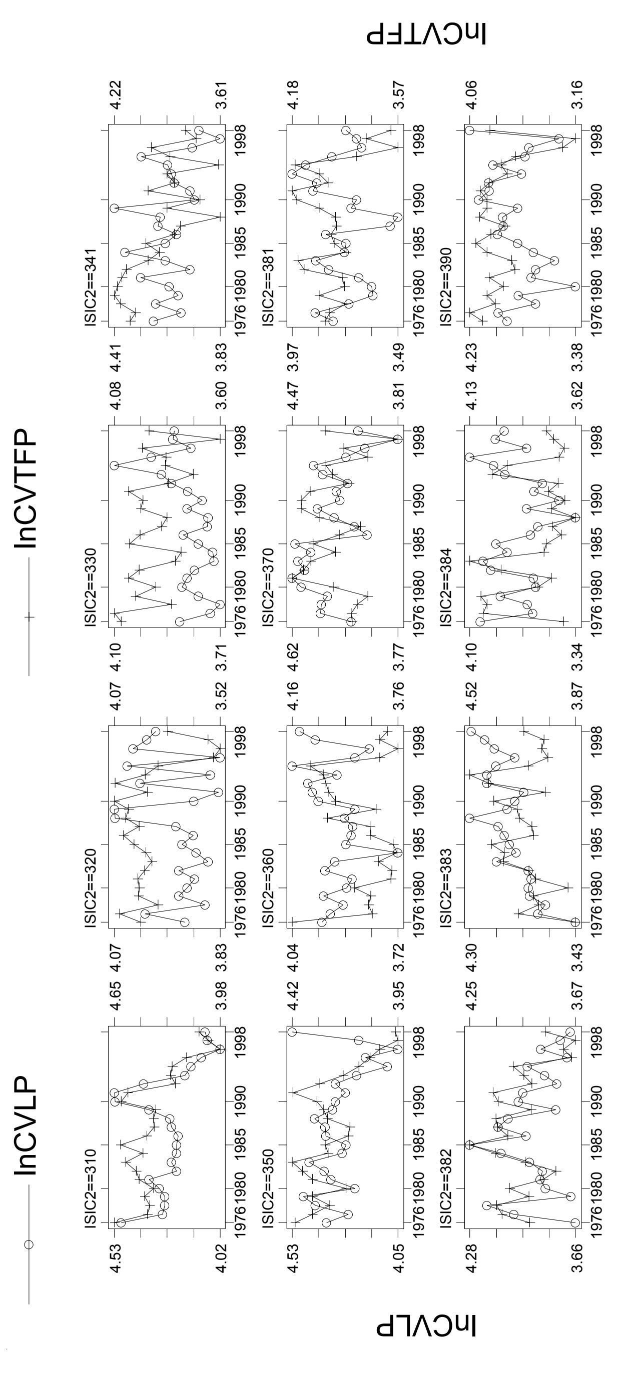
The aggregate productivity level and the aggregate productivity growth rate include a substantial amount of dispersion in productivity levels and divergence in development at the plant level.

Graph 8.6 shows that there is indeed a considerable amount of variation in the labour and total factor productivity levels between plants within manufacturing industries, measured by the log of the input-weighted coefficient of variation of labour productivity (*lnCVLP*) and total factor productivity (*lnCVTFP)*. Of course,

[118] Several aspects that are relevant at this point are included in the analysis by Sener (2001).

this variation is likely to reflect not only true differences between plants in terms of technology and the ability or incentive to use technology efficiently, but also a large amount of other noise-like measurement errors or temporary differences in capacity utilisation etc.

Graph 8.6 Labour (lnCVLP) and total factor productivity dispersion (lnCVTFP) in manufacturing industries, weighted by input



Notes: Plants employing fewer than 20 persons have been excluded from these calculations. Indicators are input-weighted.
Graphs by ISIC2.

The fact that the amount of dispersion varies between industries may be a reflection of inherent differences in the characteristics of technology and the economic environment.

However, it is interesting to see that there have been many changes in the amount of dispersion over time that may indicate changes in the economic environment, for example. Moreover, the patterns over time vary across industries. It is important to know what factors drive these developments (see Baldwin 1993). This is not only because large productivity dispersions may be a symptom of wasteful usage of resources in industries, but also because the same factors may affect both productivity and wage dispersions.

We notice, among other things, that the dispersion of TFP has been relatively high (right-hand scale) in some industries (in the food industry, for example). Secondly, a sharp decline in dispersion can be found in many industries during the 1990s. On the other hand, periods of long-lasting increases in productivity dispersion characterise development in some industries (e.g. electrical machinery and non-metallic minerals). Finally, we observe that the labour and total factor productivity dispersions usually share reasonably similar patterns over time. This observation gives support to the assumption that the (in)efficiency of an industry can be assessed relatively reliably by a simple performance indicator, i.e. output per labour input, as Baldwin (1993) does.

8.2.5 Wage dispersion

Graph 8.7 shows the development of wage dispersion between plants within the 12 industries, again measured by the log of the labour input-weighted coefficient of variation of hourly wages (*lnCVWH*).[119] In order to inspect the co-movements of

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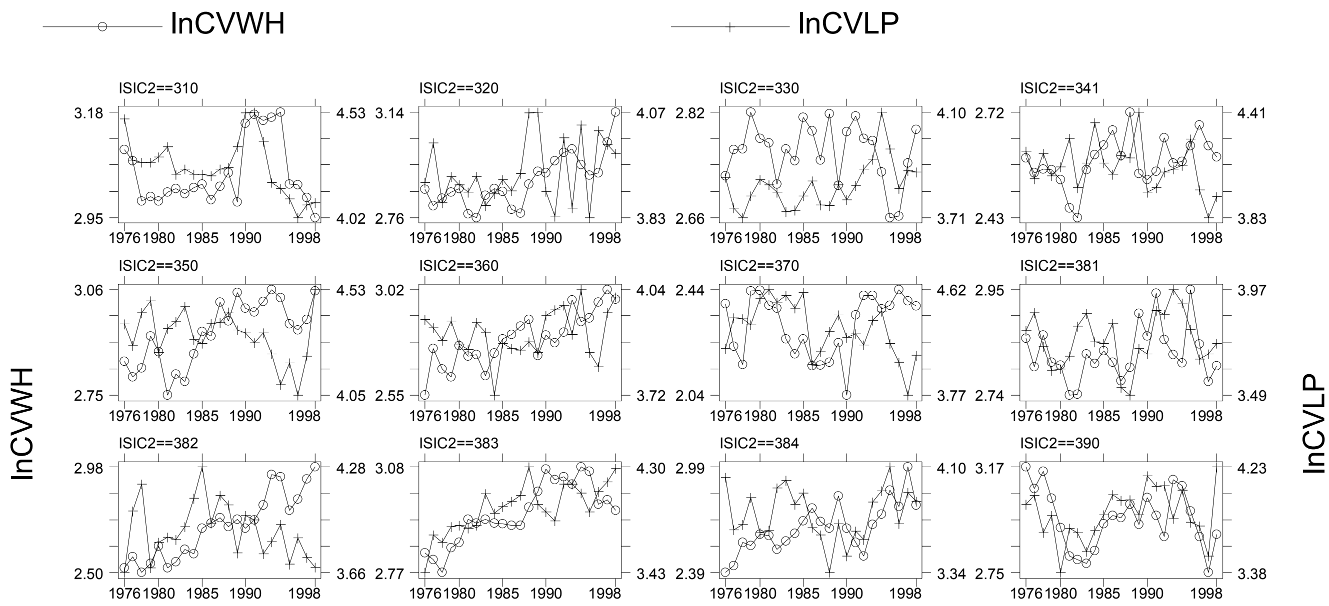
[119] The measurement of wage and productivity dispersion is performed with nominal units in this study. Measurement by using the units of some fixed base year obtained from industry-specific price indexes (at the 4-digit level, for example) would be a mistake. Calculations of that kind may give a seriously biased picture of the time pattern of dispersion changes. My experiments demonstrate that the measures of dispersion tend to increase after the base year, irrespective of what base year is used (I have used 1975, 1980, 1985 or 1995 as the base years). For example, in Dunne, Foster, Haltiwanger and Troske (2000) the plants' labour productivity indicators are expressed in 1987 prices (deflated by detailed industry-specific price indexes). A clear upward tendency in productivity dispersion since the year 1987 is found in their paper. This is exactly what one would expect to find if there is negative correlation between price and productivity change among sub-industries, as is likely. Of course, this problem does not arise when the productivity dispersions are calculated for industries defined narrowly enough. Sometimes authors do not report clearly on whether productivity measures are expressed in nominal terms or in prices of some (arbitrary) base year when they analyse the development of productivity dispersion. However, that would be a valuable piece of information as my experimentation has shown.

Graph 8.7 Labour productivity dispersion (lnCVLP) and wage dispersion (lnCVWH) in manufacturing industries, weighted by input



Notes: Plants employing fewer than 20 persons have been excluded from these calculations. Indicators are input-weighted.
Graphs by ISIC2.

wage and productivity dispersion, as predicted by various theoretical considerations discussed in Section 2.4.7, I have also reproduced the measure of labour productivity dispersion shown in Graph 8.6. We see that the series often shares similar patterns over time, even though they do not appear to be quite synchronised in all cases.

8.3 Econometric modelling of the between component of TFP

Typically the basic econometric equation used in the macro and micro analysis of productivity growth takes the form

$$\Delta P_{it} = \alpha + \beta_{RD} \cdot RD_{it} + \boldsymbol{\beta}_X \cdot \mathbf{X}_{it} + \varepsilon_{it}, \tag{8.1}$$

where P_{it} is a productivity indicator, Δ is the difference operator, RD_{it} is R&D intensity, $\mathbf{X}_{it}$ is a set of other possible explanatory variables, ε_{it} is an error term with the usual properties. Time is denoted by *t* and an industry or a country or a firm by *i*. In this specification, parameter β_{RD} indicates the rate of return on R&D investments.

The novelty of this study is that it focuses on one of the components of aggregate productivity growth, the between component, which provides us with an indicator for the intensity of the creative destruction process. This is to say, the dependent variable is BW_{it} instead of ΔP_{it}. On the basis of theoretical considerations we would expect that R&D improves aggregate productivity partly through the restructuring component, with a lag that is necessary for selection, job destruction and creation.

My estimation equation takes the following form:

$$BW_{it} = \beta_{BW(t-1)} BW_{i(t-1)} + \sum_{k=0}^{n} \beta_{RD(t-k)} \cdot RD_{i(t-k)} + \boldsymbol{\beta}_X \cdot \mathbf{X}_{it} + \varepsilon_{it} \tag{8.2}$$

The hypotheses are tested with an econometric exercise by using a panel of 12 manufacturing industries covering the period from the mid-1970s to the latter part of the 1990s.[120] I have included, in addition to the R&D intensity variable, the export and import intensity, and (the log of) the total factor productivity level relative to the United States. As noted above, all these variables are widely used in the analysis of aggregate productivity and all of them can be argued to affect or to be

[120] The length of the time-series may vary, depending on how many lags are used in the specification and which variables are included in the model.

associated with the creative destruction process. The examination of still another potential determinant, human capital, is left for future work (see discussion at the end of Chapter 6).

As a preliminary investigation before going on to a more in-depth analysis with industry-level panels, I first show the results of a simple model estimated with a manufacturing time-series.[121] This model explains the between component of the total factor productivity by the value of exports to western markets per nominal value added, nominal R&D expenditure per nominal value added and the difference between the Finnish and US total factor productivity levels (these explanatory variables are in log forms). A trend variable is included as well.

$$\underset{(0.044)\,(***)}{BW_t = 0.226} + \underset{(0.010)\,(***)}{0.040}*\ln(EXPWEST)) + \underset{(0.011)\,(***)}{0.033}*\ln(RD_{t-4}) + \underset{(0.004)\,(***)}{0.016}*\ln(TFPGAP_{t-1}) - \underset{(0.001)\,(**)}{0.002}*TREND \qquad (8.2')$$

N = 20, R^2 = 0.828, adj. R^2 = 0.782. (***) denotes 1 % and (**) 5 % significance level.

This admittedly parsimonious model yields a surprisingly good fit (see also Maliranta 2001, 45). At least it provides some possible explanations for a couple of turns in the between component in Finnish manufacturing from the late 1970s to the late 1990s (see Figure 5.13, p. 45 in Maliranta 2001). It appears that the increase in R&D intensity in the early 1980s as well as the increased exports to Western markets in the 1980s resulted in accelerated total factor productivity growth via the increased between component. According to the model the "chill" in the between component toward the end of the 1990s can be attributed to the narrowing gap to the technology frontier in the mid-1990s. There was less micro-structural inefficiency to be "cleansed" through restructuring in the latter part of the period under consideration, which may have resulted in a "chill" in the ongoing re-structuring process.[122]

In the model above, the variables are assumed to be stationary (with the allowance for deterministic trends). Although tests of stationarity with a sample this small should be interpreted very cautiously they seem to suggest that the variables are rather I(1) than I(0) processes.[123] Therefore a more careful investigation might

[121] These estimations were originally made for the study by Maliranta (2001).

[122] In addition to the fact that the simple model seems to have quite a bit of explanatory power reflected in reasonably high R^2 statistics, it also has other reasonably good statistical properties. The Breusch-Godfrey LM test suggests that the model is not plagued by a serial correlation problem. The ARCH test tells that autoregressive conditional heteroscedasticity is not a problem, either. The Ramsey RESET test does not give any indication whatsoever of potential specification errors. The model passes stability tests with recursive residuals. The coefficients seem to be reasonably stable over time, as well. No evidence of non-normality was found.

[123] In view of the nature of the between component we might expect the *BW* variable to be stationary.

be needed. Maliranta (2001) performs an analysis with differenced variables and these results give some further confirmation to the earlier conclusions.

Table 8.2 reports estimation results for the determinants of the between component obtained with the panel of the 12 industries obtained by Equation (8.2). Estimations are performed by using the feasible generalised least squares method (FGLS). It provides consistent and efficient estimates when the error term is not independently, identically and normally distributed.

Models (1)-(3) include fixed industry effects. Furthermore, different trends are allowed for each of the 12 industries in these models. I have experimented with various specifications that are not reported here. For example, I have used a common trend or year dummies instead of using industry-specific trends. The results remain broadly similar.

The theoretical considerations guide us basically up to the point that it is possible to form predictions about the signs of the effects and that some lags in the effects can be anticipated (see Graph 8.1). I have sought the proper variable composition by estimating a large number of models by adding and dropping variables step by step. For instance, lag structures can be identified by adding additional lags as long as the new variable is significant in the model. Different model selection approaches resulted in more or less similar outcomes. For the main part, the findings seem reasonably stable over the different alternatives.

It is interesting to see what the time pattern of effects is like, e.g. how long it takes before an increase in R&D is reflected in productivity-enhancing restructuring at full stretch. Equally important is to know, what the magnitude of the long-run effect is. In order to compute point estimates, standard errors, etc. for the long-run effect of an explanatory variable we need to consider a non-linear combination of estimators. In the case of R&D intensity, the point estimate of interest is obtained by

$$\hat{\beta}_{RD(long\,run)} = \frac{\sum_{k=0}^{n} \hat{\beta}_{RD(t-k)}}{\left(1 - \hat{\beta}_{BW(t-1)}\right)} \tag{8.3}$$

Calculations can be performed by the so-called "delta method" (see Stata Manual, Release 8).

As mentioned, under certain assumptions the feasible generalised least squares method provides us with consistent and efficient estimates. This method has its limitations, however. Let us consider the following dynamic model:

$$BW_{it} = \beta_{BW(t-1)} BW_{i(t-1)} + \sum_{k=0}^{n} \beta_{RD(t-k)} RD_{i(t-k)}$$

$$+ \sum_{k=0}^{m_X} \boldsymbol{\beta}_{X(t-k)} \mathbf{X}_{i(t-k)} + \eta_i + \delta_t + \varepsilon_{it} \tag{8.4}$$

$i = 1, \ldots, 12$; $t = 1976, \ldots, 1996$

The unobserved industry effect, η_i , is taken to be constant over time and specific to each industry *i*. The individual effects are allowed to correlate with the explanatory variables. Any time-specific effects that are not included in the model are accounted for by the industry-invariant time effects, δ_t .

In the models whose results were given in Table 8.2, a lagged dependent variable was also included as an additional explanatory variable. As a consequence, the within-group estimator generates inconsistent estimates in dynamic specifications, if the number of time periods is fixed (see Nickell 1981). On the other hand, as we have relatively long time periods available, the magnitude of bias should be inconsequential.

A more serious concern is that when the models are estimated by FGLS, it is assumed that all explanatory variables are strictly exogenous, i.e. uncorrelated with the past, present and future realisations of ε_{it} . This assumption is violated, for instance, if an unexpected shock to input reallocation in an industry affects R&D efforts or export intensity in the industry.

This potential problem can be overcome by estimating model (8.4) with the Arellano-Bond (1991) GMM method for the first differenced equation.[124] Although differencing eliminates the individual effects, it induces a negative correlation between the lagged dependent variable, $\Delta BW_{i(t-1)}$, and the disturbance term. The Arellano-Bond method overcomes this problem by employing linear orthogonality conditions, $E\left(BW_{i(t-s)} \Delta\varepsilon_{it}\right) = 0$ for $t = 3, \ldots, T$ and $2 \leq s \leq t-1$, as for choosing appropriate instruments for the lagged dependent variable. In addition, all leads and lags of strictly exogenous explanatory variables can be employed as instruments for all equations in first differences.

In some cases, the assumption of strict exogeneity is not tenable. It may be the case, for instance, that the current R&D efforts are correlated with error terms in the past or in the future. That is to say that $E\left(RD_{it}\varepsilon_{is}\right) = 0$ does not hold for all *t* and *s*. It may be the case that a shock will have some effect on R&D efforts in the

[124] For other possible alternatives see e.g. Hayashi (2000).

Table 8.2 Determinants of the between component of aggregate TFP growth, the FGLS estimations

Dependent variable	(1) BW	(2) BW	(3) BW	(4) BW	(5) BW
BW(t-1)	0.055	0.059	0.059	0.232***	0.206***
	(0.91)	(0.97)	(0.96)	(3.66)	(3.45)
RD(t)	-0.102*	-0.115**	-0.122**	-0.083	-0.071
	(1.84)	(1.96)	(1.98)	(0.82)	(0.76)
RD(t-1)	0.101	0.069	0.059	0.023	0.050
	(1.55)	(0.97)	(0.82)	(0.17)	(0.39)
RD(t-2)	0.093	0.095	0.087	0.058	0.101
	(1.34)	(1.29)	(1.18)	(0.41)	(1.01)
RD(t-3)	0.096	0.075	0.070	-0.030	
	(1.38)	(0.99)	(0.92)	(0.21)	
RD(t-4)	0.150*	0.212***	0.205**	0.002	
	(1.92)	(2.59)	(2.46)	(0.02)	
RD(t-5)	0.145**	0.107	0.110	0.121	
	(2.01)	(1.32)	(1.34)	(0.94)	
IMP(t-2)		0.068**	0.065**	-0.000	
		(2.30)	(2.12)	(0.02)	
$IMP(t-2)^2$		-0.043**	-0.043**	0.001	
		(2.07)	(1.97)	(0.17)	
EXP(t-2)		-0.014	-0.014	0.000	
		(1.42)	(1.48)	(0.01)	
lnTFP(t-2)			-0.002		
			(0.33)		
Industry-specific trends	yes	yes	yes	no	no
Industry effects	yes	yes	yes	dropped	dropped
Year effects	no	no	no	yes	yes
Long-run effects of R&D[1]	.512***	.470***	.435**	.118***	.102***
Observations	228	228	228	228	240
Number of industries	12	12	12	12	12
Diagnostics					
AR(1)	0.0182	0.0140	0.0171	0.0084	0.0278
Log likelihood	821.23	818.23	816.21	761.44	798.46
Joint signif. of industry-specific trends[2]	0.0004	0.0005	0.0009		
Joint signif. of industry effects[2]	0.0004	0.0004	0.0009		
Joint signif. of year effects[2]	-	-		0.0151	0.0161

Notes: Absolute value of z statistics in parentheses. All models are estimated by the feasible generalised least squares method (FGLS), where heteroscedasticity with a cross-sectional correlation is allowed. [1]The estimates for the long-run effects are obtained by the delta method. [2]The joint significance of the sets of explanatory variables is tested by the WALD test. These test statistics are reported as p values. As for evaluating autocorrelation, a common AR(1) is also allowed.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8.3 Determinants of the between component of aggregate TFP growth, the GMM estimations

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	ΔBW	ΔBW	ΔBW	ΔBW	ΔBW	ΔBW
ΔBW(t-1)	0.180***	0.166**	0.062	0.163***	0.169**	0.159***
	(3.53)	(2.36)	(0.79)	(2.73)	(2.60)	(2.79)
ΔRD(t)	-0.089	-0.092	-0.104*	-0.127**	-0.079	-0.113**
	(1.59)	(1.59)	(1.72)	(2.22)	(1.42)	(2.17)
ΔRD(t-1)	0.159***	0.042	0.013	0.085	0.035	0.066
	(2.64)	(0.49)	(0.13)	(1.03)	(0.37)	(0.78)
ΔRD(t-2)		0.149	0.056	0.159	0.156	0.171
		(1.42)	(0.54)	(1.38)	(1.47)	(1.57)
ΔRD(t-3)			-0.056			
			(0.75)			
ΔRD(t-4)			0.015			
			(0.11)			
ΔRD(t-5)			0.184			
			(1.61)			
ΔIMP(t)	0.027**	0.029**	0.041***	0.035***	0.069***	0.077***
	(2.44)	(2.46)	(3.09)	(3.28)	(2.60)	(2.94)
ΔIMP(t)^2					-0.045**	-0.048**
					(2.09)	(2.26)
ΔIMP(t-1)	-0.015	-0.017	-0.028**	-0.021		
	(1.14)	(1.16)	(2.00)	(1.54)		
ΔEXP(t)	0.007	0.009	0.001	0.017*	0.017	0.019**
	(0.69)	(0.89)	(0.06)	(1.71)	(1.42)	(2.05)
ΔEXP(t-1)	0.020	0.016	0.010	0.007		
	(1.61)	(1.30)	(1.16)	(0.65)		
Dummies for years	Yes	Yes	Yes	No	Yes	No
Dummy for year 1988				0.009***		0.008***
				(3.58)		(3.54)
Long run effects[1]						
R&D intensity	.085*	.118*	.115*	.140**	.134*	.147**
Imports	.015*	.015*	.014*	.017*		
Exports	.033*	.030*	.012	.029**	.020	.023**
Observations	228	216	180	216	216	216
Number of industries	12	12	12	12	12	12
Diagnostics						
Joint signif. of time dummies[2]	0.0031	0.0001	0.0000		0.0340	
First-order auto-correlation	0.0052	0.0035	0.0028	0.0035	0.0034	0.0031
Second-order autocorrelation	0.4503	0.7159	0.5687	0.5276	0.8188	0.6395
Sargan test of overrid. restr.[3]	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Notes: One-step results are reported. Robust t statistics in parentheses. [1]The estimates for the long-run effects are obtained by the delta method. [2]The joint significance of the year dummies is tested by the WALD test. [3]The Sargan test for the validity of over-identifying restrictions is obtained from the corresponding estimations where homoscedastic error is assumed (the other results of these estimations are not given here). All test statistics are reported as p values.

* significant at 10%; ** significant at 5%; *** significant at 1 future, i.e. $E(RD_{it}\varepsilon_{is}) \neq 0$ for $s < t$. If $E(RD_{it}\varepsilon_{is}) = 0$ for all $s \geq t$ then R&D is said to be predetermined. However, it may be the case that the current R&D is correlated with the current error, i.e. $E(RD_{it}\varepsilon_{is}) \neq 0$ for $s \leq t$ (but $E(RD_{it}\varepsilon_{is}) = 0$ for all $s > t$). In this case the R&D variable is an endogenous variable and should be treated similarly to the lagged dependent variable. Levels of the R&D variable lagged by two or more periods can be used as instruments.

The set of valid instruments becomes larger as *t* increases. Monte Carlo experiments show that using the full set of moment conditions in the later cross-sections may result in over-fitting biases in the estimates (see Arellano and Honore 2001). The second, technical problem is that the instrument matrix may become too large to compute. For both reasons the maximum number of lags is set as three. The results for the GMM estimations are given in Table 8.3.

Tests for first-order and second-order autocorrelation do not give any indication that the estimates are inconsistent. Thus the null hypothesis of no first-order autocorrelation in the differenced residuals is rejected, but it is not possible to reject the null hypothesis of no second-order autocorrelation. The validity of the over-identifying restrictions can be tested by the Sargan test, if the error term is assumed to be homoskesdastic. These tests also speak for the validity of my GMM estimates.

Regarding economic interpretation, the GMM estimates give further support to the main findings made with the FGLS estimations. These are discussed in greater detail below.

8.3.1 Results for R&D intensity

Basically all the models reported (and unreported) here provide a reasonably consistent and robust picture of the positive effects of R&D intensity on subsequent productivity-enhancing restructuring. The findings obtained with this industry panel closely parallel those obtained with the manufacturing time-series above.

As expected, R&D intensity positively affects the between component of aggregate TFP change with a lag. Models (1) - (3) in Table 8.2 suggest that it takes about half a decade before R&D efforts stimulate productivity-enhancing restructuring with full intensity. Going back to Graph 8.1, it seems that the length of the period from *t2* to *t4* is five years, according to the empirical findings.

According to the models (1) - (3) in Table 8.2 a permanent increase in R&D intensity by one percentage point increases the annual between component by 0.44 -0.51 percentage points. The manufacturing time-series estimate of 0.033 for the variable ln(RD), which is reported in Equation 8.2, suggests that an increase of

R&D intensity from 3 % to 4 % would result in an increase of 0.9 percentage points in the between component. One possible explanation for the bigger estimated effect in the latter case is that the between component obtained from total manufacturing includes productivity-enhancing restructuring between industries, in addition to that within industries (see also Graph 5.21).

In models (4) and (5) of Table 8.2 industry-specific trends are replaced by time dummies. The long-run effect of an increase in R&D intensity falls substantially, but is still economically and statistically significant. The WALD test for the joint significance of the year dummies indicates that the null hypothesis that at least one year dummy is significant is rejected at the 5 per cent significance level, but not at the 1 per cent significance level.

Some of the findings made here accord in an interesting way with the aggregate level results obtained by Rouvinen (2002) from an unbalanced panel of 14 industries in 12 OECD countries from 1973 to 1997. He observes that R&D affects TFP with a considerable lag. In most cases the fourth lag is the highest, which is by and large the time needed for plant-level restructuring according to my estimates.[125]

Someone might expect that the influence of a single industry may be reflected in the results. Creative destruction seems to have been particularly strong in the electrical machinery industry. I have checked that the conclusions are not sensitive to the exclusion of this industry.

I have made quite a bit of efforts to find proper functional forms for the models. As an experiment I have used the log of R&D intensity as an explanatory variable, as in Equation (8.2’) or Gustavsson, Hansson, and Lundberg (1999), when studying the effect of R&D on aggregate *TFP*. In this study, specifications like that seem to provide a somewhat poorer fit with this industry panel.

The GMM estimations reported in Table 8.3 lend further support to the main conclusions made above. An increase in R&D intensity decreases productivity-enhancing restructuring initially, but appears to have a positive effect subsequently. The long-run effect of an increase in R&D intensity by one percentage point is over 0.1 percentage point per annum according to most of the models. Although this should be interpreted as a conservative estimate of the effect, it is still economically quite significant.

[125] As a fascinating aside, we noted in Section 6.3 that it takes about four years before an increase in the average schooling is positively reflected in a plant’s productivity growth.

8.3.2 Results for international trade

I have used a number of different formulations of the indicators and different functional forms to explore the role of international trade in productivity-enhancing intra-industry restructuring. The results reported here give quite a representative picture of the main findings.

Reasonably robust evidence of the positive effect of imports is found with both the FGLS and GMM estimations. In order to avoid simultaneity bias in the FGLS estimations, the international trade variables are measured with 2-year lags. However, the relationship between imports and restructuring does not seem to be linear over the whole range, but concave, usually reaching a peak somewhere at the 80 per cent intensity level. All the models yield quite similar patterns, which suggest that the import intensity effect is clearly positive within the usual ranges of import intensity. To give an example, the increase in import intensity from 6 % to 12 % that was experienced in the food industry in the early 1990s increased the annual aggregate productivity growth rate through a creative destruction process by about one third of percentage points per year.

Regarding export orientation (variable *EXP*) empirical evidence is somewhat more mixed. No statistically significant evidence is found with the FGLS estimations. This seems to be at odds with the earlier findings for manufacturing time-series. But as stated earlier, that analysis focused on those exports that were delivered to Western markets. Besides, the endogeneity problem may be more serious in the FGLS estimations than in the case of imports (despite the use of lags). High exports may be a consequence of the fact that the industry is already competitive and there is no need for cleansing through restructuring anymore, for example. Some evidence of the positive effects of exports is given in the GMM estimations. So the GMM results are broadly in line with the view of Melitz (2002) that imports and exports are both important for the productivity-enhancing intra-industry reallocation of resources.

8.3.3 Results for technology level

The impact of the initial technology level is studied here by including a log of total factor productivity relative to the United States (*lnTFP*) in the models. The danger of creating a spurious relationship between initial productivity and subsequent growth is great. This is one of the reasons why I have measured the initial productivity level with a two years' lag.[126]

[126] We have tried different lags in the model as well as the use of lags as instruments, but the results were generally insignificant.

No solid evidence can be found with the FGLS or GMM estimations (the latter are not reported here) that backwardness in the total factor productivity level leads to ensuing productivity-enhancing restructuring. Above we noticed some evidence with the manufacturing time-series that supports the view that a large productivity gap is reflected in a subsequent high between components. Two problems in the indicator of technology level, especially when applied at the industry level, raise some concern. Inaccuracy due to measurement error can be expected to be much larger at the industry level than that at the total manufacturing level. In addition, the validity of the indicator (which is total factor productivity relative to the United States) as a measure of distance to the international technology frontier can be questioned for some industries. It is likely to be an appropriate indicator at the level of total manufacturing, but this may not be the case for every single industry (see Scarpetta and Tressel 2002).

8.3.4 The effects of productivity and wage dispersion

Instead of past R&D intensity I next include past productivity dispersion (measured by a log of the coefficient of variation) in the model. According to the FGLS estimations given in Table 8.4, the positive effect peaks at the third lag in the case of labour productivity. The time pattern is somewhat less clear when total factor productivity is used, which may reflect inaccuracies in the measurement of capital productivity. Wage dispersion is included in some models as well. No evidence whatsoever can be found that greater wage dispersion between plants stimulates the reallocation of labour in a productivity-enhancing way. If anything, the effect might even be negative.

Largely similar conclusions can be drawn from the GMM results given in Table 8.5, where productivity and wage dispersion are allowed to be endogeneous. Econometric evidence suggests that increases in productivity dispersion and international trade lead to creative destruction within industries.

The findings recorded here accord with those obtained by Dwyer (1998), who found that dispersion in productivity is larger in industries with more rapid productivity growth. The empirical findings outlined here suggest that greater heterogeneity among plants in terms of productivity has the potential for extra growth through reallocation of input shares among the incumbent plants.

The GMM estimations do not provide us with any evidence that greater wage dispersion is useful for micro-level restructuring.

Table 8.4 The between component, productivity and wage dispersion, the FGLS estimations

	Labour productivity			Total factor productivity		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	BW	BW	BW	BW	BW	BW
BW(t-1)	-0.112*	-0.136**	-0.031	-0.036	-0.014	-0.042
	(1.82)	(2.14)	(0.49)	(0.63)	(0.25)	(0.67)
Productivity	0.010***	0.010***		0.010***	0.010***	
dispersion (t-1)	(4.77)	(4.19)		(3.17)	(3.47)	
Productivity	0.011***	0.014***		0.003	0.003	
dispersion (t-2)	(4.97)	(5.97)		(0.78)	(0.93)	
Productivity	0.016***	0.016***		0.002	0.002	
dispersion (t-3)	(7.05)	(7.46)		(0.66)	(0.72)	
Productivity	0.008***	0.009***		0.003	0.003	
dispersion (t-4)	(3.32)	(3.92)		(0.91)	(0.77)	
Productivity	0.005**	0.003		0.008**	0.006*	
dispersion (t-5)	(2.52)	(1.26)		(2.30)	(1.76)	
Wage	-0.005		0.014**	0.007		0.007
dispersion (t-1)	(1.01)		(2.55)	(1.12)		(1.17)
Wage	-0.003		0.001	-0.009		-0.013**
dispersion (t-2)	(0.71)		(0.21)	(1.31)		(2.13)
Wage	-0.013***		-0.010*	0.006		-0.001
dispersion (t-3)	(2.62)		(1.68)	(0.87)		(0.10)
Wage	0.007		0.012***	0.008		0.021***
dispersion (t-4)	(1.61)		(2.61)	(1.32)		(3.89)
Wage	-0.017***		-0.017***	-0.017***		-0.019***
dispersion (t-5)	(4.42)		(4.37)	(2.83)		(3.59)
IMP(t-2)	0.015*	0.005	0.006	0.001	-0.000	0.020***
	(1.95)	(0.79)	(0.94)	(0.18)	(0.05)	(3.03)
EXP(t-2)	-0.055***	-0.067***	-0.053***	-0.013	-0.018*	-0.011
	(9.11)	(10.94)	(12.16)	(1.33)	(1.93)	(1.30)
Industry-specific trends	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Long-run effects[1]						
Prod. dispersion	.045***	.045***		.024***	.024***	
Wage dispersion	-.028***		.0009	-.005		-.004
Imports	.013**	.005	.006	.001	-.0003	.019***
Exports	-.050***	-.060***	-.052***	-.013	-.018*	-.011
Observations 216	216	216	204	204	216	
Number of industries		12	12	12	12	12
12						
Diagnostics						
AR(1)	-0.0064	-0.0093	-0.0423	0.0317	0.0293	0.0323
Log likelihood	764.211	756.838	752.440	750.602	748.534	782.720
Joint signif. of industry-specific trends[2]	0.0000	0.0000	0.0000	0.0002	0.0001	0.0000
Industry effects[2]	0.0000	0.0000	0.0000	0.0002	0.0001	0.0000

Notes: Absolute value of z statistics in parentheses. All models are estimated by the feasible generalised least squares method (FGLS), where heteroscedasticity with a cross-sectional correlation is allowed. [1]The estimates for the long-run effects are obtained by the delta method. [2]The joint significance of the sets of explanatory variables is tested by the WALD test. These test statistics are reported as p values. As for evaluating autocorrelation, a common AR(1) is allowed.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8.5 The between component, productivity and wage dispersion, the GMM estimations

	Labour productivity			Total factor productivity		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	ΔBW	ΔBW	ΔBW	ΔBW	ΔBW	ΔBW
ΔBW(t-1)	-0.046	-0.062	0.018	0.164***	0.152***	0.197***
	(0.40)	(0.57)	(0.15)	(3.86)	(3.59)	(3.78)
Productivity	-0.021***	-0.021**		0.005	0.006	
dispersion (t)	(2.90)	(2.58)		(0.86)	(1.16)	
Productivity	0.013**	0.014**		0.014**	0.014***	
dispersion (t-1)	(2.02)	(2.15)		(2.59)	(2.66)	
Productivity	0.013	0.012				
dispersion (t-2)	(1.29)	(1.22)				
Productivity	0.013**	0.014**				
dispersion (t-3)	(2.27)	(2.56)				
Wage	-0.011		-0.016	-0.001		0.002
dispersion (t)	(0.92)		(1.12)	(0.04)		(0.17)
Wage	0.020		0.029*	-0.004		-0.004
dispersion (t-1)	(1.24)		(1.70)	(0.57)		(0.51)
Wage	-0.011		-0.008			
dispersion (t-2)	(0.93)		(0.68)			
Wage	-0.004		0.001			
dispersion (t-3)	(0.62)		(0.05)			
IMP(t)	-0.009	-0.013	0.005	0.024	0.026*	0.020
	(0.57)	(0.87)	(0.22)	(1.63)	(1.84)	(1.35)
IMP(t-1)	0.028	0.032	0.013	-0.010	-0.011	-0.009
	(1.28)	(1.59)	(0.48)	(0.64)	(0.74)	(0.53)
EXP(t)	0.015	0.013	0.015	0.017	0.011	0.016
	(0.79)	(0.77)	(0.70)	(1.31)	(0.91)	(1.30)
EXP(t-1)	-0.002	-0.001	-0.001	0.013	0.018	0.018
	(0.19)	(0.14)	(0.07)	(0.97)	(1.49)	(1.50)
Long run effects[1]						
Productivity dispersion	.0170**	.0176**		.023***	.024***	
Wage dispersion	-.006		.005	-.006		-.002
Imports	.018	0.017*	.018	.017*	.017*	.015*
Exports	.012	0.011	0.014	.036**	.035**	.042**
Observations	204	204	204	228	228	228
Number of industries	12	12	12	12	12	12
Diagnostics						
Joint signif. of time dummies[2]	0.0000	0.0001	0.0643	0.0101	0.0000	0.0000
First-order auto-correlation	0.0030	0.0031	0.0045	0.0052	0.0053	0.0053
Second-order auto-correlation	0.7594	0.8161	0.5036	0.6288	0.5608	0.6136
Sargan test of overrid. restr.[3]	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Notes: One-step results are reported. Robust t statistics in parentheses. [1]The estimates for the long-run effects are obtained by the delta method. [2]The joint significance of the year dummies is tested by the WALD test. [3]The Sargan test for the validity of over-identifying restrictions is obtained from the estimations where homoscedastic error is assumed. All test statistics are reported as p values.
* significant at 10%; ** significant at 5%; *** significant at 1%

8.4 Determinants of productivity dispersion

The relationship between R&D intensity and productivity dispersion is the final missing link in the chain from R&D to productivity enhancing restructuring. The verification of this relationship completes the picture of the creative destruction process outlined in Graph 8.1.

Narrowing labour input-weighted labour productivity dispersion among plants (ó-convergence) can be a consequence of a negative correlation between the initial productivity level and subsequent productivity growth (â convergence) or, with unchanged relative productivity levels, a reallocation of labour input away from plants of the lowest productivity (see results in Table 7.1 in Chapter 7). The former factor can be evaluated with the catching-up term and the latter with the between plants component. For example, tightening competitive pressure may suppress productivity dispersion by forcing low productivity plants to improve their conduct (adoption effect) or by cleansing the low productivity plants (selection effect) (Boone 2000).

This issue is evaluated by performing a simple regression analysis with manufacturing time-series data on productivity dispersion and the micro-level components of productivity. The differenced log of the labour-weighted coefficient of the variation of labour productivity ($\Delta ln(CVLP)$) is used as the dependent variable. The explanatory variables include productivity components attributable to external adjustment (the between component, *BW*) and internal adjustment (the catching up component, *CH*). Again, a trend variable is included in the model. The results are very much in accordance with expectations.

$$\mathrm{dln}(CVLP(\mathrm{t})) = \underset{(0.037)}{-0.020} - \underset{(1.86)}{3.77}*BW(\mathrm{t}) - \underset{\substack{(1.84)\\(**)}}{5.34}*BW(\mathrm{t-1}) + \underset{\substack{(0.76)\\(***)}}{2.94}*CH(\mathrm{t}) + \underset{\substack{(0.65)\\(**)}}{1.59}*CH(\mathrm{t-1}) - \underset{\substack{(0.003)\\(**)}}{0.006}*TREND \qquad (8.5)$$

N = 22, $R^2 = 0.687$, adj. $R^2 = 0.589$. (***) denotes 1 % and (**) 5 % significance level.

The restructuring of labour among plants, which is reflected in the between component of the manufacturing labour productivity growth rate (variable *BW*), tends to compress productivity dispersion.[127] Moreover, above-average productivity growth among the low productivity plants curbs the increase of labour productivity dispersion, which can be inferred from the positive coefficient of the catching-up variable.[128] Maliranta (2001) noted that the between component of total

[127] Earlier the between component was explained by productivity dispersion. However, it should not be concluded that the between component is endogenous in (8.8) or later in Tables 8.6 or 8.7. The earlier models imply that the between component is dependent on the past dispersion.

[128] Diagnostic tests indicate that the model is quite satisfactory.

factor productivity also seems to predict labour productivity dispersion. I have also estimated models where the explanatory variables are differenced and the dependent variable is differenced twice. These results validate the discovery that the micro-structural component is important for the development of productivity dispersion (the results are not reported here). Maliranta (1997b, pp. 23-24) has used a slightly different indicator of industry inefficiency, but finds evidence of a negative relationship between the between component and industry inefficiency change.

All in all, the simple model quite well predicts the changes in manufacturing productivity dispersion over time. It suggests that the downward tendency in productivity dispersion in Finnish manufacturing since the mid-1980s can be explained by the appearance of productivity-enhancing structural changes at the plant level.[129] This finding is striking for two related reasons. The tendency in Finnish productivity dispersion is in sharp contrast with that in the United States. Moreover, the results by Foster, Haltiwanger, and Krizan (2001) obtained with a method most comparable with *MBJ* (that is, the GR method with input weights) suggest that the between component has played a minor role in the evolution of aggregate labour productivity growth in US manufacturing (see also Graphs 5.23 and 5.24).

Next I move from manufacturing time series analysis to industry panel evidence. Now I use both labour and total factor productivity measures. They are in the differenced form. The results of the FGLS estimations are given in Table 8.6. Some evidence is found that initially an increase in R&D intensity is negatively associated with productivity dispersion change, but the lagged effects seem to be positive. However, the long-run effects do not differ significantly from zero for labour productivity and have significant negative effects for total factor productivity, which is opposite to what might be expected. The negative long-run effects derive from the large negative current effects.

Imports seem to compress productivity dispersion, but increased exports lead to increased divergence among plants in terms of productivity. The between component of productivity change is also included (Models (2) and (4)). Positive coefficient estimates suggest that creative destruction entails compression of productivity dispersion.

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[129] We have also performed the analysis by measuring productivity dispersion with the standard deviation of log labour productivity and with the P90-P10 differential of log productivity (with labour input weights). It should be noted that there were some differences in the pattern of the series. The latter measure of productivity dispersion, in particular, does not exhibit a downward tendency in labour productivity dispersion. My measure of labour productivity dispersion, i.e. ln(*CVLP*) appears to be more closely correlated with the P50-P10 differential of log productivity (r=.62) than with the P90-P10 differential (r=.20). See also Graph 1.5 in Chapter 1.

The results from the corresponding GMM estimations are given in Table 8.7. Some further support for the previous findings can be seen in the case of labour productivity. However, I do not find statistically significant evidence that R&D has positive long-run effects on productivity dispersion. Again, we note that the be-

Table 8.6 The determinants of the change in productivity dispersion, the FGLS estimations

	Labour productivity (1)	(2)	Total factor productivity (3)	(4)
Δ(prod. disp.) (t-1)	-0.304***	-0.245***	0.489***	0.396***
	(5.13)	(4.18)	(9.08)	(6.59)
ΔRD(t)	-1.125	-2.177***	-4.804***	-6.024***
	(1.50)	(2.70)	(4.30)	(5.06)
ΔRD(t-1)	0.897	0.399	1.665	2.499**
	(1.19)	(0.48)	(1.44)	(2.02)
ΔRD(t-2)	1.362*	0.767	-1.921	-1.507
	(1.73)	(0.88)	(1.58)	(1.18)
ΔIMP(t)	-0.166	-0.235	0.463**	0.378**
	(1.15)	(1.45)	(2.14)	(2.09)
ΔIMP(t-1)	-0.604***	-0.697***	-0.580**	-0.725***
	(3.95)	(4.13)	(2.57)	(3.79)
ΔEXP(t)	-0.243*	-0.197	0.209	-0.016
	(1.67)	(1.29)	(1.07)	(0.09)
ΔEXP(t-1)	0.763***	0.866***	0.636***	0.575***
	(5.16)	(5.63)	(3.17)	(3.18)
BW		-2.168***		-2.782***
		(4.19)		(3.56)
Year effects	Yes	Yes	Yes	Yes
Long-run effects[1]				
R&D intensity	.870	-.812	-9.903**	-8.324***
Imports	-.591***	-.749***	-.228	-.574
Exports	.400**	.538***	1.656***	.925**
Observations	252	252	240	240
Number of tol79s	12	12	12	12
Diagnostics				
AR(1)	-0.0278	-0.0725	-0.0784	-0.0592
Joint signif. of year effects[2]	0.0000	0.0000	0.0000	0.0000

Notes: Absolute value of z statistics in parentheses. All models are estimated by the feasible generalised least squares method (FGLS), where heteroscedasticity with a cross-sectional correlation is allowed. [1]The estimates for the long-run effects are obtained by the delta method. [2]The joint significance of the sets of explanatory variables is tested by the WALD test. These test statistics are reported as p values. As for evaluating autocorrelation, a common AR(1) is allowed.

* significant at 10%; ** significant at 5%; *** significant at 1%

tween component is negatively related to the change in productivity dispersion. The results for total factor productivity are more fragile. In fact, they do not give any support whatsoever to the hypothesis regarding the relationship between R&D and productivity divergence.

Table 8.7 The determinants of the change in productivity dispersion, GMM estimations

	Labour productivity		Total factor productivity	
	(1)	(2)	(3)	(4)
Δ(prod. disp.) (t-1)	0.364***	0.324***	0.432***	0.423***
	(6.62)	(6.77)	(12.06)	(11.31)
ΔRD(t)	-0.815	-0.557	-2.623**	-2.815**
	(1.21)	(0.88)	(2.52)	(2.29)
ΔRD(t-1)	2.250***	1.893***	4.218***	4.215***
	(3.32)	(2.64)	(3.85)	(4.06)
ΔRD(t-2)	-0.139	-0.210	-1.427**	-1.579**
	(0.11)	(0.19)	(2.23)	(2.28)
ΔIMP(t)	0.002	-0.131	-0.085	-0.037
	(0.01)	(0.71)	(0.77)	(0.33)
ΔIMP(t-1)	-0.144	-0.043	0.024	-0.012
	(0.97)	(0.30)	(0.15)	(0.08)
ΔEXP(t)	-0.226	-0.156	-0.008	0.014
	(1.05)	(0.71)	(0.04)	(0.08)
ΔEXP(t-1)	0.022	0.143	0.210	0.175
	(0.22)	(1.47)	(1.45)	(1.28)
BW		-1.250***		0.223
		(3.54)		(0.67)
Long-run effects				
R&D	2.039	1.665	.296	-.311
Imports	.265	-.257	-.107	-.085
Exports	-.322	-.018	.356	.329
Observations	216	216	216	216
Number of industries	12	12	12	12
Diagnostics				
Joint signif. of time dummies	0.0000	0.0000	0.0000	0.0000
First-order autocorrelation	0.0055	0.0076	0.0286	0.0321
Second-order autocorrelation	0.4399	0.3523	0.8754	0.8421
Sargan test of overrid. restr.[3]	1.0000	1.0000	1.0000	1.0000

Notes: One-step results are reported. Robust t statistics in parentheses. [1]The estimates for the long-run effects are obtained by the delta method. [2]The joint significance of the year dummies is tested by the WALD test. [3]The Sargan test for the validity of over-identifying restrictions is obtained from the estimations where homoscedastic error is assumed. All test statistics are reported as p values.
* significant at 10%; ** significant at 5%; *** significant at 1%

To sum up, the between component appears to do the job of cleansing low productivity input use. These results give support to the conclusion made by Baldwin (1993) that turnover directly improves industry efficiency.

8.5 Discussion

In this chapter I have shown that innovation activities, measured by R&D efforts, and international trade affect industry productivity growth through plant-level restructuring. This channel of effects can be argued to be a neglected part of the analysis of industry development.

I have deliberately ignored other micro-level components of industry productivity growth in this analysis. Although the annual entry and exit components are certainly part of the creative destruction process, these numbers are likely to be less reliable than those of the between component. However, we have obtained evidence that exits, in particular, are related to the between component, which suggests that both of these indicators gauge the intensity of the productivity-enhancing restructuring process (see Graph 5.8). Furthermore, Graphs 5.16 and 5.19 show that a dominant portion of the between component can be attributed to relatively young plants, which proves that entry is an important constituent of renewal, when it is viewed as a time-consuming process.

I have experimented by explaining the within plants component with similar kinds of models to those used here for explaining the between component. The results are much less robust. However, if one is interested in the determinants of productivity growth through internal adjustment, i.e. plant productivity growth, an approach that is a more suitable for that purpose should be used. Such is the approach that I applied in Chapter 6, where the factors of plant productivity growth were investigated (see Tables 6.3 and 6.4).

9 Micro-level dynamics of factor income shares

At the end of Chapter 8 we found that the compression of productivity dispersion between plants is one of the consequences of external adjustment. In this chapter we analyse how productivity-enhancing restructuring is reflected in the micro-level dynamics of factor income shares.[130]

9.1 Introduction

The downward tendency in the labour income share in the Finnish economy since the 1980s has attracted attention (see for example Pohjola 1998a; Sauramo 2000; Ripatti and Vilmunen 2001). This type of drift in income shares can be found in manufacturing and in many other sectors (Kyyrä 2002). Not so surprisingly, this has raised discussion on whether a response should be made in collective bargaining between the trade unions, confederations of employers and the government.

The increase in the capital income share is a direct consequence of the rapid aggregate labour productivity growth that has exceeded the real wage growth. Earlier studies in this field are characterised by use of the representative firm model. Ripatti and Vilmunen (2001), for instance, argue that it is essential to have a flexible representation of technology when analysing technological change and the changes in factor income shares. However, even though the production structure is gauged with a flexible representation, each and every firm and plant are still assumed to share the same technology and productivity level. It is also worth remarking that aggregate productivity growth is usually measured with some ideal productivity index based on a flexible function, which provides us with a close approximation to an arbitrary technology. As shown in Section 3.2, when aggregate productivity growth is decomposed into micro-level sources by some appropriate method, there is no need to assume that all firms (and plants) share the same productivity level, or factor income shares for that matter.

In this chapter I assert that it is essential to take into account that firms and plants are different in terms of technological level, profitability and labour demand, but are more or less similar in terms of the available labour supply. Productivity-enhancing restructuring, which is entailed by technological advances, is likely to be reflected in the micro-level dynamics of factor income shares between labour and capital.

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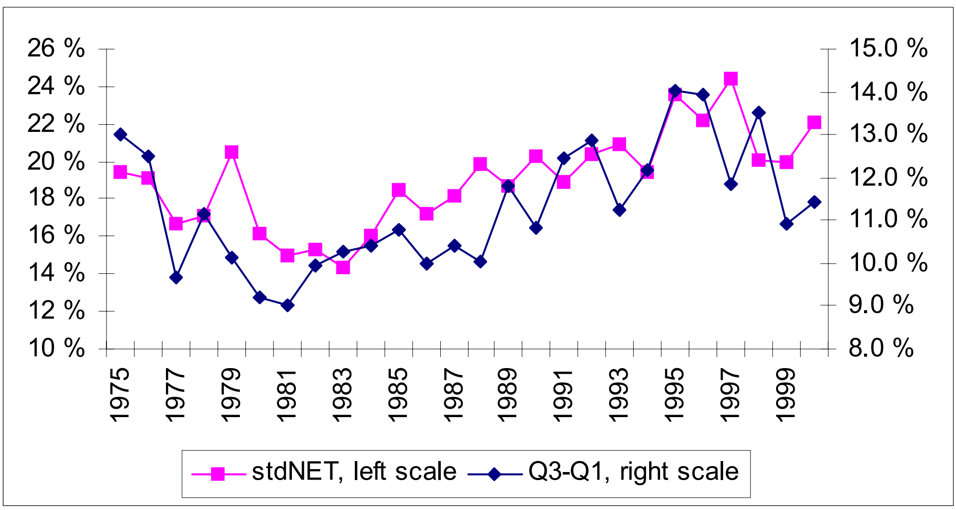
[130] The stimulus for this chapter came from several discussions with Pekka Sauramo about the development of factor income shares in Finland.

Plant-level restructuring is a consequence of the fact that labour demand varies between plants. For example, we noted in Graph 5.9 that those plants that will disappear in the near future have accounted for an increasing share of employment in Finnish manufacturing since the mid-1980s. At the same time, new plants have had an increasing share in manufacturing sector employment. As was argued earlier, while entries and exits are usually only certain steps taken during the life-cycle of a typical plant, the march of renewal may be better portrayed in the short run by analysing the changing shares among incumbents that are in different stages of their life-cycles.

To provide an illustration of the trends in the intensity of restructuring in Finnish manufacturing, I measure the growth of employment in plant *i* in year *t* by $NET_{it} = (L_{it}-L_{i,t-1})/(L_{it}/2+L_{i,t-1}/2)$, where L is now the number of employees. The divergence in this indicator of growth among incumbent plants can be measured by the labour input-weighted standard deviation (*stdNET*) or by the difference of the labour-weighted 3rd and 1st quartiles of the distribution. Graph 9.1 demonstrates that plant-level restructuring markedly intensified from the mid-1980s up to the latter part of the 1990s. In other words, the heterogeneity of labour demand seems to have increased.

In Section 5.3.3.2 (see Graph 5.20) and in Chapter 8 we saw evidence that increased R&D intensity and exposure to global competition have played an important role in the restructuring of Finnish manufacturing. Though a noticeable acceleration in labour productivity growth can be found from the mid-1980s, productivity growth within plants stayed relatively stable over the period 1975-2000 (this was seen clearly in Graph 5.14).

Graph 9.1 Dispersion of labour growth among incumbent plants



These considerations invite us to ask whether the steady decline in the labour income share in Finnish manufacturing and the increased productivity-enhancing restructuring experienced especially since the mid-1980s (and possibly the increased R&D intensity) have something to do with each other.

The rest of this chapter is organised as follows. A simple model of the life-cycles of firms and the determination of the aggregate labour income share is presented and some of its implications are discussed in Section 9.2. The empirical analysis of income shares is performed in Section 9.3 by using decomposition methods. Section 9.4 concludes the chapter.

9.2 A simple model of the life-cycles of firms

9.2.1 The phases of a firm's life-cycle

I illustrate the restructuring process by means of a simple overlapping-generations model. At each point of time there are two single-plant firms, each belonging to a different sequential technology generation.[131] The new firm of decade t is denoted by 2 and the incumbent by 1.

Firm 2's profits in its first and second decade are π_{2t} and $\pi_{2,t+1}$, respectively. Analogously firm 1's profits were $\pi_{1,t-1}$ in decade t-1 and are π_{1t} in decade t. To generate value added y each firm uses in each decade one unit of labour whose unit cost is w. In the first decade each firm generates tangible and intangible assets by means of investments i that are needed for the implementation of the technology choice. Production is sold in a competitive market at price 1.

In the first decade the profits of firm 2 are

$$\pi_{2t} = y_{2t} - w_{2t} - i_{2t} \qquad (9.1)$$

and in the second decade

$$\pi_{2,t+1} = y_{2,t+1} - w_{2,t+1} \geq 0 \qquad (9.2)$$

Production is required to be profitable in the second decade (the operating margin is positive). In this model a firm stops operating after two decades. Later, I will mostly consider situations in which the operating margin would be negative in the third decade, due to an increase in wages in the labour markets. Alternatively, we may assume that firms' capital becomes unusable after two decades.

[131] Of course the firm demographics of this type involving only entries and exits overlook the time-consuming nature of appearance and disappearance that is emphasised on several occasion in this study. In the empirical part of this chapter I will study what happens among continuing plants.

Firm 2 decides to enter if

$$\pi_{2t} + \beta \cdot \pi_{2,t+1} \geq 0, \tag{9.3}$$

where the discount factor $\beta < 1$.

9.2.2 Labour markets

Wages and employment are determined by centralised bargaining.[132] The efficient outcome that is reached involves identical wages for identical workers, that is to say $w_{1t} = w_{2t}$, and full employment (i.e. both of them are employed). Each firm is presumed to take the wage as given (as in competitive labour markets). The wage is increased at the rate of aggregate productivity growth in the previous period, so that labour and capital income shares stay constant. Given full employment, this can be expressed formally as follows

$$w_{1,t+1}/w_{1,t} = (y_{1t}+y_{2t})/(y_{0,t-1}+y_{1,t-1}), \tag{9.4}$$

where y_0 is the value added of a firm in decade t-1.

The level of wages is set so that firms do not earn excess profits over their life cycles. As there is full employment, labour and capital income shares are determined in the collective bargaining as well. In other words, labour share a in the economy is as follows:

$$a_t = (w_{1t}+w_{2t})/(y_{1t}+y_{2t}) \tag{9.5}$$

9.2.3 Productivity

Here technology parameter A includes the intangible and tangible capital needed to produce value added y by using one unit of labour, i.e.

$$y_{2t} = A_{2t} \text{ and } y_{1t} = A_{1t} \tag{9.6}$$

Technological development is assumed to take place in cumulative steps that can be characterised by a quality ladder model (see, for example, Klette and Griliches 2000). The next generation firm benefits from the new technological opportunities created by the previous technology. Each implemented technology A is presumed to enclose potential new production possibilities $b \cdot A$ ($0 < b < 1$) for the next genera-

[132] The model bears some resemblance to the so-called EFO model that is used to characterise the determination of inflation and wage growth in Scandinavian countries.

tion. However, seizing the opportunity requires investments in knowledge formation. To discover and implement new production potential, a firm needs to make R&D investments as well as investments in tangible assets.[133]

To keep things as simple as possible, let us assume that to take the next technology step, $A_{2t}/A_{1,t-1} = (1+b)$, requires R&D expenditures to the amount of $b \cdot y_{1,t-1}$ and other investments $d \cdot y_{1,t-1}$, where d is a constant.[134]

When a technology step is taken, a new entry is made with investments to the amount of $i_{2t} = (b + d) \cdot y_{1,t-1}$.

A plant may also experience productivity growth in the second decade due to learning-by-doing,

$$y_{2,t+1} = (1+c) \cdot y_{2t}. \qquad (9.7)$$

If $c > 0$ productivity increases due to more efficient use of the initial technology A_{2t}. If production potential deteriorates over time, c may be negative.

In this model technological opportunities are determined exogenously, but they are materialised through the R&D (and other investments) of the new generation firms. In this respect the model bears some resemblance to those of Caballero and Hammour (1994) and Campbell (1997) that emphasise the potential role of entry and exit in technological development (see also Stein 1997). The aggregate productivity growth rate and R&D efforts are high when the number of new technological opportunities is high.

There is a strict positive relationship between aggregate R&D intensity and aggregate productivity growth by construction. This is in keeping with the usual empirical findings that suggest that social return on R&D exceeds private return.[135] Secondly, the productivity growth rate within firms is independent of the R&D intensity rate. This accords with the empirical evidence of Maliranta (2000b) who found no clear difference in productivity growth rates within plants between high and low R&D intensity plants.[136] Here R&D helps to build new high technology

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[133] The models by Pakes and Schankerman (1984) and Klette and Griliches (2000), for example, predict that increased innovative opportunities lead to a higher aggregate R&D intensity.

[134] So in this case the productivity growth rate equals R&D intensity, measured by R&D expenditures per value added. The investment ratio and tangible capital productivity are constant over time.

[135] A recent paper by Bassanini, Scarpetta, and Hemmings (2001) provides evidence on the effect of R&D intensity and a comprehensive review of growth-regression studies.

[136] It is worth noting that the returns on R&D investments are so high that a profit maximising firm will make any R&D efforts that are needed to fully utilise the opportunities available. Of course, any extra investments beyond that point would be a waste of money according to this model.

and high productivity firms (or plants) but is worthless in retooling the current technology in hand.

9.2.4 *Some properties of the model*

9.2.4.1 Aggregate productivity growth

The aggregate productivity growth rate p is

$$p = \frac{(y_{1t} + y_{2t})}{(y_{0,t-1} + y_{1,t-1})} - 1$$

$$\Leftrightarrow p = \frac{y_{1t} + (1+b) \cdot y_{1t} \cdot (1+c)^{-1}}{y_{1t} \cdot (1+b)^{-1} + y_{1t} \cdot (1+c)^{-1}} - 1$$

$$\Leftrightarrow p = \frac{y_{1t} \cdot (1+c)^{-1} [(1+c) + (1+b)]}{y_{1t} \cdot (1+c)^{-1} \left[(1+c) \cdot (1+b)^{-1} + 1\right]} - 1$$

$$\Leftrightarrow p = \frac{(1+c) + (1+b)}{(1+c) \cdot (1+b)^{-1} + 1} - 1$$

$$\Leftrightarrow p = \frac{(1+b)\left[(1+c) \cdot (1+b)^{-1} + 1\right]}{(1+c) \cdot (1+b)^{-1} + 1} - 1$$

$$\Leftrightarrow p = b \tag{9.8}$$

So the long-run aggregate productivity growth is independent of the productivity growth rate within plants. This is because now it is assumed that the new plant will not benefit from the productivity gains obtained in incumbent plants through learning-by-doing.

9.2.4.2 Labour share

The labour share is

$$a_t = \frac{w_{1t} + w_{2t}}{y_{1t} + y_{2_t}} . \tag{9.9}$$

At each point of time all workers are assumed to share the same wage. Therefore we have

$$\Rightarrow a = \frac{2 \cdot w_{1t}}{y_{1t} + (1+b) \cdot y_{1t} \cdot (1+c)^{-1}}$$

$$\Leftrightarrow a = \frac{2 \cdot w_{1t}}{y_{1t} \cdot \left[1 + (1+b) \cdot (1+c)^{-1}\right]} \tag{9.10}$$

The wage is set so that the expected present value of profits of the plants are squeezed to zero, i.e.

$$y_{1,t-1} - w_{1,t-1} - i_{1,t-1} + \beta\left(y_{1t} - w_{1t}\right) = 0 \tag{9.11}$$

The labour share is stable when the wage increases at the same rate as aggregate productivity. Using this property and (10.11) we obtain

$$y_{1,t} \cdot (1+c)^{-1} - w_{1t} \cdot (1+b)^{-1} - i_{1t} \cdot (1+b)^{-1} + \beta \cdot y_{1t} - \beta \cdot w_{1t} = 0$$

$$\Leftrightarrow y_{1t} \cdot \left[(1+c)^{-1} + \beta\right] - w_{1t} \cdot \left[(1+b)^{-1} + \beta\right] - i_{1t} \cdot (1+b)^{-1} = 0$$

$$\Leftrightarrow w_{1t} = \frac{y_{1t} \cdot \left[(1+c)^{-1} + \beta\right] - i_{1t} \cdot (1+b)^{-1}}{\left[(1+b)^{-1} + \beta\right]}$$

$$\Leftrightarrow w_{1t} = \frac{y_{1t} \cdot \left[(1+c)^{-1} + \beta\right] - (b+d) \cdot y_{1t} \cdot (1+c)^{-1}(1+b)^{-1}}{\left[(1+b)^{-1} + \beta\right]}$$

$$\Leftrightarrow w_{1t} = \frac{y_{1t} \cdot \left[(1+c)^{-1} + \beta - (b+d)(1+c)^{-1}(1+b)^{-1}\right]}{(1+b)^{-1} + \beta} \tag{9.12}$$

Inserting (9.12) into (9.10) we obtain the following formulation

$$\Leftrightarrow a = \frac{2 \cdot \left[(1+c)^{-1} + \beta - (b+d)(1+c)^{-1}(1+b)^{-1}\right]}{\left[1 + (1+b) \cdot (1+c)^{-1}\right]\left[(1+b)^{-1} + \beta\right]} \tag{9.13}$$

9.2.4.3 Numerical illustration of outcomes

A standard state is defined by the following parameter values:

- the technological step rate $b = 0.4$,
- the rate of learning by doing $c = 0.1$,
- the investment ratio $d = 0.6$, and
- the discount factor $\beta = 0.9$.

Under these circumstances the labour share $a = 63.2$ % and the investment ratio $i_t/(y_{1t}+y_{2t}) = 24.0$ %. The firms would have a negative operating margin in their third decade, so they will be closed down before that. A slight decrease in b (<0.39) or increase in c (>0.13) would make it profitable to operate in the third decade, as value added still exceeds the labour costs. So it is obvious that the survival (and entry) rates can be expected to be dependent on the parameters of our interest, e.g. b and c, as well.[137]

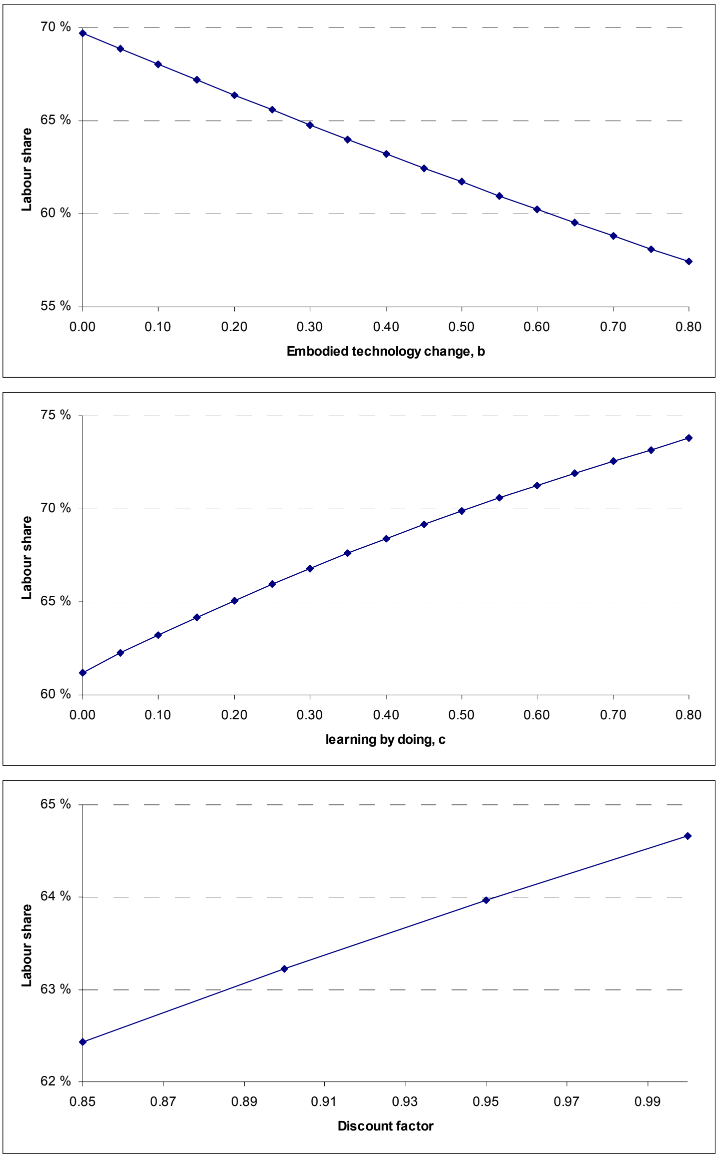
Graph 9.2 illustrates how the labour share changes, ceteris paribus, when the parameters b, c or β are varied. We see that the labour share is negatively dependent on b and positively on c and β. A doubling of the growth rate of technological opportunities (and R&D intensity and productivity growth) from 0.4 to 0.8 would mean a drop in the labour income share from 63 % to 57 %. This is, of course, due to the fact that it was assumed in (9.11) that sunk costs needed to capture higher technology opportunities by R&D and other investments must be met. On the other hand, the higher the productivity growth over a plant's life-cycle through learning-by-doing, the smaller is the proportion of value added needed to cover the given expenses.

9.2.4.4 Temporary increase in *b* or *c*

Next we look at a situation where in some decade, say in decade 3, an abnormal amount of technological opportunities emerge unexpectedly so that $b_{\text{decaded 3}}=0.4+0.1 = 0.5$ ($b_{\text{decaded 4}}=0.4$). A firm that happens to make an entry in that particular period will benefit from an unexpected technology stride potential that it will realise when making its investment decision. It will manage to reap a positive present value of profits during its life-cycle. In decade 3 the aggregate productivity growth rate is 0.456 but the wage increase is due to a lag that is assumed to be still 0.4 in decade 3. Therefore the labour income share will fall. In the next two decades the wage increase exceeds the aggregate productivity so that the labour share begins to recover (see Graph 9.3). Because the wages of both firms are determined according

[137] If flexibility in wage levels between firms that have varying labour productivity is allowed, i.e. $w_{1t}=f{\cdot}w_{2t}$ (f>1), old firms would, of course, have better prerequisites for survival.

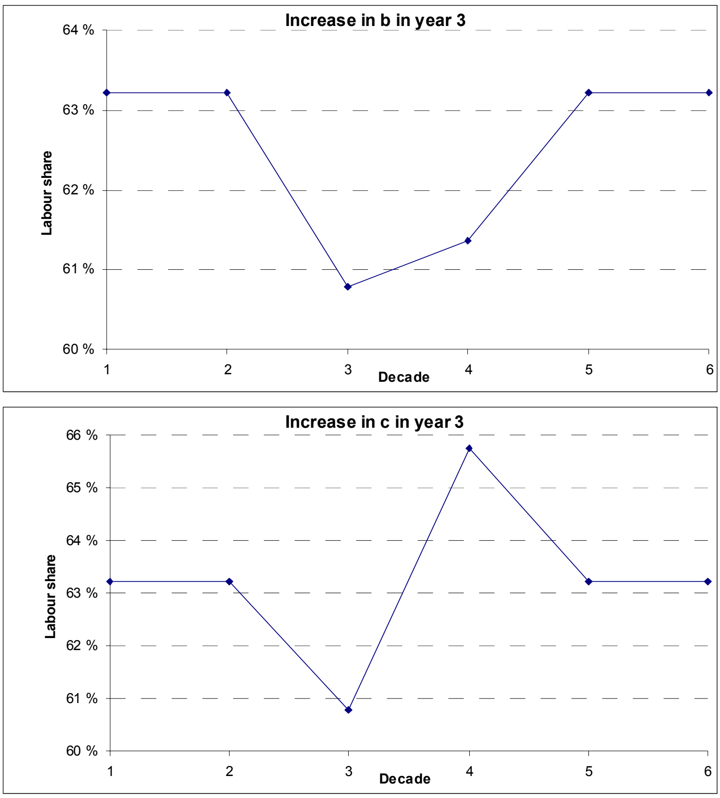
Graph 9.2 Labour share and productivity growth due to embodied technological change and learning-by-doing



to the aggregate productivity growth in the past, the second generation firm after the shock will also gain some positive profits.

The consequences of an unexpected temporary increase in learning-by-doing (c) from 0.1 to 0.2 are somewhat different. Contrary to what was the case with b, in this particular model a temporary increase in c does not have permanent consequences for the later technology and output levels (see equation (9.8)). A firm experiencing abnormal growth in productivity in the latter part of its life-cycle gains a positive present value of profits, but the next new firm suffers a loss due to increased aggregate productivity growth stimulated by the gainer.[138] Of course, a mirror-image is obtained when *c* unexpectedly falls due to recession, for example. Then the incumbent of the recession period suffers a loss through its low productivity growth rate, and the labour share increases. However, the next generation plant gains extra profits thanks to the previously lowered aggregate productivity growth rate. Thus, an income transfer takes place between plants belonging to different generations.

Graph 9.3 Unexpected increase in b and c



Note: In the first case (upper diagram) the shock involves an increase in *b* from 0.4 to 0.5 and in the second case (lower diagram) an increase in c from 0.1 to 0.2. In both cases, a shock takes place in decade 3.

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[138] Of course, in this case the next generation firm would not have made an entry, if it had known that the rise in learning-by-doing rates was temporary.

9.2.5 Characterisation of the model with micro-level decomposition

Next I analyse what we can expect to find with the MBJ/INP method when development can be characterised by the simple model presented above. I explore the micro-level dynamics of aggregate productivity, aggregate factor incomes shares and aggregate wage growth.

9.2.5.1 Aggregate productivity growth

In the standard state of the model defined in the previous section, the aggregate productivity growth rate is 33.3 % measured by the MBJ/INP method. The within component is 9.5 %, which in this case indicates the rate of learning-by-doing.[139] In the model there is no restructuring among incumbents so that the between component is zero. The catching up term is zero as well.

The entry effect is 12.8 % and the exit effect 11.3 %. Of course, the entry and exit effects are positively dependent on the value of *b*. When $b = 0.6$, the entry effect is 20.5 % and the exit effect 17.0 %. The parameter *c* in turn is negatively related to the entry and exit effects.[140]

The effects of a temporary increase in *b* and *c* on the entry and exit components are depicted in Graph 9.4. When there is an embodied technological shock indicated by an increase in *b*, we note that productivity-enhancing restructuring is intensified for some time. So this is a broadly similar picture to what we had in Graph 5.8. When the shock is such that it increases productivity growth among the incumbent plants, i.e. *c* increases, the dynamics of the "creative destruction" components are quite the opposite – as can be seen in the upper diagram of Graph 9.4. So the earlier evidence shown in Chapter 5, for example, supports the view that parameter *b* has increased in Finnish manufacturing.

9.2.5.2 Changes in aggregate factor income shares

Next I apply the decomposition method in the analysis of aggregate income shares. While I am interested in the role of restructuring in the determination of aggregate income shares, it is useful to set labour compensation as the denominator and value added as the numerator. So I examine the development of the inverse of the labour

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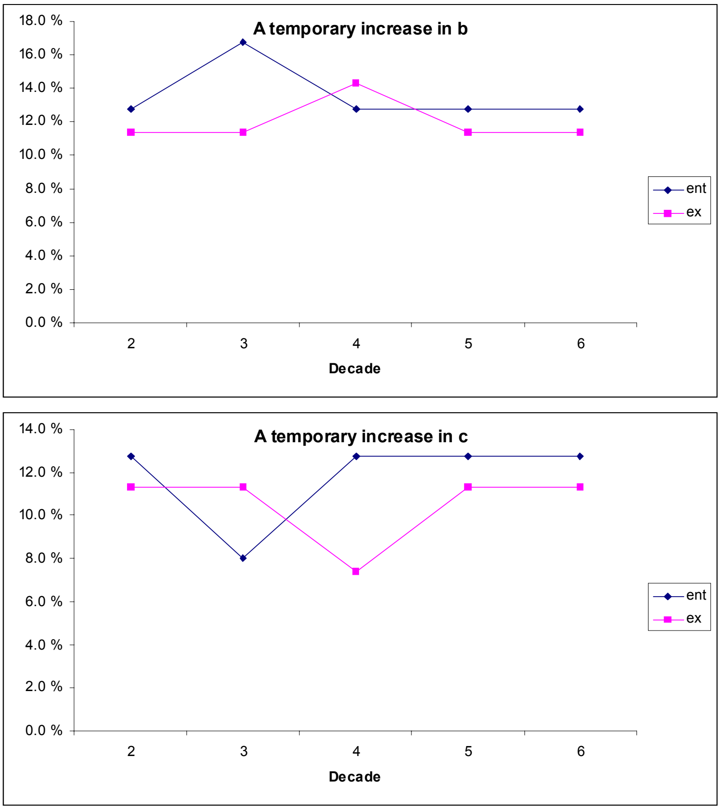
[139] It should be noted that the rate of growth is measured here by $\Delta Y/\overline{Y}$ instead of $\Delta Y/Y_{t-1}$. For example, when $\Delta Y/Y_{t-1}= 0.1$ then $\Delta Y/\overline{Y} \approx 0.095$.

[140] It is worth remarking that it would be difficult to interpret the results obtained by the FHK or GR methods. In the standard state, the numbers with the FHK method for the within, entry and exit components are 4.8, 22.9 and 6.0 percent respectively.

Graph 9.4 Dynamics of productivity growth



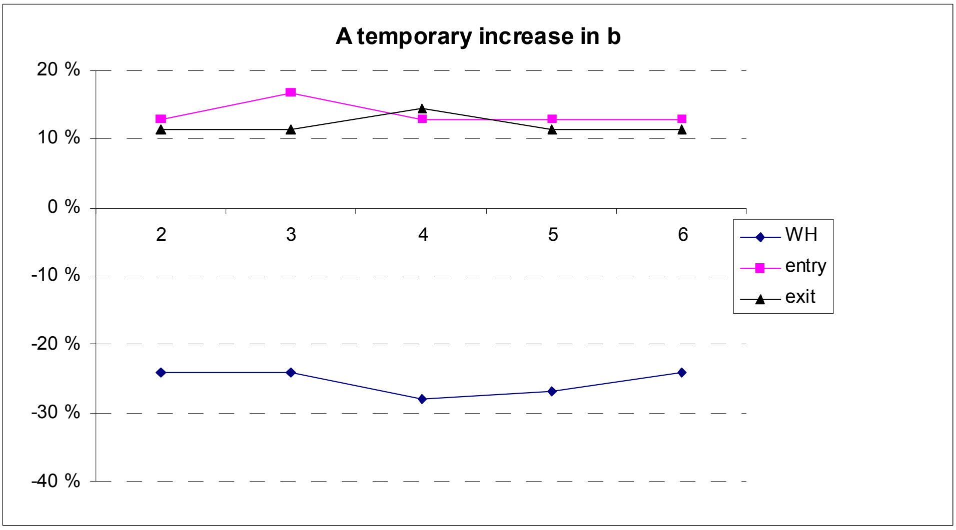
Note: Aggregate productivity growth is decomposed by the MBJ/INP method.

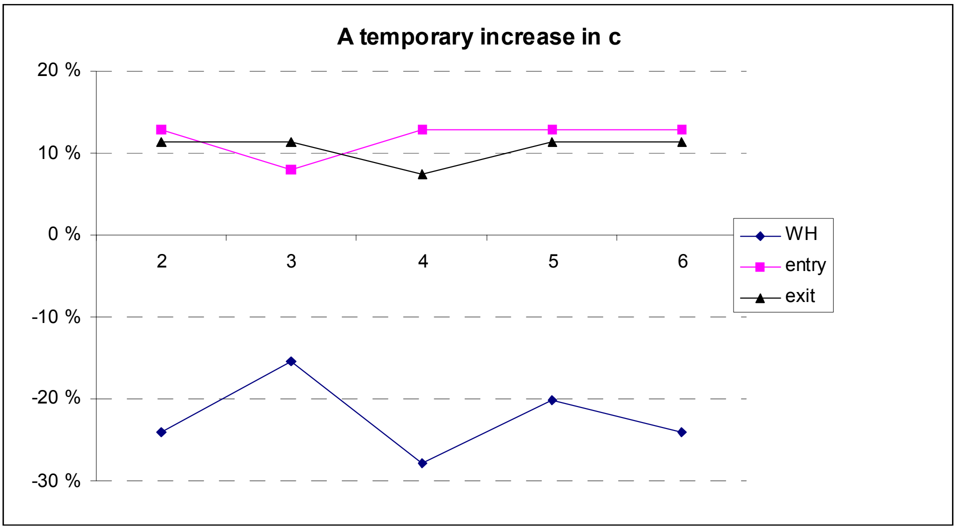
income share. Again, the decomposition of aggregate change is done by the MBJ/INP method shown in Equation (3.4).

Again, as there is only one incumbent at each point of time in the model, the between and catching up components are zeros. In the standard state of the model the within component is -24.0 %, indicating that the labour share increases within plants. As for the "creative destruction" components, the results are similar to those for productivity. This is because now it is legitimate to measure labour input by labour compensation in the cross-sectional productivity comparisons. The entry effect is 12.8 % and the exit effect 11.3 %. When b is higher (b = 0.6), the entry and exit effects are higher (entry is 20.5 % and exit 17.0 %) and the within component more negative (-37.0 %).

A temporary increase in b from 0.4 to 0.5 is reflected in the components in the manner illustrated in Graph 9.5. An increase in b is reflected in the restructuring

Graph 9.5 Dynamics of the inverse of labour share





Note: The aggregate growth of value added per labour compensation is decomposed by the MBJ/INP method.

components, so that first the entry effect is lifted and later the exit effect. The within component (*WH*) reacts with a delay by first declining and then recovering gradually to the initial level. So a technology revolution first increases the capital share through the entry and later through the exit effect. The return to the initial standard state of income shares takes place through the within component with a lag (the within component is lowered). Again, the dynamics are quite different when the shock involves a temporary increase in *c*.

9.2.5.3 Aggregate wage growth

The decomposition method can be used for the analysis of wage increases, too. One pivotal feature of the model is that identical workers share an identical wage. As a consequence both entry and exit components are zeros and the wage increase takes place within plants.

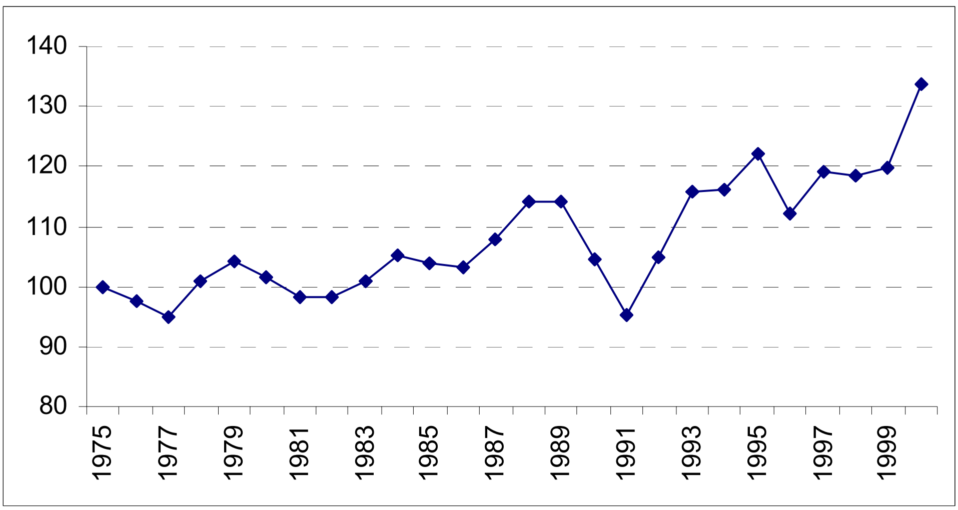
9.3 Empirical analysis

9.3.1 Manufacturing-level analysis

Next I study the micro-level dynamics of factor income shares and wage growth in Finnish manufacturing. In particular, I investigate whether the empirical evidence is consistent with the conjecture that, on the one hand, Finnish labour markets are characterised by wage compression between plants, while on the other hand there has been technological progress that requires micro-level restructuring.

Again, the data are from the LDPM data set. Graph 9.6 exhibits the development of aggregate value added per labour compensation. We see that the ratio started to increase in the mid-1980s, declined during the recession, but then bounced back to an upward trend. Labour's income share declined from 65 to 47 per cent from 1975 to 2000, which means that the value added per labour compensation ratio increased by 34 per cent[141] in this period.

Graph 9.6 Development of value added per labour compensation in Finnish manufacturing



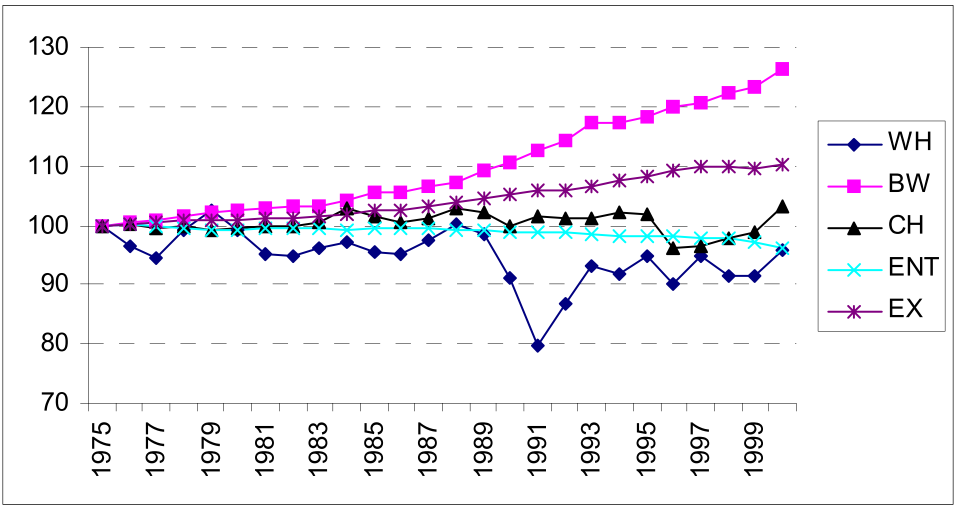
[141] The growth rate is measured here in a similar way to the MBJ method.

Next I will investigate the micro-level sources of the development depicted above. I will perform similar decomposition as earlier for productivity, but now labour input is replaced by labour compensation. Both the numerator, which is value added, and the denominator are measured in nominal terms. This, of course, is equivalent to deflating output and wages with the same deflators.

I have computed the components of the annual changes in "labour productivity"[142] by using the MBJ/INP method. To see the cumulative effects of the various micro-level sources, I have computed index series for the period 1975-2000 (1975=100).

We can see some decline in the "labour productivity" within plants, which is in agreement with the above considerations (Graph 9.7). The catching up component does not exhibit a trend in either direction. The entry component seems to have a (gentle) downward trend, which might be at odds with someone's expectations. However, as stated earlier, this is a short-run indicator of entry that fails to

Graph 9.7 The components of the aggregate value added to labour compensation ratio, 1975 = 100



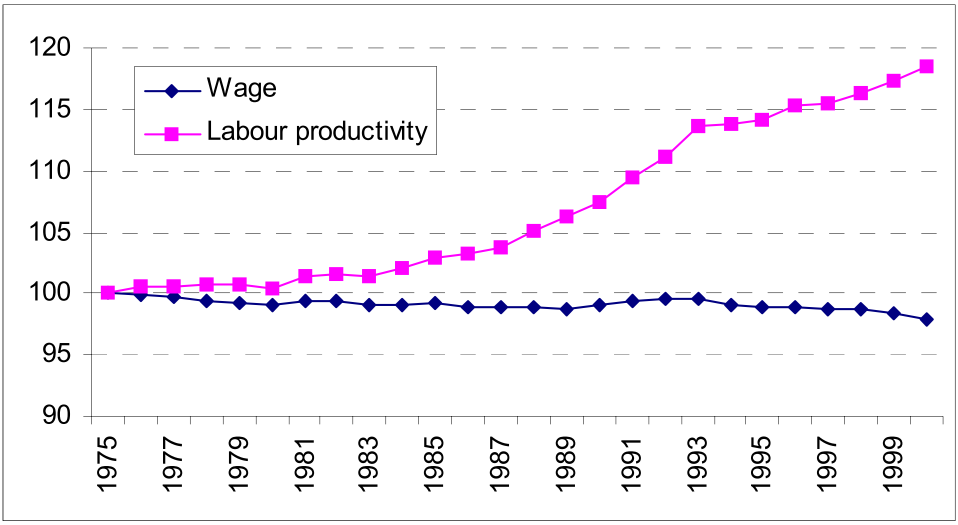
Note. The components of the annual changes are computed by the MBJ/INP method. The cumulative effect is measured by the index INDt=INDt-1·(1+0.5·at) · (1-0.5·at)-1, where at is the component of the annual growth rate in year t. IND1975=100.

[142] The quotation marks around "labour productivity" are due to the fact that this value added per labour compensation ratio may sometimes be interpreted as a measure of labour productivity.

capture the time-consuming process of entry. The annual between component is likely to pick up the important part of the renewal. As we see in Graph 9.7, the between component exhibits a positive trend, which became steeper in the mid-1980s. The cumulative effect of the between component has been substantial. In fact, the between and exit components are together larger than the increase in the aggregate value added per aggregate labour compensation ratio.

The between component of the value added to labour compensation ratio shows a similar time pattern to the corresponding component of the labour productivity, but the cumulative effect has been somewhat lower for the latter. Another way to examine this issue is to decompose aggregate hourly wage increases (measured in product wages) into micro-level sources.[143] As the change of labour's income share is directly dependent on the rate of wage growth relative to the rate of labour productivity growth, we can now conclude that the wage growth within plants exceeds the labour productivity growth within plants. This is one of the implications of my life-cycle model. The decomposition computations for aggregate hourly wage growth confirm the prediction. The wage growth within plants has indeed been about 10 per cent higher than labour productivity growth in the last quarter

Graph 9.8 The between component of wage and labour productivity growth



Note: Wage denotes total labour compensation per hours worked. Decompositions are done with the MBJ/INP method.

[143] In the following computations, wages include supplements, etc. To be precise, I look at the total labour compensation.

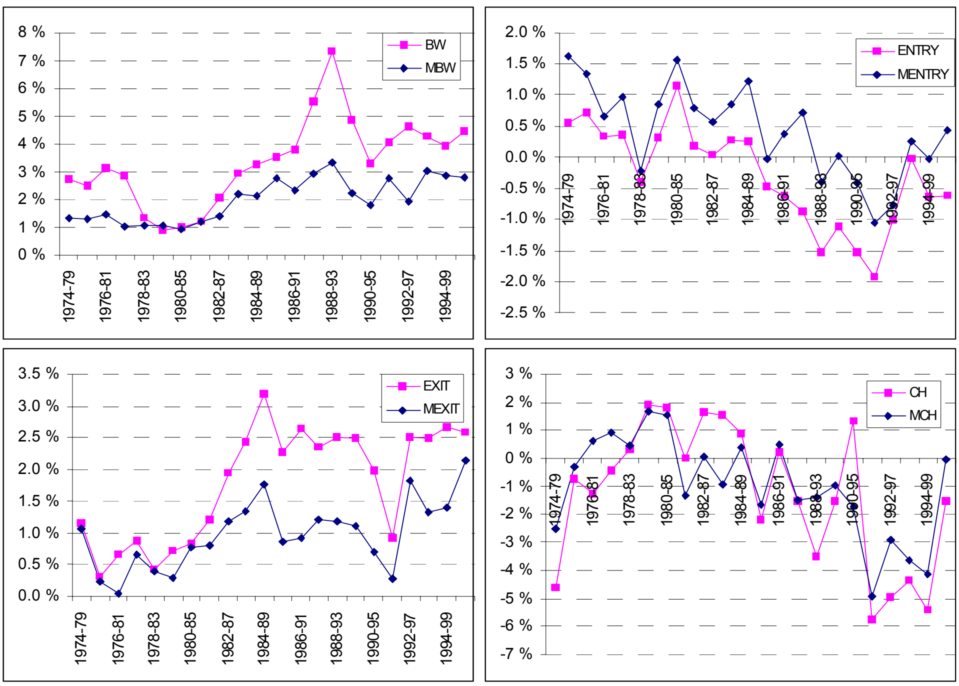
century. The between component of wage growth has been slightly negative, which explains the large between component of the value added to labour compensation change. The divergence of the between components of the wage and labour productivity (note, now without quotation marks!) growth is illustrated in Graph 9.8.

This and earlier analysis indicates that the restructuring has been towards high productivity plants, but not towards high wage plants. So we do not find evidence that restructuring has been "skill-biased" from this point of view, which is in line with the conclusion made in Chapter 6.

9.3.2 *Industry-level analysis*

Next I explore to what extent plant-level restructuring has changed the factor incomes shares through changes in industry structures. At the same time I examine whether there has been restructuring within industries that can be expected when

Graph 9.9 Micro-level sources of the changes in factor income shares in total manufacturing and within 3-digit industries



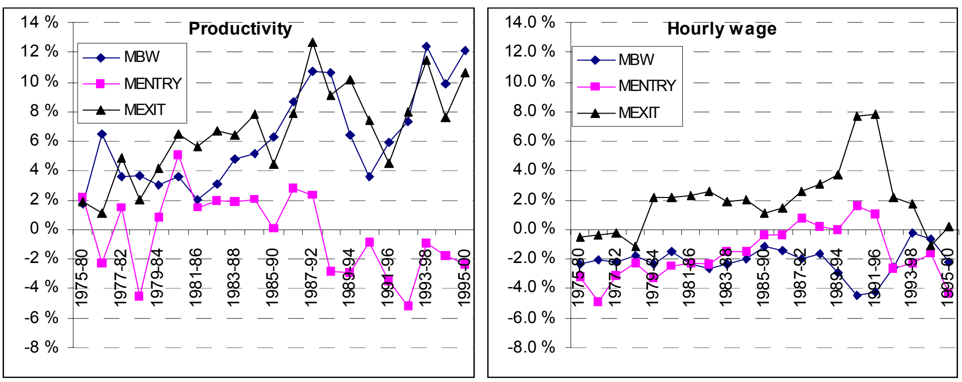
Note: The *M* letter denotes that the component is aggregated from industry-level components by using labour compensation shares as the weight.

the new technologies used in producing certain types of products are substituted for old, less profitable technologies. I have performed decompositions separately for different industries and aggregated the industry-level results at the manufacturing level. Aggregation from the 3-digit industry-level results (87 industries), which is done by using the industry shares of labour compensation as weights, is indicated by the letter *M* (see Graphs 9.9 and 9.10). To better capture the long-run tendencies, these computations are made for 5-year moving windows. For the sake of comparison I have also shown computations made at the total manufacturing level (components without the letter *M*).

A couple of conclusions can be drawn from the graph. First, it turns out that a significant proportion of the increase in the aggregate capital share of total manufacturing can be attributed to changes in industry structures (i.e. there is a gap between the *BW* and *MBW* components). Still, restructuring among incumbents within 3-digit industries has been at least equally important. We can also note that the entry component rises when the industry effect is taken into account. The entry effect is now usually positive, or at least not very much negative. A quite drastic change can be found for the exit effect. Labour's income share in the exiting plants does not differ very much from the industry-average. We see that in the most recent two decades *EXIT* has been clearly higher than *MEXIT*, which suggests that exits are particularly common in those industries where labour share is high.

Quite in keeping with the previous findings, we noted from Graph 5.21 that roughly one half of labour productivity enhancing restructuring among incumbent

Graph 9.10 The proportion of the between, entry and exit components of the aggregate labour and hourly wage growth at the 3-digit industry level

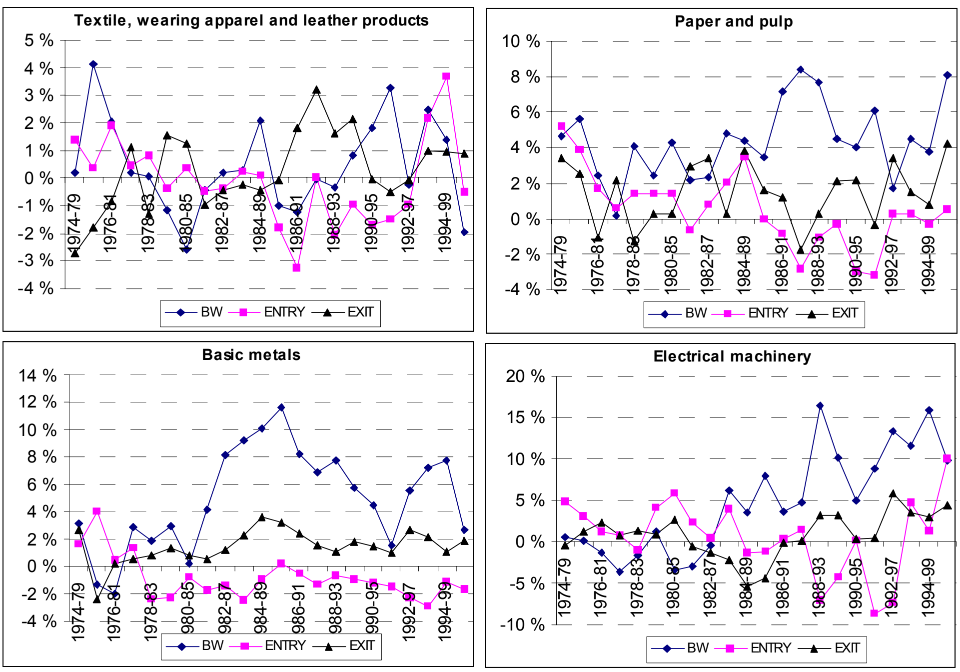


Note: The *M* letter indicates that these manufacturing-level results are obtained by aggregating industry-level results (3-digit level, 87 industries) by using worked hours (average of initial and final year) as weights.

plants has taken place within 3-digit industries. Unreported results indicate that the entry effect is clearly higher at the detailed industry level (usually positive) than at the total manufacturing level. The exit effect, in turn, is lower when the productivity of disappearing plants is proportioned to the industry-average instead of the manufacturing-average.

In Graph 9.10 the effects of micro-level restructuring on aggregate productivity and wage growth at the 3-digit industry level are compared. Exceptionally I now present the effects of the components as the shares of the aggregate change rate. We see that while the between component (*MBW*) has an important positive impact on productivity, the effect of this component has been even negative on aggregate wage growth. These findings tell us that while high productivity plants have gained labour input shares at a detailed industry-level, high wage plants have lost shares. Broadly consistent with the model, the entry and exit components of wage growth are usually relatively small in absolute values and often even nega-

Graph 9.11 Restructuring components of aggregate income share change in the selected four industries



Note: Decompositions are performed for 5-year moving windows by using the MBJ method. Plants employing fewer than 20 persons are excluded from the analysis.

tive.[144] However, the high exit effect on aggregate wage growth in the periods 1990-95 and 1991-96 seems to be the exception that proves the rule here. The entry effect of wage growth is usually negative, but we see that those plants established during the recession often had a relatively high wage level (the entry effect of hourly wage growth is positive in the early 1990s), whereas their relative labour productivity level was quite low at these times (see also Graph 5.10).

All in all, aggregate hourly wages and labour productivity have increased more or less at the same rate in the long run (labour productivity growth has been somewhat higher). But wage growth takes place mainly within plants, whereas micro-level restructuring has a significant role to play in labour productivity growth.

The findings shown above may hide a lot of differences across different industries. The restructuring components of the aggregate income share change in four different industries are shown in Graph 9.11. We find that the timing of the components may vary across industries. This suggests that technology and other shocks that may have stimulated turbulence at the plant level are at least partly industry-specific.

The between component was at its highest during the recession in the paper industry, whereas in basic metals the most intensive restructuring phase was experienced before that. Development in the manufacture of textiles and wearing apparel, a typical sunset industry, in turn is characterised by a high exit component during and before the recession and a high between component during the recovery period. In the electrical machinery industry, which is the most typical sunrise industry in Finland, the between component has risen since the late 1980s and has been very sizeable in recent years.

9.4 Discussion on the micro-level dynamics of factor income shares

I have shown that the main part of the increase in the capital income share in Finnish manufacturing in the 1990s can be attributed to plant-level restructuring. Profitable plants that have high capital income shares have increased payroll shares at the cost of low profitability plants. The restructuring contributed very little to the

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[144] In the period 1987-92 the restructuring components, i.e. the between, entry and exit components, account for 25.7 percent (15.0 percent before the recession in 1984-89) of the aggregate labour productivity growth. The corresponding number for the aggregate hourly wage growth is 1.4 percent (-1.4 percent in 1984-89). In the last period of the analysis, 1995-2000, the restructuring components make up 20.4 percent of labour productivity and -6.3 percent of hourly wage growth.

aggregate changes in the income shares up to the mid-1980s, but has been an important component since then. An important part of the restructuring has taken place within industries, even if changes in industry structures have played a role as well. There are interesting differences in the magnitudes and time patterns of the restructuring component of income share change between industries.

Plant-level restructuring has been productivity-enhancing, but has had little effect on aggregate wage growth. Wage growth within plants has exceeded that of labour productivity growth in the 1990s, which means that the labour income share has increased within plants, in contrast to what has happened at the aggregate level. On the other hand, the differences in the wage and productivity growth rates within plants are substantial in the short run. The labour share increases during downturns and decreases during booms. One of the purposes of this chapter is to explain why plant-level restructuring may affect aggregate capital income share and productivity change positively, but is irrelevant for aggregate wage growth.

The turbulent episode starting in the latter part of the 1980s in Finnish manufacturing has involved a considerable increase in R&D intensity, an outstanding acceleration of aggregate productivity growth that has taken place mainly through plant-level restructuring, and a declining aggregate labour income share. The plant-level restructuring process culminated in the recession and some signs of cooling down can be found in the late 1990s.

As a framework for this chapter I use a simple model of a firm's (plant's) life cycle that turns out to provide a coherent interpretation of the course of events. A central feature of the model is that a productivity leap requires implementation of technological discoveries at new plants.

This model implies that a technological advance needs to be embodied into new plants and it becomes materialised at the aggregate level through the restructuring components of aggregate productivity, while the within plants component remains unaltered. The earlier findings about the components of aggregate productivity in Finnish manufacturing are in keeping with the model in these respects. R&D intensity and (relatively) new plants have had an important role to play in the productivity-enhancing restructuring process. It is worth noting that the within component was roughly the same in low and high R&D intensity plants as it was in relatively new and old plants, again consistently with the model (see Section 5.3.3).

Although technological opportunities are determined exogenously, absorbed for example from Western markets, implementation requires investments involving sunk costs. When the rate of increase in technological opportunities is high, as may have been the case during integration with Western markets, R&D intensity needs to be high. In addition, a high operating margin is needed, since sunk costs need to be covered by the end of the plant's life-cycle. Thus high aggregate productivity growth can be expected to be associated with high R&D intensity and low labour income share.

It is assumed that under normal circumstances an efficient outcome is reached in centralised wage bargaining. It involves equal pay for equal work, full employment and wage increases that allow the investment costs of firms to be met. So the model bears features of the Rehn-Meidner model (see Erixon 2000). The policy rule according to which wages are increased at the rate of the past aggregate productivity growth is consistent with these goals. This guarantees non-negative profits and stable income shares between labour and capital as long as the aggregate productivity rate is unaltered.

Because wages are increased on the basis of aggregate productivity growth and because there is a lag in wage increases, a firm that makes an entry when a positive technology shock occurs derives the largest profits. Not all the fruits of a positive technology shock are harvested until the old plant established before the shock has disappeared. This is why the aggregate productivity growth rate is abnormally high even after the shock. The second generation plant after the shock is also able to capture some profits but, from the third period, workers are able to avail themselves fully of the outgrowth of the cake due to the initial positive technology shock.

Of course, the consequences of diminished growth of technological opportunities may be serious, if a simple policy rule of increasing wages at the rate of the past aggregate productivity growth is applied. Entry would not occur, since the later wage growth would exceed a rate that would guarantee non-negative profits.

We have not found much evidence that plant-level restructuring has led to disproportionate job destruction in low wage plants and disproportionate job creation in high wage plants. To put it differently, wage growth within plants has agreed with the aggregate wage growth with reasonable accuracy, as is assumed in the model. So, assuming that wage differences reflect skill differences, we do not find support for the view that productivity-enhancing restructuring has been essentially an outcome of a skill-biased technology shock.

While giving a description of the events compatible with many empirical features of Finnish manufacturing development, this simple model fails, however, to capture all the elements. A renewal process seems to have been in operation during the latter part of the 1980s, a period characterised by high and stable employment, which is in accordance with the model. The recession at the beginning of the 1990s entailed a 20 percent collapse in manufacturing employment in a couple of years and huge flows of workers from manufacturing plants to unemployment. One interpretation is that the recession was a separate episode caused by a huge demand shock or by a failure in monetary policy. The within component of the growth of value added to labour compensation ratio made a deep plunge (the labour income share within plants arose) and then quickly surged during the recovery. According to an alternative interpretation, the recession was a kind of culmination of the restructuring process that emerged gradually from the mid-1980s.

10 Conclusions and discussion

10.1 Motivation behind the study

This study has explored the plant-level sources of productivity growth. The Finnish manufacturing sector provides us with an interesting research subject for at least three reasons:

1. For the past two decades, the development of the Finnish manufacturing sector has been characterised by rapid productivity growth and catching up of the international technology frontier (Maliranta 1996). This provides us with an excellent opportunity to learn more about the micro-level determinants of fast productivity growth.

2. R&D intensity and innovation activities have increased markedly in Finnish manufacturing, which opens up the possibility of evaluating their effects on productivity development.

3. The Finnish manufacturing sector, like the whole of the Finnish economy, experienced an exceptionally deep recession in the early 1990s. Analysing the micro-level dynamics of productivity before, during and after such a hideous episode of economic development will help us to understand the key factors, features and consequences of the Finnish recession.

10.2 The role of "creative destruction" components

The decomposition of aggregate productivity growth into micro-level sources turns out to be an indispensable tool when trying to explore the characteristics of aggregate development. The analysis showed that the so-called "creative destruction" process among plants (and firms), as outlined by Schumpeter, has played a crucial role in the development of productivity in Finnish manufacturing and its industries. By using appropriate decomposition methods, one may conveniently identify and quantify the productivity influences of selection, experimentation and incessant reallocation of resources among plants. More work may be needed, however, to develop ideal productivity decomposition methods, equipped with thoroughgoing theoretical justifications.

The fact that aggregate productivity growth has exceeded productivity growth at the plant level suggests that the so-called "creative destruction" components i.e. the entry, exit and between components of aggregate productivity growth, have a role to play in the process of economic development. The exit component is positive when the exiting plants have a lower productivity level than the continuing ones while the between component is positive when input shares shift from low productivity plants to higher productivity plants among the incumbent plants. In the preferable decomposition methods the entry component is positive when new plants have higher productivity levels than the older ones.

The acceleration of manufacturing labour productivity growth in the mid-1980s can almost entirely be attributed to an increase in the "creative destruction" components. In fact, in the period from the mid-1970s to the mid-1980s, these components had little effect on labour productivity growth. The emergence of these growth effects for the years 1985-2000 cumulatively increased the aggregate labour productivity level by some 30 percent (see Graph 5.14). The importance of the "creative destruction" components has been even greater for total factor productivity, which can be seen as a more comprehensive indicator of productivity performance, as it is a combined indicator of labour and capital productivity. The analysis indicates that the reallocation of both labour and tangible capital shares among plants has fuelled aggregate total factor productivity growth. A related study by Böckerman and Maliranta (2003) shows that intra-industry reallocation has been most effective in term of productivity increases in Southern Finland and least effective in Eastern Finland.

All in all, the "creative destruction" components have been large enough to explain the outstanding speed of catching up of the international productivity frontier starting from the latter part of the 1980s (see Graph 1.4 for total factor productivity and Graph 4.4 for labour productivity). International comparisons of the "creative destruction" components of aggregate productivity growth confirm the exceptional intensity of productivity-enhancing restructuring in Finnish manufacturing.

A closer look at the "creative destruction" components reveals that both the exit and between components have been essential. Furthermore, these components appear to be quite closely correlated with each other. It seems that they both consistently gauge the intensity of the "creative destruction" process.

The entry component, in contrast, contributes negatively to labour productivity growth. This tells us that new plants, on average, have a lower labour productivity level than incumbent plants. Two remarks should be made at this point, however. Firstly, although the emergence of new plants lowers the average labour productivity level in the short run, the entries are crucial for development in the long run. Entry should be viewed as a time-consuming process. Entries entail a lot of experimentation and selection. The new plants, or at least some of them, carry the potential for high productivity. The results confirm conjectures about the significance of the entrants in the longer perspective. A disproportionately high share of the positive between component can be attributed to young plants (aged about a decade or less). Moreover, the increase in the between component in the mid-1980s was particularly pronounced for young plants (see Graphs 5.16 and 5.19). Secondly, when capital input is taken into account by the use of the total factor productivity indicator, the entries often have a slightly positive effect. This tells us that the new plants typically use tangible capital more productively than the older ones.

10.3 Time-patterns of the "creative destruction" components

So plant-level restructuring started to boost productivity growth in the mid-1980s. Productivity growth by means of external adjustment was most intensive at the turn of the decade. Some signs of chilling in the restructuring components in the latter part of the 1990s can be found. This suggests that there was some kind of "transition period" from the mid-1980s to the mid-1990s in Finnish manufacturing. One characteristic of this period is that the Finnish manufacturing sector caught up with the international frontier of labour and total factor productivity. The statistical evidence also shows that the between and exit components vary counter-cyclically in the short run. So even though aggregate productivity usually varies pro-cyclically, some components do go in the opposite direction. This finding lends support to the view that recessions do the job of cleansing low productivity activities from production.

It should be emphasised, however, that the "creative destruction" story of this study is not a "recession story" or a "Nokia story" (see Daveri and Silva 2002). The increase in the intensity of productivity-enhancing micro-level restructuring started long before the recession. Furthermore, the process seems to have chilled down substantially by 1997 or 1998 when the Nokia-driven ICT expansion started. Finally, productivity-enhancing restructuring has also been intensive in many industries other than the electronics industry, which encompasses the production of cell phones.

10.4 Skills and productivity-enhancing restructuring

When evaluating the reasons for and consequences of productivity-enhancing restructuring it is important to take labour skills into account. One might expect that low skilled and less efficient workers would be laid off from low productivity plants during recessions. Consequently the average skill and efficiency level of the workforce should increase and this might be reflected in the between and exit components of aggregate productivity growth. However, very little empirical evidence was found that the restructuring components are upwardly "skill-biased", due to ignorance of the efficiency differences between workers. Productivity decompositions are also made by controlling the efficiency of plants' labour input by various labour quality indicators. These indicators capture the effects of age (general experience) and formal schooling on labour efficiency by borrowing from standard human capital theory. In fact, the between and exit components are usually even more positive when the differences in labour quality across plants are controlled. If we believe that the role of skills is essentially to augment labour input with a given technology, as is the case when applying growth accounting methodology, for example, it is rather the within plants component that appears to be overestimated.

Moreover, the rate of growth in the average formal schooling level in manufacturing (and outside manufacturing) was reasonably stable in the period 1988-1998. So no support was found for the view that the recession has resulted in an acceleration of the increase in the average skill level in terms of formal schooling. In contrast, the average age of the manufacturing labour force rose quite rapidly up to 1992. It seems that the rapid productivity growth during the recession can be explained by an increase in the average skill level, if one believes that relative high age characterises efficient workers and that general experience is a particularly important component of human capital.

However, the analysis indicates that the role of formal education is essentially something apart from augmentation of the labour input in production. We can expect labour skills to improve a plant's ability to create, adopt and implement new technologies. Perfectly consistent with that view, it was found that an increase in the formal schooling level of plants does boost productivity growth, albeit with a considerable lag. This seems to apply especially to education obtained in the fields of engineering and natural sciences. It takes time to build new technology and implement it efficiently at plants.

A worker needs to be equipped with proper technology in order to fully utilise his or her skills in a productive way. As a consequence, in order to turn higher skills into higher aggregate productivity, new technologies must be created. Then labour input must be reallocated to those plants that have managed successfully to implement high productivity technologies. So skill upgrading needs to be accompanied by incessant plant level restructuring through more or less simultaneous job destruction and creation. All in all, a high education level may stimulate productivity-enhancing restructuring, probably with some time lag. In addition, a high skill level probably facilitates productivity-enhancing restructuring because then the workers can easily learn to use the new machines and techniques at their new jobs. From this perspective the recent findings concerning the high basic skills of Finnish pupils are, of course, encouraging. It seems that workers will be able to adopt new techniques that are created by the current high R&D intensity.

10.5 Job and worker flows

Although external adjustment has been important in the development of Finnish manufacturing, it has also caused many costs and much trouble. Jobs need to be destroyed and new ones need to be created. Workers must leave their current jobs and find new jobs. Some become unemployed during this process. It was found that jobs in plants with the lowest productivity are particularly threatened. Worker outflows into other plants and into unemployment are high from these plants when various characteristics of the plants and their labour forces are controlled. An earlier study by Ilmakunnas and Maliranta (2002) showed that new establishments utilise the pool of unemployed especially during a recovery. In the period 1994-97, more than 15 percent on average of the labour force of new establishments in the Finnish business sector had been unemployed one year earlier. Among the establishments of stable employment (-2 % ≤ employment growth rate ≤ 2 %) the corresponding number was 1.5 percent.

10.6 Productivity growth within plants

Of course, not all productivity progress is materialised through external adjustment between plants; it also improves within plants through internal adjustment. The within plants component typically constitutes 50-80 percent of aggregate productivity growth. On the other hand, this is a tremendous departure from the 100 percent that is assumed in the representative firm model. Hopefully, findings such as these will push theoretical work on economic growth beyond the representative firm models more widely in the future. They also pose a challenge for appropriate interpretations of traditional growth accounting computations which have become popular in the analysis of the so-called "new economy", for instance.

Within plants productivity growth may also involve a lot of reorganisation of production that can be expected to bear resemblance to the characteristics found in analyses of restructuring within industries. The composition of the labour force changes as a result of worker flows from and into plants, and this can be expected to affect plants' productivity now and later. An in-depth analysis of this process is left outside the focus of this study, though (see e.g. Ilmakunnas, Maliranta and Vainiomäki 2003b).

One of the novelties of this study is that productivity decompositions are performed with some new formulas that include an additional component for the analysis of productivity growth within plants. This component is here called the catching up component. When this component has a negative number, it suggests that low productivity plants have been able to achieve high productivity growth. The dynamics of this component reveal some interesting aspects of industry productivity development. The catching up component of labour productivity growth was particularly negative in the periods 1977-80 and 1992-97. The former is a period of severe recession in Finnish manufacturing and the latter is a period of strong recovery. Finding evidence of intensified internal adjustment by the catching up component in these seemingly quite different periods is not very surprising, however. Both periods can be expected to be times of adjustment to a changed economic environment. The low catching up component in these periods could be interpreted to mean that many low productivity plants were "struggling", à la Boone (2000), in order to improve their relative productivity levels through internal adjustment. It seems that this component reflects competitive pressure. The catching up component turns out to be a significant predictor of changes in productivity dispersion between plants. When the catching up component is negative, then productivity dispersion is compressed due to the fact that low productivity plants have caught up with high productivity plants.

10.7 Determinants of the "creative destruction" components

The determinants of the "creative destruction" process are investigated by an industry panel that includes 12 industries and covers more than two decades. The between component is used as an indicator of this element of industry productivity growth. It is found that R&D intensity stimulates productivity-enhancing restructuring. The effect appears with a lag of a couple of years. First R&D increases productivity dispersion between plants, which in turn triggers reallocation of labour and capital input shares across plants. The productivity-enhancing restructuring process also compresses productivity dispersion, which was initially expanded by the innovation activities. The external adjustment is not instant either, but persists for a few years. All in all, it takes about half a decade before all the fruits of an increase in R&D intensity are harvested through external adjustment. International trade and imports also appear to contribute positively to industry productivity growth through the "creative destruction" process.

10.8 Institutions

Productivity growth through "creative destruction" poses a challenge for institutions. Competitive pressure in product markets is likely to be crucial. Well-functioning factor markets are also needed to ensure that resource reallocation is intensive and, above all, productivity-enhancing. The latter condition states that job destruction and capital scrapping must be concentrated in low productivity plants and that job creation and investments must be focused on those plants that are able to use resources productively. The increase in the "creative destruction" components in Finnish manufacturing industries coincided with the deregulation of financial markets in Finland that may have supported more efficient allocation of financial resources across firms (and plants). The deregulation in the Finnish product markets, in turn, probably increased competitive pressure in a dynamic sense. High productivity performance seems to have become increasingly important for profitability and survival. Competitive pressure may also have increased the incentives for innovation.

Wage increases and the terms of working conditions are determined in collective bargaining at the centralised level (between the central organisations of employers and employees and the government) and at the industry level. As a rule, the agreements define the minimum wage increases for firms in the same industries. The system has resulted in a tendency towards uniformity in wage increases across industries as well. There have also been at least some aims related to wage compression on the part of the trade unions. However, it should be noted that the rigidity appertains to minimum wage growth. All firms are allowed to increase wages more if they feel a need for it in order to attract workers or induce their greater efforts. In addition, flexibility in the agreements concerning working conditions at the plant or firm level has increased in recent years.

Studies of job and worker flows have shown that the reallocation of labour at the micro-level is quite high in the Scandinavian countries, which share broadly similar wage settlement systems. The rigidity in wage increases at the micro-level seems to have led to "flexibility" in employment increases among firms and plants (see Bertola and Rogerson 1997). Restrictions on the use of strikes at the micro-level limit the ability of insider workers to extract rents. Another factor that has probably contributed positively to intensive micro-level restructuring is that layoff costs are relatively low in Finland, just as in other Scandinavian countries.

10.9 Wage dispersion

The effects of wage dispersion between plants on productivity-enhancing restructuring have been studied as well. One might expect that the desire among high productivity plants to attract workers and expand production would be reflected in high wage dispersion across firms and plants. Further, one might hypothesise that high wage dispersion between plants stimulates productivity-enhancing restructuring. Wage differences may induce workers to search for jobs in high productivity firms while low productivity firms lose their labour.

An opposite prediction arises from the view that a high wage dispersion reflects the fact that some workers in some plants and firms have been able to extract (quasi-) rents that have been generated by fixed costs due to investments in knowledge formation, for example. To the extent that wage dispersion between plants and firms reflects ex post bargaining over surplus, it can be expected to be negatively related to the subsequent productivity-enhancing restructuring. High productivity plants and firms are then punished in the form of higher wages that in turn curb subsequent labour demand. Empirical evidence obtained here gives little support to the view that high wage dispersion between plants within an industry leads to productivity-enhancing restructuring. Some results point to negative effects, but in general the evidence is not very solid in either direction.

10.10 Dynamics of factor income shares

The micro-level dynamics of factor income shares are also examined. The analysis indicates that the "creative destruction" process has expressed itself in the growth of capital's aggregate income share, too. Capital's aggregate income share has increased since the mid-1980s mainly due to the fact that the profitable plants that have high value added per labour compensation ratios have created jobs in net terms more than the other plants. Capital's income share has declined within plants, which is a direct consequence of the fact that wages (in product prices) have increased more than labour productivity within plants.

10.11 Policy questions

This analysis has shown that incessant restructuring at the micro-level is fundamental to fast aggregate productivity growth. Public policy should support this process, or at least avoid disturbing it without good reason. Deregulation of product markets probably has substantial positive influence on productivity growth, as it is likely to stimulate innovation activities (Aghion et al 2002) and, furthermore, boost productivity-enhancing restructuring at the micro level. Further development of the Finnish financial markets should be encouraged in order to support productivity-enhancing restructuring. Efficient reallocation of labour calls for efficient employment exchange and continual upgrading of labour skills, in both of which the government has an important role to play.

On the other hand, all such interventions by the government that threaten to weaken the relationship between productivity performance and profitability, or between productivity performance and survival or growth at the firm and plant level may be harmful for long-run development. Subsidies may insulate low productivity plants and firms from healthy market selection, and curb incentives for improving productivity performance. Business failures and plant shutdowns are the unavoidable by-products of the development process. Higher priority should be given to creating better general prerequisites for technology transfer from abroad, innovation and entrepreneurship, than to preventing job destruction. Of course, some business subsidies are more easily justified than others. For example, there might be a case for supporting innovations. However, it is worth bearing in mind that while stimulating the creation of jobs that are equipped with modern techniques, it simultaneously makes some other techniques obsolete. So some supporting measures, like education, may be necessary in order to alleviate the turbulence.

As mentioned, the reallocation of workers is essential for economic development and therefore the effects of various public policies should also be evaluated against this perspective. Workers need incentives for regional and occupational mobility. For example, the high transaction costs involved in finding a new residence may hamper productivity-enhancing restructuring. Owning a dwelling may encourage saving and may have some positive social effects, but the possible negative influence on labour mobility should also be recognised when designing public support for owner-occupied housing blocks.

It is also worth remarking that finding a good match between an employee and an employer is difficult in this incessantly changing world. For that reason, workers (and employers) need time and good prerequisites for their search efforts. Job creation after job destruction may not be productivity-enhancing, if worker flows are too impetuous. An unemployment benefit system should be designed to provide the unemployed with proper incentives to find a job, while also allowing them enough time to find a high productivity job.

The flip side of the “creative destruction” process deserves attention from the government for at least two reasons. One is normative and the other is more practical. Firstly, in a fair and just society, the troubles of less fortunate citizens must be compensated somehow. Secondly, if a decent social security system is guaranteed by the government, it may be easier for insider workers to accept painful measures such as low layoff costs or the deregulation of the product markets, which stimulate incessant micro-level renewal of production and long-run growth.

References

Abramovitz, Moses (1986), '*Catching up, forging ahead and falling behind'*, Journal of Economic History, 46, 2, 385-406.

Abramovitz, Moses (1990), '*The catch-up factor in postwar economic growth'*, Economic Inquiry, Vol. 28, January, 1-18.

Abramovitz, Moses (1993), '*The search for the sources of growth: areas of ignorance, old and new'*, Journal Economic History, 53, 2, 217-243.

Abranovic, Wynn Anthony (1997), '*Statistical thinking and data analysis methods for managers'*, Addison-Wesley.

Acemoglu, Daron. (1996), '*A microfoundation for social increasing returns in human capital'*, Quarterly Journal of Economics, 111, 779-804.

Acemoglu, Daron, and Robert Shimer (2000), '*Wage and technology dispersion*', Review of Economic Studies (2000) 67, 585-607.

Adler, Paul, and Kim Clark (1991), '*Behind the learning curve: A sketch of the learning process*', Management Science 37 (3), 267-281.

Aghion, Philippe, Nicholas Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt (2002), '*Competition and innovation: An inverted U relationship'*, IFS Working Paper no. 02/04.

Aghion, P., E. Caroli, and C. Garcia-Penalosa (1999), '*Inequality and economic growth. The perspective of the new growth theories',* Journal of Economic Literature 37, 1615-1660.

Aghion, Philippe and Peter Howitt (1992), *'A model of growth through creative destruction'*, Econometrica, Vol. 60, No. 2 (March, 1992), 323-351.

Aghion, Philippe, and Peter Howitt (1994), *'Growth and unemployment'*, Review of Economic Studies, 61, 477-494.

Aghion, Philippe, and Peter Howitt P. (1998), *'Endogenous growth theory'*, MITT Press, Cambridge, Mass.

Aghion, Philippe, and Gilles Saint-Paul (1998), '*On the virtue of bad times: an analysis of the interaction between economic fluctuations and productivity growth'*, Macroeconomic Dynamics, 2, 322-44.

Ahn, Sanghoon (2001), '*Firm dynamics and productivity growth: a review of micro evidence for the OECD countries'*, OECD Economics Department Working Paper No. 297.

Albæk, Karsten and Bent E. Sørensen (1998), '*Worker flows and job flows in Danish manufacturing, 1980-91*', Economic Journal 108, 1998, 1750-1771.

van Ark, Bart (1993), '*International comparisons of output and productivity: manufacturing productivity performance of ten countries from 1950 to 1990'*, Monograph Series, No. 1, Groningen University (downloadable from http://www.eco.rug.nl/ggdc/index-publ.html#top).

van Ark, Bart (1996), '*Issues in measurement and international comparison of productivity. An overview'*, in OECD, Industry Productivity. International Comparisons and Measurement Issues, Paris, 19-47.

van Ark, Bart, and Remco D. J. Kouwenhoven (1994), '*Productivity in French manufacturing: An international comparative perspective'*, Research Memorandum 572 (GD-10), University of Groningen.

van Ark, Bart and Angus Maddison (1994), '*An international comparison of purchasing power, real output, and productivity in manufacturing industries: Brazil, Mexico and the USA in 1975'*, Research Memorandum, no. 569 (GD8), Groningen Growth and Development Centre.

van Ark, Bart, and Dirk Pilat (1993), '*Productivity levels in German, Japan, and the United States: differences and causes'*, Brookings Papers: Microeconomics 2, 1993.

Arrelano, M. and S. R. Bond (1991), '*Some tests of specifications for panel data: Monte Carlo evidence and an application to employment equations',* Review of Economic Studies 58: 277-297.

Arrelano, M. and B. Honore (2001), '*Panel data models: Some recent development's',* in Heckman, J. J. and E. Leamer (eds.), Handbook of Econometrics, Vol. 5, Amsterdam: North-Holland, 3229-3296.

Arrow, Kenneth (1962), '*The economic implications of learning-by-doing'*, Review of Economic Studies 29, 3 (June 1962), 155-173.

Asplund, Rita (1999), '*Earnings and human capital: evidence from Finland'*, In Asplund, Rita, and Pedro T. Pereira (eds.), '*Returns to human capital in Europe: A literature review*', 44-77, ETLA, Series B 156, Helsinki: Taloustieto Oy.

Aw, Bee Yan, Sukkyun Chung, and Mark J. Roberts (2000), '*Productivity and turnover in the export market: micro-level evidence from the Republic of Korea and Taiwan (China)*', World Bank Economic Review, 14, 65-90.

Bahk, Byong-Hyong, and Michael Gort (1993), '*Decomposing learning by doing in new plants'*, Journal of Political Economy, 101, 4, (August 1993), 561-83.

Baily, Martin Neal, Eric J. Bartelsman, and John C. Haltiwanger (1996), '*Labour productivity: structural change and cyclical dynamics*', NBER Working Papers No. 5503.

Baily, Martin Neal, Eric J. Bartelsman, and John C. Haltiwanger (2001), '*Labour productivity: structural change and cyclical dynamics*', The Review of Economics and Statistics, Volume 83, Number 3, 420-433 .

Baily, Martin Neal, and Hans Gersbach, '*Efficiency in manufacturing and the need for the global competition'*, Brookings Papers on Economic Activity: Microeconomics (1995), 307-358.

Baily, Martin Neal, Hulten, C, and Campbell, D. (1992), '*Productivity dynamics in manufacturing plants'*, Brookings Papers on Economic Activity, Microeconomics 1992, 187-267.

Baldwin, John R. (1993), '*The dynamics of industrial competition. A North American perspective'*, Cambridge University Press.

Baldwin, John R., Desmond Beckstead, and Andrée Girard (2002), '*The importance of entry to Canadian manufacturing with an appendix on measurement issues'*, Statistics Canada, Research Paper No. 189.

Barnes, Matthew, and Jonathan Haskel (2001), '*Job creation, job destruction and small firms: the evidence for the small firms*', Queen Mary, University of London, June 2001

Barnes, Matthew, Jonathan Haskel, and Mika Maliranta (2002), '*The sources of productivity growth: micro-level evidence for the OECD*', mimeo.

Barro, Robert J., and Xavier, Sala-i-Martin. (1995), '*Economic growth*', McGraw-Hill, 1995.

Bartel, Ann, and Frank Lichtenberg (1987), '*The comparative advantage of educated workers in implementing new technology*', Review of Economics and Statistics, 69, (1), 1-11.

Bartelsman, Eric, Stefano Scarpetta, and Fabiano Shivardi (2002), '*Comparative analysis of firm demographics and survival: micro-level evidence for the OECD countries*', mimeo.

Barth, Erling and Harald Dale-Olsen (1999), '*The employer's wage policy and worker turnover*', in J.C. Haltiwanger et al., (eds.), '*The creation and analysis of employer-employee matched data*', Amsterdam: North-Holland, 1999, 285-312.

Bassanini, Andrea, Stefano Scarpetta, and Philip Hemmings (2001), '*Economic growth: the roles of policies and institutions. Panel data evidence from OECD countries'*, OECD, Economics Department Working Papers No. 283.

Basu, Susanto, and John Fernald (2001), '*Why is productivity procyclical? Why do we care?*', in Hulten, C. R., Dean, E. R., and Harper, M. J. (eds.), '*New developments in productivity analysis*', Chicago: University of Chicago Press (for NBER), 225-296.

Bauer, Thomas K., and Bender, Stefan (2002), '*Technological change, organisational change, and job turnover*', IZA Discussion Paper No. 570, September 2002.

Baumol, William J., Sue A. B. Blackman, and Edward N. Wolff (1989), *'Productivity and American leadership. the long view'*, Cambridge, MITT Press.

Becker, Gary (1962), '*Investment in human capital: A theoretical analysis'*, Journal of Political Economy 70, no. 5, part 2 (October 1962), 9-49.

Bellman, Lutz, and Tito Boeri (1998), '*Internal and external adjustment to new technologies*', Economics of Innovation and New Technology 5, 325-343.

Benhabib, Jess and Spiegel, Mark M. (1994), '*The role of human capital in economic development – Evidence from aggregate cross-country data*', Journal of Monetary Economics 34, 143-173.

Bernard, Andrew B, J. Eaton, J. B. Jensen, and S. Kortum (2000), '*Plants and productivity in international trade',* NBER Working Paper 7688.

Bernard, Andrew B., and Jones, Charles I. (1996), *'Productivity across industries and countries: Time series theory and evidence'*, The Review of Economics and Statistics, Vol. LXXVII, Number 1, 135-145.

Bernard, Andrew B., and J. Bradford Jensen (1999), '*Exceptional exporter performance: Cause, effect, or both?'* Journal of International Economics, 47, 1-25.

Bertin, A. L., T. F. Bresnahan, and D. M. G. Raff (1996), '*Localized competition and the aggregation of plant level increasing returns: Blast furnaces, 1929-1935',* Journal of Political Economy, 1996, vol 104, No 2, 241-266.

Bertola, Giuseppe, and Richard Rogerson (1997), '*Institutions and labour reallocation'*, European Economic Review 41, 1147-1171,

Bloom, David E., David Canning, and Jaypee Sevilla (2002), '*Technological diffusion, conditional convergence, and economic growth'*, NBER Working Paper 8713.

Blundell, Richard, Rachel Griffith, and John Van Reenen (1995), '*Dynamic count data models of technological innovation'*, Economic Journal, Vol. 105 (1995), 333-344.

Borenstein, Severin, and Joseph Farrell (1999), '*Do investors forecast fat firms? Evidence from the gold mining industries'*, National Bureau of Economic Research, Working Paper 7075.

Borenstein, Severin, and Joseph Farrell (2000), '*Is cost cutting evidence of X-inefficiency?'* NBER/ Sloan Project Report, '*Industrial technology and productivity: incorporating learning from plant visits and interviews into economic research'*, Papers presented at the Annual Meeting of the American Economic Association, January 2000, 15-20.

Bottasso, Anna, and Alessandro Sembenelli (2001), '*Market power, productivity and the EU market program: evidence from a panel of Italian firms'*, European Economic Review, 45: 167-186.

Brezis, Elise, Paul Krugman, and Daniel Tsiddon (1993), '*Leapfrogging in international competition: A theory of cycles in national technology leadership'*, American Economic Review, 83, 5 (December), 1211-1219.

Boone, Jan (2000), '*Competitive pressure: The effects on investments in product and process innovation'*, RAND Journal of Economies, Vol. 31, No. 3, Autumn 2000, 549-569.

Bureau of Economic Analysis (1995), '*Survey of current business'*, U.S. Department of Commerce, Economics And Statistics Administration, July 1995.

Burgess, Simon, Julia Lane, and David W. Stevens (2000), '*Job flows, worker flows and churning'*, Journal of Labor Economics, 18, 473-502.

Böckerman, Petri, and Mika Maliranta (2001), '*Regional disparities in gross job and worker flows in Finland*', Finnish Economic Papers, Vol. 14, Number 2 (Autumn 2001), 84-103.

Böckerman, Petri, and Mika Maliranta (2003), '*The micro-level dynamics of regional productivity growth: The source of divergence in Finland'*, the Research Institute of the Finnish Economy (ETLA), Discussion Papers No. 854.

Börsch-Supan, Axel (1998), *'Capital's contribution to productivity and the nature of competition*', Brookings Papers: Microeconomics 1998, 205-248.

Caballero, Ricardo J., and Mohammed L. Hammour (1994), '*The cleansing effect of recessions',* American Economic Review 84 (5), 1350-1368.

Caballero, Ricardo J., and Mohammed L. Hammour (1996), '*On the ills of adjustment'*, Journal of Development Economics, 51 (1), 161-192.

Caballero, Ricardo J., and Mohammed L. Hammour (1998), '*Jobless growth: Appropriability, factor substitutio, and unemployment',* Carnegie-Rochester Conference Series on Public Policy, 48, June 1998, 51-94.

Caballero, Ricardo J., and Mohammed L. Hammour (2000), '*Creative destruction and development institutions, crises, and restructuring'*, paper prepared for the Annual World Bank Conference on Development Economics, Washington, D.C., April 18-20, 2000.

Cameron, G., Proudman, J., and Redding, S. (1999), '*Technology transfer, R&D, trade and productivity growth'*, CEP Discussion Paper 428, 1999.

Campbell, Jeffrey R. (1997), '*Entry, exit, technology, and business cycles'*, NBER Working Paper No. 5955.

Carlsson, Bo (1981), '*The content of productivity growth in Swedish manufacturing'*, Research Policy, vol 10, 336-54.

Caselli, Francesco (1999), *'Technological revolutions'*, American Economic Review 89, 78-102.

Caselli, Francesco, and Wilbur John Coleman II (2002), '*The U.S. technology frontier'*, The American Economic Review, May 2002, Papers and Proceedings, 148-152.

Caselli, Francesco, Gerardo Esquivel and Fernando Lefort (1996), '*Reopening the convergence debate: a new look at cross country growth empirics'*, Journal of Economic Growth, Vol. 5 (September), pp 87-120.

Caves, Richard E. (ed.) (1992), '*Industrial efficiency in six nations'*, The MIT Press.

Caves, Douglas W., Laurits R. Christensen, and W. Erwin Diewert (1982a), '*Multilateral comparisons of output, input, and productivity using superlative index numbers'*, The Economic Journal, 92, (March), 73-86.

Caves, Douglas W., Laurits R. Christensen, and W. Erwin Diewert (1982b), '*The economic theory of index numbers and the measurement of input, output, and productivity'*, Econometrica, 50, 6 (November), 1393-1414.

Chambers, Robert G. (1988), '*Applied production analysis'*, Cambridge University Press 1988.

Chari, V. V., and Hugo Hopenhayn (1991), '*Vintage human capital'*, Journal of Political Economy 99, no.6 (December 1991), 1142-1165.

Clerides, Sofronis, Saul Lach, and James R. Tybout (1998), *'Is 'learning by exporting' important? Micro-dynamic evidence from Columbia, Mexico and Marocco'*, The Quarterly Journal of Economics, 113, 903-947.

Coe, David T., and Elhanan Helpman (1995). '*International R&D spillovers',* European Economic Review, 39, 859-887.

Cohen, W. M. (1995), '*Empirical studies of innovative activity*', in (P. Stoneman, ed.), '*Handbook Innovation and Technological Change'*, Oxford: Blackwell.

Cooper, R. W., and Haltiwanger, John C. (1993), '*The aggregate implications of machine replacement: theory and evidence'*, The American Economic Review, 83(3), 360-382.

Corrado, C, Gilbert, C, and Raddock, R. (1997), '*Industrial production and capacity utilization: Historical revision and recent developments,'* Federal Reserve Bulletin, February 1997, 67-92.

Crafts, N. (1992), '*Productivity growth reconsidered*', Economic Policy, 15, 388-425.

Daveri, Francesco, and Olmo Silva, (2002), '*Not only Nokia'*, ftp://ftp.igier.uni-bocconi.it/homepages/daveri/NotOnlyNokia.pdf, manuscript July 3.

Davis, Steven J. and John C. Haltiwanger (1999), '*Gross job flows'*, O. Ashenfelter and D. Card., (Eds.), Handbook of Labor Economics, vol. 3B, 1999, Ch. 41

Davis, Steven J., John C. Haltiwanger, and Scott Schuh (1996), '*Job creation and destruction*', MIT Press, 1996.

Diewert, W. Erwin (1976), '*Exact and superlative index numbers*', Journal of Econometrics, 4, 115-145.

Diewert, W. Erwin (1989), '*The measurement of productivity'*, Department of Economics, The University of British Columbia, Discussion Paper No. 89-04.

Disney, Richard, Jonathan Haskel, and Ylva Heden (2003), '*Restructuring and productivity growth in UK manufacturing',* Economic Journal, 113, 666-694.

Dowrick Steve, Mark Rogers (2002), '*Classical and technological convergence: Beyond the Solow-Swan growth model'*, Oxford Economic Papers 54 (2002), 369-385.

Drechsler, László (1973), '*Weighting of index numbers in multilateral international comparisons'*, The Review of Income and Wealth, 19, 1 (March), 17-34.

Dunne, Timothy, Lucia Foster, John Haltiwanger, and Ken Troske (2000), '*Wages and productivity dispersion in U.S. manufacturing: The role of computer investment'*, NBER Working Paper No. 7465.

Dwyer, Douglas W. (1998), '*Technology locks, creative destruction, and nonconvergence in productivity levels'*, Review of Economic Dynamics 1, 430-473.

Eeckhout, Jan (2000), '*Competing norms of cooperation*', University of Pennsylvania, January 2000.

Engelbrecht, Hans-Jûrgen (2001), '*The role of human capital in economic growth: Some empirical evidence on the 'Lucas vs Nelson-Phelps' Controversy'*, Massey University, Discussion Paper No. 01.02 – May 2001.

Englander, A. Steven, and Andrew Gurney (1994), '*Medium-term determinants of OECD productivity',* OECD Economic Studies, No. 22, 49-109.

Ericson, Richard, and Ariel Pakes (1995), '*Markov perfect industry dynamics: A framework for empirical work',* Review of Economic Studies, 62, 53-82.

Eriksson, Tor, and Markus Jäntti (1997), '*The distribution of earnings in Finland 1971-1990'*, European Review, 41(9), 1763-1780.

Erixon, L. (2000), '*'The third way' revisited. A revaluation of the Swedish model in the light of modern economics'*, Trade Union Institute for Economic Research FIEF, Working Paper Series 2000, No. 159.

Espost, R., and P. Pierani, 2003, '*Building the knowledge stock: Lags, depreciation, and uncertainty in R&D investment and link with productivity growth'*, Journal of Productivity Analysis 19, 33-58.
Eurostat, New Cronos-database, Survey 1996.

FitzRoy, Felix R., and Kornelius Kraft (1987), '*Cooperation, productivity, and profit sharing'*, Quarterly Journal of Economics, Volume CII, February, issue 1, 23-35.

Flanagan, Robert J. (1999), '*Macroeconomic performance and collective bargaining: An international perspective*', Journal of Economic Literature, 38, 1150-1175.

Fosgerau, Mogens, Svend D. Hougaard Jensen, and Anders Sørensen (2002), '*Measuring educational heterogeneity and labour quality: A note*', Review of Income and Wealth, Series 48, 2, June 2002, 261-269.

Foster, Lucia, John Haltiwanger, and C. J. Krizan, (2001), '*Aggregate productivity growth: Lessons from microeconomic evidence*', in Hulten, C. R., Dean, E. R., and Harper, M. J. (eds.), '*New developments in productivity analysis*', Chicago: University of Chicago Press (for NBER), 303-363.

Friedman, M. (1992), *'Do Old Fallacies Ever Die?'* Journal of Economic Literature 30 (1992), 2129-2132.

Färe, R., Grosskopf, S., Norris, M. and Zhang, Z. (1994), *'Productivity growth, technical progress, and efficiency change in industrialized countries'*, American Economic Review, 1, 84 (1994), 66-83.

Gerschenkron, Alexander (1962), '*Economic backwardness in historical perspective',* Harward University Press, Cambridge, Mass.

Gollop, Frank M. (1979), '*Accounting for intermediate input: The link between sectoral and aggregate measures of productivity growth'*, in National Research Council, 'Measurement and interpretation of productivity', 318-333, National Academy of Sciences, Washington D.C.

Gordon, Robert J. (1990), '*The measurement of durable goods prices'*, University of Chicago Press, Chicago.

Gort, Michael, and Richard A. Wall (1998), '*Obsolescence, input augmentation, and growth accounting'*, European Economic Review, 42, 1653-1665.

Gort, Michael, Jeremy Greenwood, and Peter Rupert (1999), '*Measuring the rate of technological progress in structures'*, Review of Economic Dynamics, Vol. 2, No. 1 (January 1999), 207-230.

Greenwood, Jeremy, and Boyan Jovanovic (2001), '*Accounting for growth*', in Charles R. Hulten, Edwin R. Dean, and Michael J. Harper (eds), '*New developments in productivity analysis',* Chicago: University of Chicago Press (for NBER), 179-222.

Greenwood, Jeremy, and Mehmet Yorukoglu (1997), '*1974*', Carnegie-Rochester Conference Series on Public Policy 46 (June 1997): 49-95.

Griffith, Rachel, Stephen Redding, and Johan Van Reenen (2000), '*Mapping the two faces of R&D: Productivity growth in a panel of OECD countries'*, Centre for Economic Policy Research CEPR, Discussion Paper Series, No. 2457.

Griliches, Zvi, and Jacques Mairesse (1995), '*Production functions: The search for identifications*', NBER Working Paper No. 5067.

Griliches, Zvi, and Haim Regev (1995), *'Productivity and firm turnover in Israeli industry: 1979-1988'*, Journal of Econometrics, 65, 175-203.

Gustavsson, P., Hansson, P., and Lundberg, L. (1999), '*Technology, resource endowments and international competitiveness'*, European Economic Review 43 (1999), 1501-1530.

Hall, Robert E. (1991), *'Labor demand, labor supply, and employment volatility'*, NBER Macroeconomics Annual 6, 17-46.

Hall, Robert E. (1995), '*Lost jobs',* Brookings Papers on Economic Activity, 1: 1995, 221-273.

Haltiwanger, John C., Julia I. Lane, and James R. Spletzler (1999), '*Productivity differences across employers: The roles of employer size, age, and human capital',* American Economic Review 89, Papers and Proceedings, 94-98.

Harrigan, James (1999), '*Estimation of cross-country differences in industry production functions*', Journal of International Economics 47 (1999), 267-293.

Hausman, Jerry. A. (1978), '*Specification tests in econometrics*', Econometrica 46, 1251-1271.

Hayashi, Fumio (2000), '*Econometrics',* Princeton University Press.

Hercowitz, Zvi (1998), '*The embodiment controversy: A review essay'*, Journal of Monetary Economics 41 (1998), 217-224.

Hibbs, Douglas A. Jr., and Håkan Locking, (1996), '*Wage compression, wage drift and wage inflation in Sweden'*, Labour Economics, Vol. 3 (2), 109-141.

Hibbs, Douglas A. Jr., and Håkan Locking, (2000), '*Wage dispersion and productive efficiency: Evidence for Sweden*', Journal of Labor Economics, Volume 18, Number 4, 755-782.

Hicks, John (1935), '*Annual survey of economic theory: The theory of monopoly*', Econometrica, 3, 1-20.

Hjalmarsson, Lennart (1973), *'Optimal structural change and related concepts'*, Swedish Journal of Economics, 75 (2), 176-192.

Hobijn, Bart, and Philip Hans Franses (2001), '*Are living standards converging?*', Structural Change and Economic Dynamics 12 (2001) 171-200.

Holden, Steiner (1998), '*Wage drift and the relevance of centralised wage setting'*, Scandinavian Journal of Economics, 100th Anniversary Volume, Oxford.

Honkapohja, Seppo, and Erkki Koskela (1999), '*The economic crises of the 1990s in Finland*', Economic Policy, No. 29, 399-424.

Hopenhayn, Hugo, and Richard Rogerson (1993), *'Job turnover and policy evaluation: A general equilibrium analysis'*, Journal of Political Economy, 1993, vol. 101, no. 5, 915-938.

Hulten, Charles R. (1992), *'Growth accounting when technical change is embodied in capital'*, American Economic Review, 82 (4), 964-980.

Hulten, Charles R., (2000), '*Total factor productivity: A short biography',* NBER Working Paper 7471.

Hulten, Charles R., and Frank Wykoff (1981), '*The measurement of economic depreciation'* in Hulten, Charles (ed.), '*Depreciation, inflation, and the taxation of income from capital'*, 81-125, Washington, D.C.: Urban Institute, 1981.

Huttunen, Kristiina (2002), '*Trade, technology and the skill structure of labour demand in Finland*', Labour Institute for Economic Research, Studies 85.

Hyytinen, Ari, and Heikki Kauppi (2002), '*Rahoituksen markkinaehtoistuminen ja talouden toimialarakenne. Havaintoja Suomesta 1980-2000',* Kansantaloudellinen aikakausikirja, 98, 2/2002, 177-198.

Ilmakunnas, Pekka, Seppo Laaksonen, and Mika Maliranta (1999), '*Enterprise demography and job flows'*, in Alho, Juha (Ed.), '*Statistics, registries, and science; experiences from Finland*', Statistics Finland, 73-88.

Ilmakunnas, Pekka, and Mika Maliranta (2000), '*Työpaikkojen syntyminen ja häviäminen ja työvoiman vaihtuvuus (Job creation and destruction and worker turnover),*' Ministry of Labour, Labour Policy Studies 209, Helsinki.

Ilmakunnas, Pekka, and Mika Maliranta (2003a), '*Hiring from unemployment and separation to unemployment'*, Applied Economics Letters, forthcoming.

Ilmakunnas, Pekka, and Mika Maliranta (2003b), '*Technology, labor characteristics and wage-productivity gaps'*, the Research Institute of the Finnish Economy (ETLA), Discussion Papers No. 860.

Ilmakunnas, Pekka, and Mika Malirant (2003c), '*The turnover of jobs and workers in a deep recession: evidence from the Finnish business sector'*, International Journal of Manpower, 24, 216-246.

Ilmakunnas, Pekka, and Mika Maliranta (2003d), '*Worker inflow, outflow, and churning*', the Research Institute of the Finnish Economy (ETLA), Discussion Papers No. 861.

Ilmakunnas, Pekka, and Mika Maliranta (2002), '*The turnover of jobs and workers in Finland'*, Ministry of Labour, Labour Policy Studies 236, Helsinki.

Ilmakunnas, Pekka, Mika Maliranta, and Jari Vainiomäki (2003a) '*Does Worker Turnover Improve Productivity Growth?'*, mimeo.

Ilmakunnas, Pekka, Mika Maliranta, and Jari Vainiomäki (2003b) '*The roles of employer and employee characteristics for plant productivity*', Journal of Productivity Analysis, forthcoming.

Ilmakunnas, Pekka, Mika Maliranta, and Jari Vainiomäki (2001), '*Linked employer-employee data on Finnish plants for the analysis of productivity, wages and turnover*', in Jensen, Torben, and Anders Holm (eds.), 'Nordic labour market research on register data', TemaNord 2001:593, 205-246.

Islam, Nazrul (1995), '*Growth empirics: A panel data approach*', Quarterly Journal of Economics, Vol. 110, Issue 4 (November), 1127-1170.

Jalava, Jukka (2002), '*Accounting for growth and productivity: Finnish multi-factor productivity 1975-99',* Finnish Economic Papers, forthcoming.

Jensen, Michael C. (1986), *'Agency costs of free cash flow, corporate finance, and takeovers'*, American Economic Review Papers and Proceedings, 76(May), 323-329.

Johnson, Peter, and Simon Parker (1994), '*The interrelationships between births and deaths'*, Small Business Economics 6: 283-290.

Jorgenson, Dale W., Frank Gollop, and Barbara Fraumeni (1987), '*Productivity and U.S. economic growth*', Cambridge, Mass.: Harvard University Press.

Jorgenson, Dale W. and Zvi Griliches (1967), '*The explanation of productivity change',* Review of Economic Studies, 34, 249-283.

Jovanovic, Boyan (1982), '*Selection and the evolution of industry*', Econometrica 50 (3),: 649-670.

Jovanovic, Boyan, and Saul Lach (1989), '*Entry, exit and diffusion with learning by doing*', American Economic Review, 79, 4 (September 1989), 690-699.

Jovanovic, Boyan, and Peter L. Rousseau (2001), '*Vintage organizational capital'*, NBER Working Paper No. 8166.

Jovanovic, Boyan., and Dmitriy Stolyarov (2000), *'Optimal Adoption of Complementary Technologies*', The American Economic Review, 90, 15-29.

Kapur, Sandeep (1993), '*Late-mover advantage and product diffusion'*, Economics Letters, 43, 1 (1993), 119-123.

Kauhanen, Antti, and Hannu Piekkola (2002), '*Profit sharing in Finland: earnings and productivity effects'*, The Research Institute of the Finnish Economy ETLA, Discussion Papers No. 817.

Kiander, Jaakko, and Pentti Vartia (1996), '*The great depression of the 1990s in Finland'*, Finnish Economic Papers, 9, 72-88.

Klette, Tor Jacob, and Zvi Griliches (2000), '*Empirical patterns of firm growth and R&D investment: A quality ladder model interpretation',* The Economic Journal, 110 (April), 363-387.

Klette, Tor Jacob., and Frode Johansen (1998), '*Accumulation of R&D capital and dynamic firm performance: A not-so-fixed effect model'*, Annales d'Economie et de Statistique, No. 49/50, 389-419.

Koop, Gary, Jacek Osiewalski, and Mark F. J. Steel (1999), *'The components of output growth: A stochastic frontier analysis*', Oxford Bulletin of Economics and Statistics, 61, 4(1999), 455-487.

Kremer, Michael (1993), '*The O-Ring Theory of Economic Development*', Quarterly Journal of Economics 108, 551-575.

Kremer, Michael, and Eric Maskin (1996), '*Wage inequality and segregation by skill*', NBER Working Paper No. 5718.

Krueger, Alan B. (1999), '*Measuring Labor's Share*', NBER Working Paper 7006.

Krueger, Alan. B., and Mikael Lindahl (2001), '*Education for growth: Why and for whom?'*, Journal of Economic Literature, Vol. XXXIX (December 2001), 1101-1136.

Krugman, Paul (1987), '*The narrow moving band, the dutch disease, and the economic consequences of mrs. Thatcher: Notes on trade in the presence of dynamic economies of sca*le', Journal of Development Economics, January 1987.

Krugman, Paul (1991), '*Geography and trade'*, the MITT Press, Massachusetts.

Kyyrä, Tomi (2002), '*Funktionaalinen tulonjako Suomessa'* (abstract in English), Government Institute of Economic Research, VATT Research Reports 87, Helsinki.

Lambson, Val (1991), 'I*ndustry evolution with sunk costs and uncertain market conditions*', International Journal of Industrial Organisation 9, 171-196.

Landesmann, Michael A., and Robert Stehrer (2001), '*Convergence patterns and switchovers in comparative advantage*', Structural Change and Economic Dynamics 12 (2001), 399-423.

Lee, Jong-Wha (1995), 'Capital goods imports and long-run growth', Journal of Development Economics 48, 91-110.

Leibenstein, Harvey (1966), '*Allocative efficiency versus X-efficiency'*, American Economic Review, 56(June), 3, 392-415.

Leiponen, Aija (2000), '*Why do firms not collaborate? Competencies, R&D collaboration, and innovation under different technological regimes'*, Ch. 4 in Leiponen, A., '*Essays in the economics of knowledge: innovation, collaboration and organisational complementarities*', The Research Institute of the Finnish Economy ETLA, Series A31, Helsinki. Forthcoming in Kleinknecht, A. and Mohnen, P. (eds.), '*Innovation and Economic Change'*, Macmillan, London.

Lerner, J. (1997), '*An empirical exploration of a technology race'*, RAND Journal of Economics Vol. 28, No. 2, Summer 1997, 228-247.

Levinsohn, James, and Amil Petrin (1999), '*When industries become more productive, do firms?*' NBER Working Paper Series 6893.

Llerena, P., and V. Oltra, 2002, '*Diversity of innovative strategy as a source of technological performance*', Structural Change and Economic Dynamics 13, 179-201.

Lloyd-Ellis, H. (1999), '*Endogeneous technological change and wage inequality',* The American Economic Review, March 1999, 47-77.

Lucas, R. (1988), '*On the mechanism of economic development*,' Journal of Monetary Economics 22(1), 3-42.

Lundberg, Erik F. (1961), '*Produktivitet och räntabilitet (Productivity and Profitability)*', Stockholm: Studieförbundet Näringsliv och Samhälle.

McKinsey Global Institute (1993), *'Manufacturing productivity'*, Washington D.C.

McKinsey Global Institute (1996), *'Capital productivity'*, Washington D.C.

Mairesse, Jacques, and Elizabeth Kremp (1993), '*A look at productivity at the firm level in eight French service industries*', Journal of Productivity Analysis 4, 211-234.

Mairesse, Jacques, and Mohamed Sassenou (1991), '*R&D and productivity: A survey of econometric studies at the firm level*', STI Review 8, 9-43.

Maliranta, Mika (1994), '*Suomen työn tuottavuuden kansainvälinen taso ruoan, juomien ja tupakkatuotteiden valmistuksessa. Kahdenvälinen vertailu Ruotsiin ja Yhdysvaltoihin,*' Discussion Papers 497, The Research Institute of the Finnish Economy ETLA.

Maliranta, Mika (1996), '*Suomen tehdasteollisuuden tuottavuus; kansainvälinen tasovertailu (Productivity in Finnish manufacturing: An international comparison)*', Tilastokeskus, Tutkimuksia 215, Helsinki.

Maliranta, Mika (1997a), '*Plant level explanations for the catch up process in Finnish manufacturing: A decomposition of aggregate labour productivity growth*', in Laakonen, Seppo (Ed.), '*The Evolution of Firms and Industries. International Perspectives*', Statistics Finland, Research Reports 223, 352-369.

Maliranta, Mika (1997b), '*Plant productivity in the Finnish manufacturing. Characteristics of high productivity plants*', The Research Institute of the Finnish Economy ETLA, Discussion Papers 612.

Maliranta (1997c), '*Suomen metalliteollisuuden tuottavuus*', mimeograph.

Maliranta, Mika (1997d), '*The determinants of aggregate productivity. The evolution of microstructures and productivity within plants in Finnish manufacturing from 1975 to 1994*', The Research Institute of the Finnish Economy ETLA, Discussion Papers No. 603.

Maliranta, Mika (1999), '*Factors of performance by plant generations. Some findings from Finland'*, in Biffignandi, Silvia (Ed.), 'Micro- *and macrodata of firms. Statistical analysis and international comparisons*', Physica-Verlag, New York.

Maliranta, Mika (2000a), '*Job creation by supporting technology advances? Evidence from Finnish plants'*, in Asplund, R. (eds.), '*Public R&D funding, technological competitiveness, productivity, and job creation'*, The Research Institute of the Finnish Economy ETLA, Series B 168, 89-128.

Maliranta, M. (2000b), '*Privately and publicly financed R&D as determinants of productivity – Evidence from Finnish enterprises*', in Asplund, R, (ed.), '*Public R&D funding, technological competitiveness, productivity, and job creation'*, The Research Institute of the Finnish Economy ETLA, Series B 168, 49-85.

Maliranta, Mika (2001), '*Productivity growth and micro-level restructuring. Finnish experiences during the turbulent decades',* The Research Institute of the Finnish Economy ETLA, Discussion Papers No. 757.

Maliranta, Mika (2002a), '*Factor income shares and micro-level restructuring. An analysis of Finnish manufacturing*', The Research Institute of the Finnish Economy ETLA, Discussion Papers No. 796.

Maliranta, Mika (2002b), '*From R&D to productivity through micro level restructuring*', The Research Institute of the Finnish Economy ETLA, Discussion Papers No. 795.

Marjanen, Reijo (2002), '*Palkkaratkaisujen sisältö ja toteutuminen tulopolitiikan aikakaudella (The content and realisation of wage settlements in the period of income policy, abstract in English*)', The Research Institute of the Finnish Economy ETLA, Sarja B 188 Series, Helsinki.

Martin, Philippe M., and Carol A. Rogers (1997), *'Stabilization policy, learning-by-doing, and economic growth'*, Oxford Economic Papers, 49 (1997), 152-166.

Melitz, Marc J. (2002), '*The impact of trade on intra-industry reallocations and aggregate industry productivity*,' NBER Working Paper No. 8881.

Murphy, Kevin M., Andrei Shleifer, and Robert W. Vishny (1991), '*The allocation of talent: Implications for growth*', The Quarterly Journal of Economics 106(1991), 2 (May), 503-30.

Myllyntaus, Timo (1992), '*Technology transfer and the contextual filter in the Finnish setting. Tranfer channels and mechanism in a historical perspective',* in Vuori, Synnöve, and Pekka Ylä-Anttila (eds.), '*Mastering technology diffusion — The Finnish experience',* The Research Institute of The Finnish Economy ETLA, Sarja B 82 Series, 195-251.

Nelson, Richard, and Edmund Phelps (1966), '*Investment in humans, technological diffusion, and economic growth'*, American Economic Review 56 (1-2): 69-75.

Nickell, Stephen J. (1996), *'Competition and corporate performance'*, Journal of Political Economy, 104 (4), 724-746.

Niitamo, Olavi (1958), '*Tuottavuuden kehitys Suomen teollisuudessa vuosina 1925-52'*, Helsinki 1958.

Nurmi, Satu (2002a), 'P*lant size, age and growth in Finnish manufacturing*', Paper presented in EARIE 2002 conference in Madrid, 5-8 September 2002, http://www.fundacion.uc3m.es/earie2002/papers/paper_250_20020322.pdf.

Nurmi, Satu (2002b), '*The determinants of plant survival in Finnish manufacturing*', Helsinki School of Economics, Working Papers W-306.

OECD (1994), '*The OECD jobs study, evidence and explanations'*, parts I and II, Organisation for Economic Co-operation and Development, Paris.

OECD (2000), '*Science, technology and industry outlook 2000'*, Organisation for Economic Co-operation and Development, Paris.

OECD (2001), '*Knowledge, work organisation and economic growth',* Organisation for Economic Co-operation and Development, Paris.

Oliner, Stephen (1989), '*Constant-quality price change, depreciation, and retirement of mainframe computers'*, in '*Price measurement and their uses'*, Allan Young, Murray Foss, and Marilyn Manser (eds.), Chicago: University Chicago Press.

Olley, George S. and Ariel Pakes (1996), '*The dynamics of productivity in the telecommunication equipment industry'*, Econometrica 64 (6), November, 1263-1297.

Olson, Mancur (1982), '*The rise and decline of nations*,' New Haven: Yale University Press.

Oswald, Andrew (1996), '*A conjecture on the explanation for high unemployment in the industrialised nations: Part I'*, Warwick Economic Research Paper, 475.

Oulton, Nicholas (2000), '*A tale of two cycles: Closure, downsizing and productivity growth in UK manufacturing, 1973-89'*, National Institute Economic Review No. 173 July 2000, 66-79.

Pakes, Ariel, and Mark Schankerman (1984), '*An exploration into the determinants of research intensity'*, in (Z. Griliches, ed.), '*R&D, patents and productivity'*, Chicago: Chicago University Press.

Pakko, Michael R. (2000), '*What happens when the technology growth trend changes? Transition dynamics and growth accounting'*, The Federal Reserve Bank of St. Louis, Working Paper 2000-014A.

Parenta, Stephen (1994), '*Technology adoption, learning-by-doing, and economic growth*,' Journal of Economic Theory 63, no.2 (August 1994): 346-369.

Pehkonen, Jaakko, and J. Viskari (1994), '*Wage drift: Philips curve vs bargaining models'*, Labour, 1994, 8, 395-421.

Pilat, Dirk (1993), '*The economics of catch up: The experience of Japan and Korea*', Groningen Growth and Development Centre Monograph Series, No. 2.

Pohjola, Matti (1996), '*Tehoton pääoma. Uusi näkökulma taloutemme ongelmiin (Inefficient capital. A new perspective on our economic problems)',* WSOY, Porvoo.

Pohjola, Matti (1998a), '*Investoinnit, taloudellinen kasvu ja työttömyys (Investments, economic growth and unemployment)',* in Pohjola, Matti (ed.) '*Suomalainen työttömyys (The Finnish unemployment)',* 289-315, Taloustieto Oy 1998.

Pohjola, Matti (1998b), '*Suomalaisten työmarkkinoiden toimivuus (Functioning of Finnish labour markets',* in Pohjola, Matti (ed.) '*Suomalainen työttömyys (The Finnish unemployment)',* 21-49, Taloustieto Oy 1998.

Porter, Michael E. (1990), '*The competitive advantage of nations'*, London: Macmillan Press.

Prescott, Edward C. (1998), '*Needed: A theory of total factor productivity*,' International Economic Review, Vol. 39, 525-551.

Prescott, Edward C., and Michael Visscher (1980), '*Organisational capital,*' Journal of Political Economy 88, no. 3 (June 1980), 446-461.

Ramey, Valerie, and Matthew Shapiro (2001), '*Displaced capital: A study of aerospace plant closings'*, Journal of Political Economy, 109, 5, 958-992.

Richards, Alan (1998), '*Connecting performance and competitiveness with finance: A study of the chemical industry'*, in Arora, A., Landau, R., and Rosenberg, N. (eds.) '*Chemicals and long-term economic growth: Insights from the chemical industry'*, 461-511, New York: Wiley Interscience.

Roberts, Kevin, and Martin L. Weitzman (1981), '*Funding criteria for research, development, and exploration projects',* Econometrica 39, 1261-1288.

Ripatti, Antti, and Juha Vilmunen (2001), '*Declining labour share — Evidence of a change in the underlying production technology',* Bank of Finland Discussion Papers 10/2001.

Rogers, Everett M. (1983), '*Diffusion of innovations',* 3rd ed. New York: Free Press.

Romer, Paul (1986), '*Increasing returns and long-run growth*', Journal of Political Economy, 94, 5 (October), 1002-37.

Romer, Paul (1990), '*Endogenous technical change',* Journal of Political Economy, 98, S71-S102.

Rouvinen, Petri (2002), '*R&D-productivity dynamics: Causality, lags, and dry 'holes''*, Journal of Applied Economics, Vol. 5, No. 1 (May 2002), 123-156.

Sakellaris, Plutarchos, and Daniel J. Wilson (2001), '*Quantifying embodied technological change'*, Federal Reserve Bank of San Francisco Working Paper 2001-16 (October).

Sauramo, Pekka (1999), '*Jobs and growth in Finland: Industry-level evidence from the 1990s*', Labour Institute for Economic Research, Discussion Papers 160.

Sauramo, Pekka (2000), '*Funktionaalisen tulonjaon kehitys eri toimialoilla (Development of functional income shares in different industries)',* Talous&Yhteiskunta 3/2000, 26-32.

Scarpetta, Stefano, and Thierry Tressel (2002), 'Productivity and convergence in a panel of OECD industries: Do regulations and institutions matter?', OECD Economics Department Working Paper, No. 342.

Scarpetta, Stefano, Philip Hemmings, Thierry Tressel, and Jaejoon Woo (2002), '*The role of policy and institutions for productivity and firm dynamics: Evidence from micro and industry data*', OECD Economics Department Working Papers, No. 329.

Schettkat, Ronald (1996), 'Flows in labor markets: Concepts and international comparative results', in Schettkat, Ronald (Ed.), 'The flow analysis of labour markets', Routledge, 1996.

Schumpeter, Joseph (1939), '*Business cycles: A theoretical, historical, statistical analysis of the capitalist process*', McGraw-Hill Book Company.

Schumpeter, Joseph A. (1942), '*Capitalism, socialism, and democracy',* New York: Harper and Brothers.

Sener, M. Fuat (2001), '*Schumpeterian unemployment, trade and wages'*, Journal of International Economics 54 (2001), 119-148.

Solow, Robert (1956), '*A contribution to the theory of economic growth'* Quarterly Journal of Economics 70, no. 1 (February 1956), 65-94.

Solow, Robert (1957), 'Technical change and the aggregate production function', The Review of Economics and Statistics, 39, no. 3 (August 1957), 312-320.

Solow, Robert (1960), '*Investment and technical progress'*, in Kenneth J. Arrow, Samuel Karlin, and Patric Suppes (eds.), '*Mathematical methods in the social sciences'*, Stanford University Press.

Spence, M. (1973), '*Job market signalling*', Quarterly Journal of Economics 87 (3), 355-374.
Swan, Trevor T. (1956), '*Economic growth and capital accumulation'*, Economic Record, 32 (November), 334-361.

Stein, Jeremy C. (1997), '*Waves of creative destruction: Firm-specific learning-by-doing and the dynamics of innovation*', Review of Economic Studies, 64, 265-288.

Stigler, George J. (1947), '*Trends in output and employment*', New York: Herald Square Press (for NBER), 1947.

Stiglitz, Joseph E. (1993), '*Endogenous growth and cycles'*, NBER Working Paper, No. 4283, March 1993.

Sørensen, Anders (2001), '*Comparing apples to oranges: Productivity convergence and measurement across industries and countries: Comment'*, The American Economic Review, 91, 4, 1161-1167.

Thesmar, D., and M. Thoenig (2000), '*Creative destruction and firm organisational choice*', The Quarterly Journal of Economics, 115, 1201-1237.

Torii, Akio (1992), '*Technical efficiency in Japanese industries'*, in Caves, R. E. (eds.), *'Industrial efficiency in six nations'*, 1992 Massachusetts Institute of Technology.

Tybout, James R., and Westbrook, M. Daniel (1995), *'Trade liberalization and the dimensions of efficiency change in Mexican manufacturing industries'*, Journal of International Economics 39(1995), 53-78.

Törnqvist, Leo (1936), '*The bank of Finland's consumption price index'*, Bank of Finland Monthly Bulletin 10: 1-8.

Uusitalo, Roope (2000), '*Paikallinen sopiminen ja yritysten työvoiman kysyntä*', (abstract in English), Government Institute for Economic Research, VATT-Research Reports 62.

Uusitalo, Roope (2002), '*Tulospalkkaus ja tuottavuus'*, (abstract in English), Government Institute for Economic Research, VATT-Research Reports 276.

Young, Allyn A. (1928), '*Increasing returns and economic progress*', The Economic Journal, 38 (1928), 527-42.

Vainiomäki, Jari (1999), '*Technology and skill upgrading: Results from linked worker-plant data for Finnish manufacturing*', in Haltiwanger, John, Julia I. Lane, James R. Spletzer, Jules J.M. Theeuwes, and Kenneth R. Troske (Eds), '*The creation and analysis of employer-employee matched data*', 115-145, Elsevier Science B.V.

Varjonen, S. (1994), '*Kiinteähintaisen bruttokansantuotteen laskentavaihtoehdot (Alternative for measuring gross domestic product in fixed prices*)', in Pahkinen, E., and Ritola, V. (Eds.), *'Suhdannekäänne ja taloudelliset aikasarjat (The turn in the business conditions and the economic time-series*)', Statistics Finland, Research Reports 210.

Vasama Pyry-Matti, and Yrjö Vartia (1980),'*Johdatus tilastotieteeseen, osa I'*, Gaudeamus, neljäs korjattu painos, Pori 1980.

Vihriälä, Vesa (1997), '*Banks and the Finnish credit cycle 1986-1995*', Bank of Finland, Bank of Finland Studies E:7 1997.

Vuori, Synnöve, and Pekka Ylä-Anttila (1992.), '*Mastering technology diffusion — The Finnish experience',* The Research Institute of The Finnish Economy ETLA, Sarja B 82 Series.

Westergaard-Nielsen, Nils (2002), '*20 years of labour market policies in Denmark',* in Ilmakunnas, Seija, and Erkki Koskela (eds.), '*Towards higher employment',* 189-211, Government Institute for Economic Research VATT, Helsinki 2000.

Whelan, Karl (2002a), *'A guide to U.S. chained aggregated NIPA data'*, The Review of Income and Wealth, series 48, number 2, June, 217-234.

Whelan, Karl (2002b), '*Computers, obsolescence, and productivity'*, The Review of Economics and Statistics, August 2002, 84(3): 445-461.

Wiel, H. P. van der (1999), '*Productivity in Dutch business services: The role of entry and exit',* CPS Report 1999/2, 36-41.

Wihlborg, C. (1998), '*Economic efficiency with enabling and mandatory law'*, in Eliasson, G., and Green, C. (eds.), '*Microfoundations of economic growth. A Schumpeterian perspective'*, 109-116, The University of Michigan Press.

Williamson, Oliver E. (2000), '*Economic institutions and development: A view from the bottom'*, in Olson, Mancur, and Satu Kähkönen (eds.), 'A not-so-dismal science', pp 92-118, Oxford University Press.

Wolff, Edward N. (1994), '*Productivity growth and capital intensity on the sector and industry level: Specialisation among OECD countries, 1970-1988*', in Silverberg, Gerald and Luc Soete (eds.), '*The economics of growth and technical change, technologies, nations, agents*', Edward Elgar Publishing Ltd., 1994, 185-211.

Wolff, Edward N. (2000), '*Human capital investment and economic growth: Exploring the cross-country evidence*', Structural Change and Economic Dynamics 11 (2000) 433-472.

Wooldridge, Jeffrey M. (2002), '*Econometric analysis of cross section and panel data*', Cambridge, Mass.: The MIT Press, 2002.

Appendix 1. Comparisons of productivity levels across countries

ICOP approach

Usually the most critical point in productivity comparisons is how successfully the distinctions between values, prices and quantities are made. This holds true for international comparisons as well. In the so-called “industry-of-origin” approach the conversion of value-added into the common currency is made by means of unit value ratios (UVRs) that are used as deflators. The unit values are obtained by dividing ex-factory sales value by the corresponding quantities obtained from each country’s production census.[145]

The first step is to match the products (or product categories) between the two countries under comparison. This is done on the basis of product descriptions appearing in the production censuses. This is usually not a very simple task to do, because product classifications may be quite different. In the comparison made between Finland and the United States 275 products could be matched and they covered 42.9 per cent of the total sales value of Finland and 19.9 per cent of that of the United States. In the Finland/Sweden comparison on the other hand the product classification is basically the same and as a consequence the coverage of the matched products was substantially larger. In manufacture of food products Maliranta (1994) matched 147 products that covered 67.2 per cent of the total sales in Finland and 62.4 per cent in Sweden. Of course, substantially more accurate estimates of the relative price levels are obtained in the latter comparison. However, the United States is a more suitable benchmark for a productivity comparison from the standpoint that it has been the traditional international leader country in productivity level.

The second step is to aggregate the unit value ratios in such a way that appropriate and consistent estimates of the relative price levels are obtained for industries and eventually for total manufacturing. This should be done so that each product match has an appropriate weight. The estimates computed from the product sample, which is obtained by a matching procedure, should be representative for total production, which consists of matched and unmatched products.

The manufacturing sector was divided into 17 industries, which appear in Table 4.1 in Chapter 4. A maximum number of such sub-industries was distinguished within each of 17 industries where the same products could be found in both countries. In the comparison between Finland and the United States there were 44 such industries for which a specific estimate could be computed from the

[145] A detailed description of the methodology is provided by van Ark (1993), for example.

product matches. The criteria was that the matched products cover at least 20 per cent of the total sales of the sub-industry.

The average UVR for each sub-industry was obtained by weighting the unit values by the corresponding quantity weights of one of the two countries. The UVR calculated for the comparison of Finland (*F*) and the base country USA (*U*) is calculated by using quantity weights of the base country (Laspeyres price index)

$$UVR_{j(m)}^{FU(U)} = \frac{\sum_{i=1}^{s} p_{ij}^{F} q_{ij}^{U}}{\sum_{i=1}^{s} p_{ij}^{U} q_{ij}^{U}} \qquad \text{(A1.1)}$$

or by using quantity weights of country *F* (Paasche price index)

$$UVR_{j(m)}^{FU(F)} = \frac{\sum_{i=1}^{s} p_{ij}^{F} q_{ij}^{F}}{\sum_{i=1}^{s} p_{ij}^{U} q_{ij}^{F}}, \qquad \text{(A1.2)}$$

where $i = 1 \ldots s$ is the sample of matched products in matched industry $j(m)$.

There are a number of sub-industries for which a reliable UVR estimate cannot be determined, because no matches are made at all or they cover only a small proportion of total sales. For these sub-industries, denoted by '*j(n)*', UVRs of the industry (denoted by '*k*') are used;

$$UVR_{j(n)}^{FU(U)} = \frac{\sum_{i=1}^{s} p_{ik}^{F} q_{ik}^{U}}{\sum_{i=1}^{s} p_{ik}^{U} q_{ik}^{U}} \qquad \text{(A1.3)}$$

at quantity weights of the base country , and

$$UVR_{j(n)}^{FU(F)} = \frac{\sum_{i=1}^{s} p_{ik}^{F} q_{ik}^{F}}{\sum_{i=1}^{s} p_{ik}^{U} q_{ik}^{F}} \qquad \text{(A1.4)}$$

at quantity weights of the country *F*.

The next stage is to aggregate the sub-industries to industry (*k*). This is done by value added weights;

$$UVR_{k}^{FU(U)} = \frac{\sum_{j=1}^{r} UVR_{j}^{FU(U)} * VA_{j}^{U}}{VA_{k}^{U}} \qquad \text{(A1.5)}$$

for the UVR of industry *k* by using quantity weights of the base country *U*, and

$$UVR_{k}^{FU(F)} = \frac{VA_{k}^{F}}{\sum_{j=1}^{r} VA_{j}^{F} \big/ UVR_{j}^{FU(F)}} \qquad \text{(A1.6)}$$

for weights of county F, where $j = 1 \ldots r$ are matched or non-matched sub-industries within industry k.

In the final stage the industry UVRs are weighted for total manufacturing by means of value-added.

This procedure yields two types of UVRs; one using F country's quantity weights (Paasche index) and another using the base country's quantity weights (Laspeyres index). Usually the former gives lower UVRs (and thus higher relative productivity levels) than the latter. Thus using a country's own structures in the weighting procedure tends to give a more positive picture of productivity performance than using the structure of the other country. The difference may be substantial especially when the two countries are in very different development phases, like India and the United States (see van Ark 1993). This index number phenomenon is sometimes called the "Gerschenkron effect", as Alexander Gerschenkron (1962) provided a detailed description of it. This effect is due to the negative relationship between prices and quantities.

Measurement of capital in international comparisons

Capital input that is needed for the capital and total factor productivity indicators is usually measured with the perpetual inventory method. It is relatively easy to compute and is given justification in a study by Hulten and Wykoff (1981).

Capital stock in year t is obtained by

$$K_t = (1-\delta)\cdot K_{t-1} + I_t, \qquad \text{(A1.7)}$$

where δ is the depreciation rate and I is investments in real terms. So the current capital stock is a weighted average of past investments. The depreciation rate indicates how much weight recent investments should be given relative to the older investments.

The problem is what value should be used for the depreciation rate. Countries use very different depreciation rates in the National Accounts calculations. However, there is very little hard evidence that depreciation rates differ between countries. It is likely that the differences between countries also reflect other things than real differences in the depreciation of capital. This is critical from the standpoint of cross-country comparisons of productivity levels, as the level of the capital stock estimate is very sensitive to the depreciation rate used in the computations. In contrast, with reference to changes in the capital input over time, moderate differences in the depreciation rates normally make very little difference. Thus it may be advisable to use standardised capital stock estimates in cross-country comparisons. If there were true differences in depreciation rates between countries, it would be very important to take into account the resulting differences in the ratios of capital service to capital stock between countries anyway. The capital stock estimates obtained by using the standardised method provide us with a suitable indicator for the evaluation of the efficiency of investment efforts made in the past.

Data on investments is obtained from the STAN Industrial Database of the OECD, DSTI. The value of investments is converted into a common currency by purchasing power parities of investment goods obtained from the International Sectoral Database (ISDB) of the OECD. The industry-specific depreciation rates are determined so that the standardised series generated from the investment series by the PIM method for the United States have as similar a pattern over time as possible with the capital stock series appearing in the ISDB source. More precisely, the depreciation rate is determined by minimising standard deviation of

$$\left[\ln\left(K_0^*/K_0^{PIM}\right), \ln\left(K_1^*/K_1^{PIM}\right), \ldots, \ln\left(K_s^*/K_s^{PIM}\right)\right], \qquad \text{(A1.8)}$$

where K^* is the original and K^{PIM} the standardised estimate of capital stock and *0* and *s* refer to the initial and final years of the series respectively. In total manufacturing, the depreciation rate is 7.98 %. There are some differences between industries, the rate being 7.25 % in the manufacture of food products, beverages and tobacco, 5.40 % in the paper industry and 8.64 % in the machinery and equipment industry, for example. Another problem with estimations using the PIM method is the determination of the initial capital stock. Some possible errors in the initial stock estimate vanish, however, quite quickly over time. For Finland the initial capital stocks are obtained from the ISDB source. The standardised capital stock estimates turn out to have very similar time patterns to the ones appearing in the ISDB source since the mid-1970s, which suggest that the inaccuracy in the initial stock is not a problem here.[146]

[146] In some cases (in metal industries), I use a more detailed industry classification than the one used in the ISDB data source. In those cases, I have split the more aggregate initial stock between sub-industries on the basis of the distribution of nominal investments during the first part of the 70s.

Measurement of TFP

The relative total factor productivity levels between Finland (*F*) and the United States (*U*) are calculated as follows:

$$TFP_t^{FU} = \exp\left(\ln\left(\frac{VA_t^F / L_t^F}{VA_t^U / L_t^U} \right) - (1-\overline{w}_t)\cdot \ln\left(\frac{K_t^F / L_t^F}{K_t^U / L_t^U} \right) \right), \qquad \text{(A1.9)}$$

where *VA* is the value added expressed in commensurable units, *K* is the standardised capital stock estimate and *L* is labour input. The term giving the weight for capital intensity is

$$\overline{w}_t = 0.5 \cdot \left(\frac{W_t^F}{NVA_t^F} + \frac{W_t^U}{NVA_t^U} \right), \qquad \text{(A1.10)}$$

where *W* denotes total labour compensation (wages plus supplements) and *NVA* nominal value added.

The estimates for the relative capital intensity and the average factor income share, that are made use of in the computations of the total factor productivity indicator, are computed by using the STAN database. The relative labour productivity levels in the benchmark years (1992 in the metal industries and 1987 in the other industries) are obtained from the results by Maliranta (1996 and 1997). The relative labour productivity levels in the other years are computed by labour productivity growth series calculated from the STAN database.

Appendix 2. Micro data sets

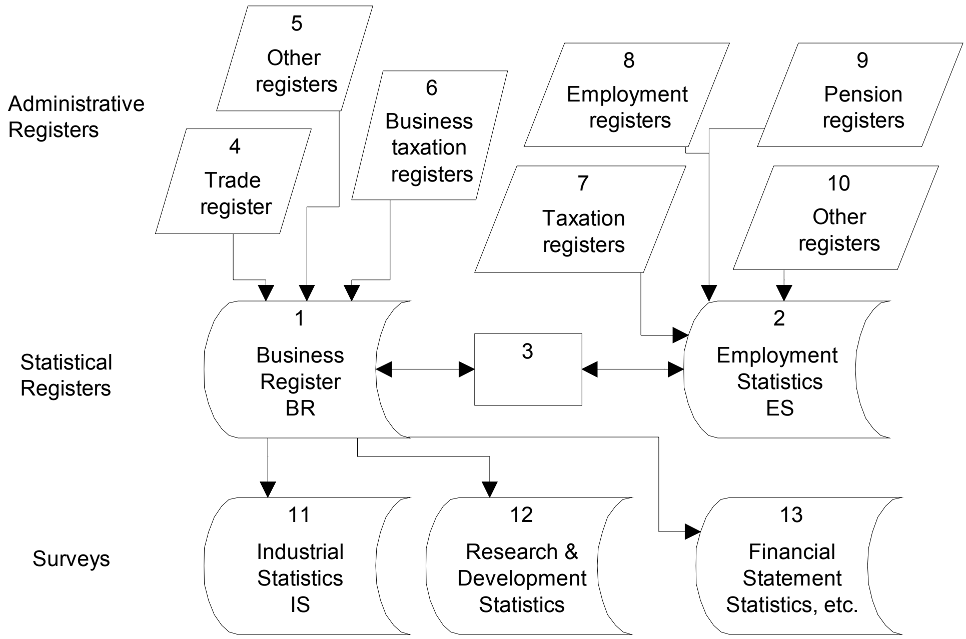
The statistical system and statistical information sources in Finland

The unique identification codes for persons, enterprises and plants used in the different registers form the backbone of the Finnish register network and the Finnish statistical system, whereby different sources of information can be integrated conveniently for various statistical purposes. A valuable feature of the identification coding system is that persons can be linked to companies and to their establishments. Statistics Finland has an important role in maintaining and co-ordinating this system.

Graph A2.1 provides a depiction of the basic structure. **Business Register on Plants and Enterprises** (item 1 in the graph) covers registered employers and enterprises subject to VAT, and their plants in Finland. It is the basic source of enterprise plant codes used in other registers and the statistics of Statistics Finland. Nowadays there are about 250,000 business sector plants in the register. Identification codes for enterprises used in the Business Register originate from the tax authorities. The identification codes for plants, in turn, are given and maintained by the Business Register; when a new plant is identified, it is successively numbered. The Business Register also follows changes in the demographic structure of plants and enterprises, such as their demise and changes in ownership. Furthermore, the Business Register includes information on the contact address, classifications such as industry, and some basic variables such as sales, employment and the wage bill. Most of the information is from administrative registers (4-6), but it is supplemented by questionnaires.

The Business Register is an important source of statistical information and, furthermore, provides the frames for various more detailed statistical surveys. One of these is **Industrial Statistics** (item 11) that compiles comprehensive information on economic activity in mining and quarrying, manufacturing, and electricity, water and gas supply. A detailed description of data are provided below. When a plant in the Business Register fulfils the selection criteria for inclusion in the Industrial Statistics Survey (employing at least five persons being the main criterion up to the year 1994), it is incorporated into the information system of Industrial Statistics. The enterprise and plant identification codes, industry groups, etc. originate at this stage from the Business Register. However, subsequently the plants' identification codes, classifications and contact information are maintained and updated, if need be, in the systems of Industrial Statistics. Therefore, it is possible that the connection with the plant's original counterpart in the Business Register may weaken or disappear over time, which causes some problems when matching Industrial Statistics with other data sources that use the codes from the Business Register (like

Graph A2.1 Finnish statistical system



Employment Statistics, see below). The Business Register is also used as a frame for firm-level **R&D Statistics** surveys, for instance.

The **Employment Statistics** database compiles information on the economic activities of individuals and their background characteristics from a large number of different administrative registers (items 7-10). It effectively covers the whole population of Finland. The enterprise and plant identification codes, industry and other general information needed in Employment Statistics are taken as such from the Business Register. The employer-employee links are determined in the Employment Statistics and Business Register systems (item 3). The employer-employee match in Employment Statistics is based on the Register of Wages and Pensions, which includes information on all employment spells during a year for all individuals in Finland and is a part of the Employment Statistics production system. For each person, a unique plant appearing in the Business Register is determined as his/her primary employer during the last week of each year. This connection is established using the enterprise identification codes in the Register of Wages and Pensions. For multi-unit enterprises, the person-plant matches are determined using a questionnaire asking enterprises to attach persons to their appropriate plants. Furthermore, check-ups and corrections are performed by comparing the geographical location of plants and the place of residence of persons. Linking an individual with the proper employer plant is a challenging task, and there remain a number of persons in Employment Statistics whose plant code is missing or may be incorrect. However, a great deal of effort is made in Employment Statistics to seek the correct plant linkage for each individual.

Various research databases are constructed by linking statistical registers and surveys together. One that is used in this study in Chapter 6 is obtained by taking plant-level averages on ages, education, monthly wages, etc. from Employment Statistics and linking this information with the Industrial Statistics data set by plant codes. Ilmakunnas, Maliranta and Vainiomäki (2001) give a detailed description of the process of linking various registers and surveys for the analysis. They provide us with examples of how these data are used in the analysis of job and worker flows, as well as in the analysis of plant productivity.

Longitudinal data on plants in Finnish manufacturing

Longitudinal data on plants in Finnish manufacturing (LDPM) is constructed from annual manufacturing surveys especially for research purposes. The first year of the data is 1974.

Units

In principle, the plant is defined as a local kind-of-activity unit. In other words, it is a specific physical location, which is specialised in the production of a certain type of product. A single local unit may thus consist of several plants that have activities in different industries. In some special cases a plant is delineated so that it includes parts that are geographically detached. However, it is required that the units are located within the same municipality. This solution seems well justified, especially when the geographically separated units are closely attached to each other operationally. Besides, this way of grouping plants may help the firm to provide more accurate information on its activities within a certain specific industry. The plant codes mostly stay the same throughout the life of a plant. Three criteria are taken into account when considering a change of a code: industry, address and ownership. In principle, at least two of these conditions need to be met before a new code is given. A brand new plant code is given in such cases where there has been a thorough-going change in the way the production is performed. This is the case, for example, when a substantial proportion of tangible assets is replaced. This treatment of plants' deaths and births accords roughly with the one needed when using this data source to analyse the life cycles of plants from the standpoint of technology adaptations.

The data include the firm code of the owner. It can be used, for example, when linking firm-level information from other sources, such as R&D expenditures (see Section 5.4.2).

Coverage

Up to the year 1994 the main criterion was that the plant employed at least five persons. Since 1995 it includes basically all plants owned by firms that employ no less than 20 persons. Therefore, since 1995 the data also include the very small plants of multi-unit firms, but, on the other hand, the plants of small firms are left outside. This break in the series needs to be taken into account especially when analysing entries and exits.

Table A2.1 gives the number of plants (*NOBS*), the number of persons (*PER*) and nominal value-added (*NVAL*) in different data sets. Data set A includes all manufacturing plants in this data. In data set B, non-production plants with non-positive value-added (and employing less than 5 persons) are dropped. In data set C, I have also dropped those plants that do not have an estimate for capital input. Finally, data set D includes those production plants that have a capital input estimate and at least 20 persons (and positive value-added). The coverage of the last data set should be comparable over the whole time period after 1974.

We note that in the first round some 10-20 per cent of the plants are dropped, but the excluded plants account for only 3-6 per cent of employment and zero per cent of value-added. In the second round still more plants are dropped. The coverage in terms of value-added or employment declines less, which implies that those plants for which we do not have the capital input estimate are typically small. In the last dropping round, a substantial decline in coverage in terms of plant observations can be found. However, in terms of employment and value-added the decline is relatively moderate. So data set D is also reasonably representative from the standpoint of total manufacturing employment and production.

Content

The data include a lot of information about the plants. Output is measured by value-added and gross value of production. Actually, there are two alternative measures for value-added.

Census value-added

The so-called "industrial" or "census value-added" is defined as gross value of output excluding non-industrial services, minus cost of raw materials, packaging, energy inputs and contract work. Consequently, the value of purchased non-industrial services, such as advertising, accountancy, etc., is not subtracted. One advantage of the census value-added concept is that it is more consistent over time, and perhaps between plants, than the total value-added used in the National Accounts.

Table A2.1 Coverage of data sets, by various selection criteria of plants

Year	1975	1980	1985	1990	1994	1995	1998
Data set A							
NOBS	6 173	7 173	7 396	7 148	6 544	3 140	3 308
PER, thousands	523	536	498	434	344	326	351
NVAL, millions	27	53	84	120	131	144	185
Data set B							
NOBS	5 518	6 494	6 576	5 739	5 038	2 831	3 018
PER, thousands	507	517	475	406	324	310	337
NVAL, millions	27	53	84	120	131	144	185
Data set C							
NOBS	5 178	5 789	5 758	5 047	4 375	2 486	2 177
PER, thousands	493	491	446	377	301	289	292
NVAL, millions	26	51	80	113	124	137	165
Data set D							
NOBS	3 253	3 486	3 291	2 931	2 322	2 190	1 979
PER, thousands	470	464	416	351	277	285	289
NVAL, millions	25	49	75	107	117	135	163
Shares of data set A, in percentages							
Data set B							
NOBS	89	91	89	80	77	90	91
PER	97	97	95	94	94	95	96
NVAL	100	100	100	100	100	100	100
Data set C							
NOBS	84	81	78	71	67	79	66
PER	94	92	89	87	88	88	83
NVAL	97	96	95	94	94	95	89
Data set D							
NOBS	53	49	44	41	35	70	60
PER	90	87	84	81	81	87	82
NVAL	93	92	90	89	89	94	88

Note: *NOBS* is the number of plants, *PER* is the number of employees and owners, *NVAL* is value-added (industrial) in *FMK*.
Data set A: consists of all plants
Data set B: includes production units with positive value-added and at least 5 persons.
Data set C: like set B but includes the capital input estimate.
Data set D: like set C but includes only plants having at least 20 persons.

Total value-added

The total value-added takes into account both the revenues and the costs from non-industrial services. The robustness of the results is usually checked by using both concepts. Normally the value-added concept being used makes very little difference. However, there seems to be a drop in total value-added by some 10 percent in 1995, because some cost components have been measured more comprehensively since then. So in order to make these total value-added numbers more comparable over the whole period, the numbers up to 1994 need to be lowered by 10 percent.

Labour

The LDPM data contain information on employment and hours worked by employed persons. The employed are disaggregated into blue-collar and white-collar employees. The number of entrepreneurs and family members working in the plant is also included, but there is no information on how many hours they have worked. In this study, we have assumed that the owners' average annual hours equal the average hours of white-collar employees in the plant in question. This estimate may be biased downward, but the overall effect is negligible.

Capital input

For the capital input measure we have two main alternatives. For the period from 1975 to 1984 (except 1980) we have the fire insurance value of the stock available, which is deflated into 1995 prices by industry-specific (15 industries in manufacturing) deflators for the investments in tangible assets obtained from the Finnish National Accounts.

In this study, however, we apply an estimate of capital stock constructed by using the so-called perpetual inventory method (PIM), which is available up to the end of the time period. The computations are based on a similar formula to that already used in Appendix 1.

$$K_t = (1-d)*K_{t-1} + I_t, \qquad \text{(A2.1)}$$

where K_t is net capital stock in the year t, I_t is real investments and δ is a constant depreciation rate, which is here assumed to be 10 % in all industries.

One problem with the PIM method is that the initial level of capital stock is also needed for those plants that were established before 1974, which is the first year in this data. The initial levels are estimated by using the industry-specific proportions of the fire insurance value. The proportion for each 15 NA industry is estimated in such a way that the PIM estimate per fire insurance value is as stable as possible in the period from 1975 to 1984 for a balanced panel of plants at the industry-level.

For each industry j the initial stock is defined by K_{j0}^{PIM}

$$K_{j0}^{PIM} = X_j \cdot K_{j0}^{FIRE} \tag{A2.2}$$

The proportion X_j is determined by minimising the standard deviation of

$$\left[\ln\left(K_{j,1975}^{PIM} / K_{j,1975}^{FIRE}\right), \ln\left(K_{j,1976}^{PIM} / K_{j,1976}^{FIRE}\right), \ldots, \ln\left(K_{j,1984}^{PIM} / K_{j,1984}^{FIRE}\right)\right], \tag{A2.3}$$

where $K_{j,1984}^{PIM}$ is the capital stock of industry j in 1984 calculated by the formula (A2.1) (and using 10 per cent as a depreciation rate) and $K_{j,1984}^{FIRE}$ is the capital stock measured by the fire insurance value. In the period from 1975 to 1984, the first value of the net capital measure of a plant i in industry j is $K_{ij0}^{PIM} = X_j \cdot K_{ij0}^{FIRE}$.

One way to assess the reliability of the capital input estimates is to compare the development of capital intensity measured by the PIM estimates to that measured by the fire insurance value estimates among those plants that have a positive estimate for both variables. Graph A2.2 shows that at the level of total manufacturing the two series provide a quite consistent picture of the development of capital input.[147] The scales of these measures differ by about a factor of three.

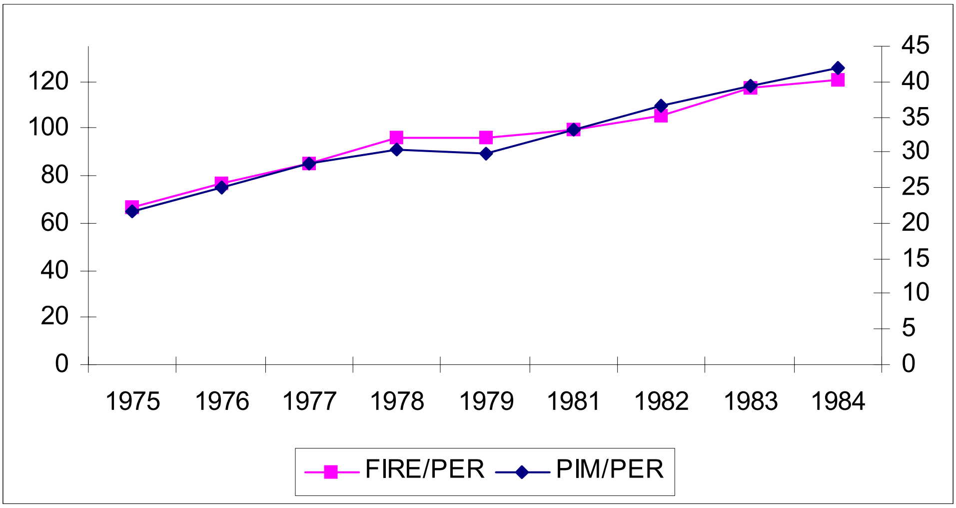
The reliability of the capital input estimates can be evaluated by means of cross-sectional variation between plants as well. We can compute the reliability of the PIM estimates and the fire insurance value estimates by assuming that these two variables are independent estimates of capital input.[148 149] The reliability ratios can be derived by regressing one indicator of capital input on the other. Both indicators are expressed in natural logarithms here. However, these two indicators are based on different concepts and therefore their scales may vary. Besides, the differences in the scales vary across industries. Therefore we have included industry dummies to control industry effects (and an intercept).

[147] Maliranta (1997b) provides us with a somewhat more detailed analysis about the quality of the capital input measure generated in this way.

[148] For example, Krueger and Lindahl (2001) have used the same technique in evaluating the reliability of schooling indicators in different country data sets.

[149] It should be noted that since for most of the plants the initial stock is estimated by using the fire insurance estimate of capital stock there may be some correlation in the measurement errors between these two indicators. However, when the initial year is far behind in the past the correlation should be quite small. We will note below that the reliability ratios are quite stable since the year 1981 and they probably give a reasonably correct picture about the reliability of these indicators.

Graph A2.2 Capital intensity, by two different gauges, EUR thousands, in 1995 prices



Note: *FIRE* denotes the capital stock estimate based on the fire insurance value of tangible capital stock requested from plants up to 1984 (information is lacking for 1980), while *PIM* denotes the capital stock estimated by the PIM method and *PER* denotes the number of persons engaged (employees and owners).

Table A2.2 gives estimates of the reliability ratios of the PIM estimates and the fire insurance value estimates. The reliability ratio for the PIM estimate is about 87 %, which indicates that the variable has a considerable signal in the cross-sectional dimension. The reliability of the fire insurance value estimate seems to be even slightly better. When the controls for the industries are dropped, the reliability ratios of the fire insurance value estimates become slightly higher by increasing to about 90 %. The reliability of the PIM estimates instead stays quite unaltered.

Table A2.2 Reliability of the two capital input indicators of LDPM data

Year	Reliability of the PIM estimate	Reliability of the fire insurance value estimate
1981	87.5 %	89.3 %
	(0.6 %)	(0.6 %)
1982	87.3 %	88.7 %
	(0.6 %)	(0.6 %)
1983	86.8 %	89.0 %
	(0.6 %)	(0.6 %)
1984	86.7 %	89.4 %
	(0.6 %)	(0.6 %)

Notes: The estimated reliability ratios are the slope coefficients from a regression of one measure of capital input on the other. All regression models also include dummies for industries. The estimates in the first column are obtained from the regression models in which the dependent variable is the log of the fire insurance value estimate. The second column reports the results from the reverse regression. Standard errors are reported in parentheses.

Appendix 3. Productivity decomposition results

Table A3.1 Labour productivity decompositions, output measured by gross output, annual averages, %

Method	Period				
	1976-80	1981-85	1986-90	1991-95	1996-00
Aggregate					
MBJ, MBBH, INP	4.9	3.2	5.7	7.5	5.5
GR, FHK	4.2	3.4	6.1	7.2	4.7
Within					
MBJ, INP	4.2	2.9	4.5	4.0	4.7
MBBH	4.6	3.2	5.0	4.4	5.1
GR	4.2	2.8	4.4	3.9	4.7
FHK	4.5	3.2	5.0	4.2	5.1
Between					
MBJ, INP	0.3	0.3	0.6	0.9	0.3
MBBH	0.9	0.9	1.4	1.6	1.1
GR	0.2	0.3	0.7	0.9	0.1
FHK	0.5	0.7	1.3	1.3	0.6
Catching up					
MBJ	0.7	0.1	-0.1	0.9	1.0
MBBH	0.9	0.3	0.2	1.3	1.3
Cross term					
MBBH	-1.1	-1.2	-1.6	-1.5	-1.5
FHK	-0.8	-0.7	-1.1	-0.6	-0.8
Net entry					
MBJ, MBBH, INP	-0.4	0.0	0.6	0.8	-0.4
GR	-0.1	0.3	1.0	1.3	-0.1
FHK	-0.1	0.3	1.0	1.2	-0.1
Entry					
MBJ, MBBH, INP	-0.8	-0.5	-0.6	-0.5	-1.1
GR	-0.8	-0.6	-0.6	-0.5	-1.3
FHK	-0.7	-0.5	-0.5	-0.5	-1.2
Exit					
MBJ, MBBH, INP	0.4	0.5	1.2	1.3	0.7
GR	0.7	0.8	1.6	1.8	1.2
FHK	0.6	0.8	1.5	1.7	1.1

Table A3.2 Labour productivity decompositions, output measured by value added, annual averages, %

Method	Period 1976-80	1981-85	1986-90	1991-95	1996-00
Aggregate					
MBJ, MBBH, INP	3.3	4.3	6.6	4.0	5.2
GR, FHK	3.4	4.0	7.1	4.0	3.8
Within					
MBJ, INP	3.2	2.9	4.8	0.9	3.2
MBBH	3.6	3.3	5.3	1.2	3.4
GR	3.3	3.1	5.0	1.0	3.1
FHK	3.7	3.4	5.5	1.3	3.4
Between					
MBJ, INP	0.1	0.5	0.9	1.2	0.8
MBBH	0.7	0.9	1.5	1.9	1.1
GR	0.0	0.5	0.9	1.3	0.6
FHK	0.5	0.8	1.5	1.7	0.9
Catching up					
MBJ	0.2	0.5	0.4	0.6	1.4
MBBH	0.4	0.7	0.5	1.0	1.5
Cross term					
MBBH	-1.3	-0.8	-1.3	-1.5	-0.7
FHK	-0.9	-0.6	-1.0	-0.6	-0.5
Net entry					
MBJ, MBBH, INP	-0.1	0.3	0.6	0.6	-0.1
GR	0.1	0.5	1.2	1.0	0.1
FHK	0.1	0.5	1.1	1.0	0.1
Entry					
MBJ, MBBH, INP	-0.4	-0.2	-0.3	-0.3	-0.8
GR	-0.5	-0.3	-0.2	-0.3	-0.8
FHK	-0.4	-0.3	-0.1	-0.3	-0.7
Exit					
MBJ, MBBH, INP	0.3	0.5	0.9	0.9	0.6
GR	0.5	0.8	1.3	1.3	0.9
FHK	0.5	0.7	1.2	1.3	0.8

Table A3.3 TFP decompositions, output measured by gross output, annual averages, %

Method	Period				
	1976-80	1981-85	1986-90	1991-95	1996-00
Aggregate					
MBJ, MBBH	2.6	0.7	2.0	6.2	4.3
INP	2.6	0.2	2.0	6.0	4.3
GR, FHK (input)	2.7	0.4	2.6	6.2	4.3
GR, FHK (output)	2.6	0.0	1.1	5.7	4.5
Within					
MBJ	1.5	-0.2	0.7	3.1	2.9
MBBH	1.9	0.2	1.3	3.1	3.1
INP	1.8	-0.3	0.9	3.6	3.3
GR (input)	1.7	-0.3	0.8	3.5	3.2
GR (output)	1.4	-0.6	0.2	3.3	3.0
FHK (input)	2.1	0.2	1.4	3.5	3.5
FHK (output)	-1.1	-2.3	-1.8	0.5	0.6
Between					
MBJ	1.4	1.3	1.3	2.1	1.1
MBBH	2.2	2.0	2.3	2.6	1.7
INP	0.9	0.7	1.1	1.7	0.8
GR (input)	0.6	0.5	1.0	1.3	0.5
GR (output)	0.6	0.3	0.1	1.2	0.9
FHK (input)	1.1	1.0	1.6	1.4	0.8
FHK (output)	-2.0	-1.5	-1.9	-1.5	-1.5
Catching up					
MBJ	-0.3	-0.4	-0.6	0.2	0.0
MBBH	0.1	-0.1	-0.2	0.6	0.4
INP	-0.5	-0.4	-0.7	-0.3	-0.4
Cross term					
MBBH	-1.5	-1.4	-1.9	-1.0	-1.2
FHK (input)	-0.8	-0.9	-1.2	0.0	-0.5
FHK (output)	5.1	3.5	4.0	5.5	4.7
Net entry					
MBJ, MBBH	-0.1	0.1	0.5	0.6	0.3
INP	0.5	0.2	0.8	0.9	0.6
GR (input)	0.4	0.2	0.8	1.0	0.6
GR (output)	0.6	0.2	0.8	1.1	0.7
FHK (input)	0.4	0.2	0.8	0.9	0.6
FHK (output)	0.6	0.2	0.8	1.1	0.7
Entry					
INP	0.3	0.1	0.4	0.5	0.6
GR (input)	0.1	0.0	0.1	0.2	0.3
GR (output)	0.6	0.3	0.6	0.9	1.1
FHK (input)	0.1	0.0	0.1	0.2	0.3
FHK (output)	0.7	0.3	0.6	1.0	1.1
Exit					
INP	0.1	0.1	0.4	0.4	0.0
GR (input)	0.3	0.2	0.7	0.8	0.4
GR (output)	0.0	-0.1	0.2	0.2	-0.4
FHK (input)	0.3	0.2	0.7	0.7	0.3
FHK (output)	0.0	-0.1	0.1	0.1	-0.4

Table A3.4 TFP decompositions, output measured by value added, annual averages, %

Method	Period				
	1976-80	1981-85	1986-90	1991-95	1996-00
Aggregate					
MBJ, MBBH	1.0	1.7	3.2	2.8	3.5
INP	1.0	1.1	3.3	2.5	3.6
GR, FHK (input)	1.9	0.9	3.7	3.9	3.5
GR, FHK (output)	0.4	1.4	3.0	1.2	3.8
Within					
MBJ	0.5	-0.3	1.5	1.3	2.0
MBBH	1.0	0.1	2.0	1.4	2.1
INP	0.6	-0.3	1.7	1.5	2.3
GR (input)	0.7	-0.3	1.8	1.6	2.2
GR (output)	-0.5	-0.3	1.5	0.1	1.8
FHK (input)	1.2	0.2	2.5	1.6	2.3
FHK (output)	-10.1	-7.7	-6.6	-8.9	-4.5
Between					
MBJ	1.5	1.6	1.5	2.3	1.2
MBBH	2.4	2.4	2.6	2.9	1.7
INP	1.1	1.0	1.3	1.9	1.0
GR (input)	0.7	0.8	1.1	1.5	0.8
GR (output)	-0.3	1.2	0.8	0.4	1.1
FHK (input)	1.3	1.3	1.8	1.6	1.0
FHK (output)	-9.9	-6.3	-7.3	-8.5	-5.2
Catching up					
MBJ	-1.3	-0.1	-0.2	-1.3	0.0
MBBH	-0.9	0.3	0.3	-0.9	0.3
INP	-1.4	0.0	-0.4	-1.6	-0.3
Cross term					
MBBH	-1.9	-1.5	-2.1	-1.1	-1.0
FHK (input)	-1.1	-1.0	-1.3	-0.1	-0.3
FHK (output)	19.2	14.9	16.1	17.9	12.7
Net entry					
MBJ, MBBH	0.3	0.3	0.4	0.3	0.4
INP	0.7	0.4	0.7	0.6	0.6
GR (input)	0.5	0.4	0.7	0.7	0.5
GR (output)	1.1	0.5	0.8	0.7	0.9
FHK (input)	0.4	0.4	0.7	0.7	0.5
FHK (output)	1.1	0.5	0.8	0.7	0.9
Entry					
INP	0.7	0.3	0.7	0.6	0.6
GR (input)	0.2	0.1	0.3	0.2	0.2
GR (output)	1.2	0.6	1.1	1.0	1.1
FHK (input)	0.2	0.1	0.4	0.2	0.2
FHK (output)	1.2	0.6	1.1	1.0	1.2
Exit					
INP	0.1	0.1	0.0	0.1	0.0
GR (input)	0.3	0.3	0.4	0.5	0.3
GR (output)	-0.1	0.0	-0.3	-0.3	-0.2
FHK (input)	0.2	0.2	0.4	0.5	0.2
FHK (output)	-0.1	0.0	-0.3	-0.3	-0.3

Table A3.5 MFP decompositions, output measured by gross output, annual averages, %

Method	Period				
	1976-80	1981-85	1986-90	1991-95	1996-00
Aggregate					
MBJ, MBBH	1.5	1.0	1.4	2.1	1.7
INP	1.5	0.8	1.2	2.0	1.6
GR, FHK (input)	1.3	0.4	0.7	1.4	1.5
GR, FHK (output)	0.8	0.5	0.7	0.6	1.4
Within					
MBJ	1.5	0.4	0.5	1.3	0.9
MBBH	1.7	0.6	1.0	1.8	1.6
INP	1.7	0.4	0.6	1.5	1.1
GR (input)	0.9	0.0	0.0	0.2	0.9
GR (output)	0.5	0.0	0.0	-0.2	0.8
FHK (input)	1.1	0.2	0.3	0.5	0.8
FHK (output)	-0.7	-0.9	-1.1	-1.4	-0.2
Between					
MBJ	0.0	0.4	0.8	0.4	0.4
MBBH	0.8	1.0	1.8	1.9	2.0
INP	-0.2	0.2	0.5	0.3	0.3
GR (input)	0.1	0.2	0.4	0.9	0.3
GR (output)	-0.1	0.3	0.4	0.5	0.3
FHK (input)	0.3	0.4	0.7	1.1	0.2
FHK (output)	-1.3	-0.6	-0.6	-0.7	-0.7
Catching up					
MBJ	-0.1	0.0	-0.2	0.0	0.1
MBBH	0.3	0.4	0.3	1.0	0.9
INP	-0.4	0.0	-0.3	-0.2	-0.1
Cross term					
MBBH	-1.5	-1.2	-2.0	-3.0	-3.1
FHK (input)	-0.4	-0.4	-0.6	-0.5	0.3
FHK (output)	2.5	1.8	2.1	2.3	2.0
Net entry					
MBJ, MBBH	0.1	0.1	0.3	0.3	0.2
INP	0.3	0.2	0.4	0.4	0.2
GR (input)	0.3	0.2	0.3	0.4	0.3
GR (output)	0.4	0.2	0.3	0.4	0.3
FHK (input)	0.3	0.2	0.3	0.3	0.3
FHK (output)	0.4	0.2	0.3	0.4	0.3
Entry					
INP	0.3	0.1	0.3	0.3	0.3
GR (input)	0.2	0.1	0.2	0.2	0.2
GR (output)	0.4	0.2	0.3	0.5	0.4
FHK (input)	0.2	0.1	0.2	0.2	0.2
FHK (output)	0.4	0.2	0.4	0.5	0.4
Exit					
INP	0.0	0.1	0.1	0.1	-0.1
GR (input)	0.0	0.1	0.1	0.1	0.0
GR (output)	0.0	0.0	-0.1	0.0	-0.1
FHK (input)	0.0	0.1	0.1	0.1	0.0
FHK (output)	0.0	0.0	-0.1	0.0	-0.1