In search of an ideal method for analyzing micro-level dynamics of a great productivity leap *

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Abstract

This paper has two aims; 1) to understand the micro-level mechanisms of a great productivity leap in Finnish manufacturing industries since 1980s and 2) find a method best suited for such analysis. Four alterantives are analytically and empirically evaluated by a use of a plant-level panel covering years 1975-2007 . The paper has three main contributions. First, as for measuring the static Olley-Pakes decomposition, a regression approach is proposed, which gives a standard error estimate for the covariance component and allows controlling for the other factors of the firm productivity. Second, as for a dynamic analysis, a preferable method with several theoretical and empiral advantages is proposed. It gives an unbiased view on the role of entries and exits as well as the reallocation between staying firms in industry productivity growth. The firm (or plant) component indicates the rate at which the productivity of an average input increases over time when it stays in the same production unit. The method is partly related to a dynamic Olley-Pakes decompositioin recently proposed by Melitz and Polanec (2009). Third, the acceleration of productivity growth in Finnish manufacturing industries is found to be almost totally attributed to the intensified micro-level restructuring. For the purpose of evaluating the decomposition methods, a number of robustness checks have been made with alternative data sets, size thresholds, time-windows and output measures.

Keywords: Productivity, index numbers, productivity decomposition methods, industry dynamics, creative destruction, catching-up

JEL classification: *C43, D24, O47, L60, J24*

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I. Introduction

The Finnish manufacturing sector has witnessed a great leap to the international productivity frontier over the past three decades. To give a flavor of the significance of the upsurge, the labor productivity level of the Finnish manufacturing sector was 68.6 percent of that in the United States in 1980 but had increased to 99.6 percent by the year 1993 according to the computations made in the Groningen University[1].[2] This paper has two aims; 1) to understand the micro-level mechanisms of this catch-up and 2) find a method best suited for such analysis. Ideally, the method should have strong theoretical justifications and intuitive economic interpretations. In addition, it should not be sensitive to imperfections of empirical micro-data.

The paper has three main contributions. First, as for measuring the popular static Olley-Pakes decomposition (Olley & Pakes, 1996), a regression approach is proposed, which gives a standard error estimate for the covariance component and allows controlling for the other factors of the firm productivity.

Second, as for a dynamic analysis, a preferable method with several theoretical and empirical advantages is proposed. It gives an unbiased view on the role of entries and exits as well as the reallocation between incumbent firms in

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[1] Groningen Growth and Development Centre, ICOP Database 1987 Benchmark, http://www.ggdc.net

[2] According to the results by O'Mahoney and Timmer (2009, page 386) for the manufacturing sector, the multi-factor productivity (MFP) level in Finland was 7% higher than in the United States in 2005. Out of 18 countries included in the comparison, Finland was at the third place after Belgium (that had 9% higher MFP than the United states) and Ireland (54%).

industry productivity growth. The firm (or plant) component indicates the rate at which the productivity of an average input increases over time when it stays in the same production unit. The restructuring component consists of the entry, exit and between components. The fifth component of the method is called the cross-component. It essentially captures the difference between the standard measure of the industry productivity growth rate (based on the sum-aggregates of output and input) and the industry productivity growth rate computed by aggregating log-productivity of the firms, as typically done in the micro-level productivity decompositions. Further, while this method takes a dynamic approach to the micro-level allocation of resources it is compatible with the view emphasized by the modern economic growth literature that incessant restructuring is an essential element of growth. Comparisons of the results obtained from alternative micro-data sources, size thresholds, time-windows and output measures suggest that the method is reasonably robust. Finally, an analytical and empirical comparison with an alternative novel method by Melitz and Polanec (2009) shows that both methods have some important similarities and seem to be complementary tools in the analysis of the micro-level dynamics of productivity growth. By a use of a further break-down by cohorts, the preferred decomposition method is particularly suitable for distinguishing empirically between the phases of experimentation, selection, restructuring and learning-by-doing in the life cycle of plants.

The third contribution of the paper is purely an empirical one. With suitable methods and with exceptional rich and long panel data, a number of important aspects in the micro-level dynamics of rapid industry productivity growth in 15 Finnish manufacturing industries are unveiled. Three periods can be distinguished in the development; 1) the pre-transition period (from 1976 to 1983), 2) the transition period (from 1984 to 1993) and 3) the post-transition period (after 1994). The average annual restructuring component of labor productivity growth in these three periods was 0.3, 1.3 and 0.8 percentage points, respectively. The corresponding numbers for multi-factor productivity (*MFP*) growth were larger being 1.1, 1.7 and 1.9 percentage points. Both productivity-enhancing restructuring between the staying plants (i.e. the between component) and the exit component positively contributed to industry labor productivity growth whereas for *MFP* growth of the industries also the entry component appears to have had a positive role to play, although the latter finding should be interpreted with some caution. Furthermore, the plants that made their entry in the years 1986-1990 is found to have had a special role in the years to come. They not only had high productivity growth rates but they also had an important contribution to productivity-enhancing intra-industry restructuring (i.e. the so-called "creative destruction").

Evidence suggests that the collapse of the trade to the former Soviet Union after 1983 triggered "creative destruction" in the Finnish manufacturing industries that paved the way for a climb to the international productivity frontier by the mid-90s. On the other hand, the results are broadly consistent with the view stated in the modern economic growth literature that micro-level restructuring is more important for such economies and industries that are on the international technology frontier than those far away it (e.g. Acemoglu et al., 2006; Bernard, Redding et al., 2007).

A number of robustness checks have been performed by using alternative measures of output, different sample selection criteria, longer time-windows in addition to annual changes, and more importantly, alternative decomposition methods as well as alternative firm- or plant-level data sources. These analyses confirmed the main findings of the study but also indicated the great value of good data and suitable methods. They indicate that the harmonization of the computation procedures for the international comparisons, as done by Bartelsman et al. (2009), is crucial but also challenging task to do.

Theoretical underpinnings of this paper comes from the mutually related literatures on economic growth (e.g. Aghion & Howitt, 2005; Caballero, 2007), economic geography (e.g. Baldwin & Okubo, 2006) as well as international trade (e.g. Melitz, 2003; Bernard, Jensen et al., 2007; Melitz & Ottaviano, 2008). These models provide elaborated explanations for a variety of fresh empirical findings made ever since the comprehensive micro-level data become increasingly accessible in many countries in the 90s.

Important contributions to the literature of micro-level decompositions of productivity growth include, among others, Baily, Hulten and Campbell (1992), Griliches and Regev (1995), Haltiwanger (1997), Bartelsman and Dhrymes (1998), and Aw, Chen and Roberts (2001). Olley and Pakes (1996) presents a method for decomposing aggregate productivity level into an unweighted average effect and allocation (covariance) effect. Discussion on the strengths and weaknesses of different methods is provided, among others, by Foster, Haltiwanger and Krizan (2001), Maliranta (2003), Diewert and Fox (2009), and Bartelsman, Haltiwanger and Scarpetta (2009).

To provide some background and motivation for the empirical part of the study, some key aspects of the Finnish manufacturing sector are highlighted in the next section. They include the unique bilateral trade arrangement with the former Soviet Union that climaxed in 1983 and ended in 1991 as well as the trends in the development of hours worked and productivity. In Section III, some alternative productivity decomposition methods are described, analytically compared and evaluated. In Section IV, the empirical analysis of the micro-level dynamics of productivity growth in 15 manufacturing industries is performed. In this section alternative decomposition methods are compared empirically. Concluding remarks are made in Section V.

II. Finnish manufacturing industries in transition

II.1 The collapse of the trade to the Soviet Union in the 1980s

The Finnish Great depression is thoroughly described in several studies including, for example, Honkapohja et al. (1996), Kiander et al. (1998) Honkapohja and Koskela (1999), Honkapohja et al. (2009), and Gorodnichenko et al. (2009). These studies typically share a couple of emphasis; one is the exceptional severity of the recession and another is the failure in the policy, including the deregulation of financial markets in the 1980s as well as monetary and fiscal policy. Also bad luck is recognized as one ingredient referring to the collapse of export to the Soviet Union. Yet, few studies acknowledge this as a main triggering factor, the paper by Gorodnichenko et al. (2009) being perhaps the main exception (see also Tarkka, 1994).

This paper takes a notice to two important points pertaining to the trade between Finland and the Soviet Union. The first is the timing of the collapse and the second its potential implications for the micro-level dynamics, both interesting aspects from the point of view of this study. A series of collapses in the trade to the Soviet Union started after 1983, i.e. several years before the great depression of the early 1990s (see Graph 1). The decline in exports to the Soviet Union between years 1983 and 1989 can be largely attributed to a decrease in the world crude oil prices for two reasons. First, Finland had a bilateral clearing arrangement with the Soviet Union unique among developed market economies.

According to the system, trade should be balanced annually and only relatively small temporary imbalances were allowed. This feature of the system can also been seen in Graph 1 where imports from the Soviet Union per total value of production in the manufacturing industries is represented by a dashed line. Second, mineral fuels accounted for above 80 percent of the imports from the Soviet Union in the early 1980s. The sharp decline in the world crude oil prices was found difficult to be compensated by an increase of other forms of imports, which led to a need to cut down exporting (see Sutela, 1991). The collapse of the trade after 1989, in turn, can be attributed to the political changes that took place in the Soviet Union in the late 1980s (the so-called Perestroika) which finally led to an end of the bilateral trade system and a further drop in the trade (see e.g. Gorodnichenko et al., 2009). From the point of view of this study it is worth noting that the reasons for the collapses of the trade with the Soviet Union between years 1983 and 1991 stem from the outside of the Finnish manufacturing industries, first it was a world oil prices and later it was the political changes in the Soviet Union.

< GRAPH 1 ABOUT HERE>

The second important aspect of the trade with the Soviet Union has to do with implications for micro-level structures. For one thing, opportunities to export to the Soviet Union concerned only a limited number of the firms (and in practice plants), and for another exporting was very profitable to these firms. Sutela (1991) reports that 600-700 firms exported to the Soviet Union in the seventies. By 1989 the number of these firms had increased to 1688 but exporting to the Soviet Union was still highly concentrated. A total of 116 exporters accounted for 90 percent of all export. As for profitability, Kajaste (1992) estimates that the prices of exports to the Soviet Union were at least 9.5 percent higher than those for exports to western markets. Gorodnichenko et al. (2009) estimates that this markup was as large as 36 percent.

So, exporting to the Soviet Union was highly profitable to the firms involved but on the other hand this opportunity concerned only a limited number of firms (and plants). All in all, the bilateral trade with the Soviet Union meant a significant subvention system to a part of the incumbent firms. Consequently, the downfall of the system since 1983 can be expected to have led a profound changes in the structures not only between different industries, as emphasized in Gorodnichenko et al. (2009), but also between firms (and plants) within industries. The fact, reported by Kajaste (1992), that a large proportion of exports was highly specialized to the Soviet markets and was difficult to convert to western markets just strengthens the point. It seems that new technology and new plants were needed to replace the capacity build for serving the Soviet markets. The years from 1983 to 1991 represents a period of a moderate increase in export to other countries (mainly to western markets) which seems more like a continuation of the trend started in the 70s rather than a reflection of a major relocation of exports. All in all, it seems that Finland can be described as a semi-transition economy during the years from 1983 to 1993 (see Tarkka, 1994).

II.2 Other developments

A trend of declining labor input in the Finnish manufacturing industries started at the beginning of the 1980s and took a steeper slope during the yearly 1990s. Between the years 1983 and 1990 the number of hours worked had decreased by 12.8 percent and between the years 1983 and 1993 by 34.3 percent. The years from 1993 to 2001 represent a period of uninterrupted growth in terms of labor input. The number of hours worked increased by 20.4 percent (see Graph A2.1).

<GRAPH 2 ABOUT HERE>

Besides labor input growth, it is an interest of this paper to have a look at the development of the other source of economic growth, i.e. labor productivity growth. Graph 2 presents two measures of productivity. The first is the productivity level of the Finnish manufacturing sector relative to that of the United States. The relative labor productivity level in 1987 is obtained from the database of Groningen University (the Groningen Growth and Development Centre, ICOP Industrial Database, 1987 Benchmark). Other years are extrapolated by using productivity time-series obtained from various sources (see further details in the note of the graph). The graph shows a great leap if in Finnish manufacturing productivity between the years 1983 and 1993. The second productivity measure shown in Graph 2 is the annual labor productivity growth (scale on the right). Both the observed and the smoothed series are shown.[3] It can be seen that an important part of the catch-up is due to the acceleration of productivity growth in Finland after 1983. Before we make use of plant-level data to examine in depth the micro-level dynamics of productivity growth in the Finnish manufacturing industries in Section IV, some methods useful in such an analysis are first examined in Section III.

III. Decomposition methods

III.1 Method 1, static approach

The industry productivity index Φ can be defined as follows:

[3] The growth rates are smoothed by using the Hodrick-Prescott filter with a parameter of 6.25, as recommended by Ravn and Uhlig (2002)

$$\Phi_1 = \sum_{i \in \Omega_1} s_{i1} \varphi_{i1} \tag{1}$$

where s_{i1} and φ_{i1} are the share of firm i in an industry in period 1 and its productivity index defined as;

$$s_{i1} = \frac{L_{i1}}{\sum_{i \in \Omega_1} L_{i1}} \tag{2}$$

$$\varphi_{i1} = \frac{Y_{i1}}{L_{i1}} \tag{3}$$

where L_{i1} and Y_{i1} denote labor input and output, respectively.[4]

Inserting (2) and (3) into equation (1) gives the form

$$\Phi_1 = \sum_{i \in \Omega_1} \frac{L_{i1}}{\sum_{i \in \Omega_1} L_{i1}} \frac{Y_{i1}}{L_{i1}} = \frac{\sum_{i \in \Omega_1} Y}{\sum_{i \in \Omega_1} L} \tag{4}$$

which is the standard aggregate (or industry) labor productivity measure that is based on the sum-aggregate values of output and input and that can be obtained from industry-level data such as the EU-KLEMS database. From the standpoint of performing micro-level decompositions of productivity it is useful to note that the standard aggregate labor productivity level is a labor input weighted arithmetic average of the firm productivity levels (see e.g. Van Biesebroeck, 2003).

Alternatively, firm productivity can be measured in terms of the log-units as

[4] Later we discuss the use of multi-factor productivity index that include more than one input.

$$\tilde{\varphi}_{i1} = \ln \frac{Y_{i1}}{L_{i1}} \tag{5}$$

In this case we obtain a measure of industry productivity that is also measured on the log-scale

$$\tilde{\Phi}_1 = \sum_{i \in \Omega_1} s_{i \in \Omega, 1} \tilde{\varphi}_{i1} \sum_{i \in \Omega_1} \frac{L_{i1}}{\sum_{i \in \Omega_1} L_{i1}} \tilde{\varphi}_{i1} \tag{6}$$

It should be noted that $\exp\left(\tilde{\Phi}_1\right)$ is a weighted geometric average of firms' productivity indices defined in (3).

The firms in period *1* can be classified into two groups: "stayers", which appeared also in the previous period *0*, and "entrants", which did not exist in period 0. The former group is denoted by Ω_S and the latter by Ω_N. The industry productivity index can then be expressed as

$$\tilde{\Phi}_1 = \sum_{i \in \Omega_S} s_{i1} \tilde{\varphi}_{i1} + \sum_{j \in \Omega_N} s_{j1} \tilde{\varphi}_{j1} \tag{7}$$

where $\sum_{i \in \Omega_S} s_{i1} + \sum_{j \in \Omega_N} s_{j1} = 1$ by definition.

Aggregate industry productivity index can be written as

$$\begin{aligned} \tilde{\Phi}_1 &= \left(1 - S_1^{entrant}\right) \tilde{\Phi}_1^{stayer} + S_1^{entrant} \tilde{\Phi}_1^{entrant} \\ &= \tilde{\Phi}_1^{stayer} + S_1^{entrant} \left(\tilde{\Phi}_1^{entrant} - \tilde{\Phi}_1^{stayer}\right) \end{aligned} \tag{8}$$

where $S_1^{entrant} = \sum_{j \in \Omega_N} s_{j1} = 1 - \sum_{i \in \Omega_S} s_{i1}$ is the employment share of the entrants (see Maliranta, 1997b; Vainiomäki, 1999; Diewert & Fox, 2009).

The second component in the second row of (8) indicates the contribution of the new firms to the current industry productivity level, i.e. how much lower or higher industry productivity level would be without the entrants. The component is positive when the aggregate productivity (i.e. the weighted average productivity) of the new firms ($\tilde{\Phi}_1^{entrant}$) is higher than that of the stayer firms ($\tilde{\Phi}_1^{stayer}$). The magnitude of the effect is dependent on the share of the new firms in period 1 ($S_1^{entrant}$) and the log-difference in the productivity level between the stayers and the entrants.

The industry productivity index can be decomposed into two components by using the static Olley-Pakes decomposition (Olley & Pakes, 1996):

$$\begin{aligned}\tilde{\Phi}_1 &= \bar{\tilde{\varphi}}_1 + \sum\nolimits_{i\in\Omega_1}\left(s_{i1} - \bar{s}_1\right)\left(\varphi_{i1} - \bar{\tilde{\varphi}}_1\right) \\ &= \bar{\tilde{\varphi}}_1 + \operatorname{cov}\left(s_{i1}, \tilde{\varphi}_{i1}\right)\end{aligned} \tag{9}$$

Obviously a similar decomposition can be made separately for the stayers

$$\tilde{\Phi}_1^{stayer} = \bar{\tilde{\varphi}}_1^{stayer} + \operatorname{cov}_1^{stayer}\left(s, \tilde{\varphi}\right) \tag{10}$$

and for the entrants

$$\tilde{\Phi}_1^{entrant} = \bar{\tilde{\varphi}}_1^{entrant} + \operatorname{cov}_1^{entrant}\left(s, \tilde{\varphi}\right) \tag{11}$$

By inserting (10) and (11) into (8) we obtain (see Melitz & Polanec, 2009)

$$\tilde{\Phi}_1 = \bar{\tilde{\varphi}}_1^{stayer} + \operatorname{cov}_1^{stayer}\left(s, \tilde{\varphi}\right) + S_1^{entrant}\left(\tilde{\Phi}_1^{entrant} - \tilde{\Phi}_1^{stayer}\right) \tag{12}$$

and further

$$\begin{aligned}&\tilde{\Phi}_1 = \bar{\tilde{\varphi}}_1^{stayer} + \operatorname{cov}_1^{stayer}\left(s, \tilde{\varphi}\right) + \\ &S_1^{entrant}\left(\bar{\tilde{\varphi}}_1^{entrant} - \bar{\tilde{\varphi}}_1^{stayer}\right) + S_1^{entrant}\left(\operatorname{cov}_1^{entrant}\left(s, \tilde{\varphi}\right) - \operatorname{cov}_1^{stayer}\left(s, \tilde{\varphi}\right)\right)\end{aligned} \tag{13}$$

The industry productivity level consists of three (equation (12)) or four components (equation (13)). In the latter both the stayers and the entrants have two sub-components; the average and covariance component. The covariance component of the stayers is the difference between the weighted (i.e. aggregate productivity level) and the unweighted average of the stayers (see (10)). It is positive when there is a positive relationship between the productivity level and the employment share among the stayers. Accordingly, entrants can contribute to the industry productivity level through two channels; through the average component and the covariance component. The former is positive when the unweighted average productivity of the new firms is higher than that of the stayers. The covariance (or allocation) component of the entrants is positive when the covariance between the size and the productivity level is larger among the entrants than among the stayers (see (13)).

The productivity index is useful in the comparisons of productivity, i.e. measuring productivity growth or relative productivity levels. Equations (12) and (13) can be used for analysing the micro-level sources of the productivity gaps between different countries or between different regions of the same country, for example. However, more common is to compare productivity levels between two different points of time, which leads to a dynamic approach of analyzing productivity and its micro-level sources.

One attractive feature in the static Olley-Pakes decomposition is that the covariance (or allocation) component can be estimated by using ordinary least square (OLS) method. Consequently, it is possible to estimate the standard error of the covariance component and thus evaluate its accuracy. To my best knowledge this possibility has not utilized in the literature so far.

Let us assume that the log-productivity of firm *i*, that is $\tilde{\varphi}_i$, includes a deterministic component α^U and a stochastic component ε_i as follows;

$$\tilde{\varphi}_i = \alpha^U + \varepsilon_i, \quad i = 1,...,n; \varepsilon_i \sim N\left(0, \sigma^2\right) \tag{14}$$

As well-known, in this case the unweighted OLS estimate of the deterministic component is

$$\hat{\alpha}^U = \frac{\sum_i \tilde{\varphi}_i}{n} = \overline{\tilde{\varphi}} \tag{15}$$

where n is the number of firms.

Next, let us consider a transformed model

$$\sqrt{L_i}\tilde{\varphi}_i = \sqrt{L_i}\alpha^W + \sqrt{L_i}\varepsilon_i, \quad i = 1,...,n; \varepsilon_i \sim N\left(0, \sigma^2 / L_i\right) \tag{16}$$

It is straightforward to show that the OLS estimate of the deterministic component is

$$\hat{\alpha}^W = \sum_i \frac{L_i}{L}\tilde{\varphi}_i = \tilde{\Phi} \tag{17}$$

Inserting (15) and (17) into (9) gives

$$\operatorname{cov}\left(s_{i1}, \tilde{\varphi}_{i1}\right) = \hat{\alpha}^W - \hat{\alpha}^U = \hat{\lambda} \tag{18}$$

After having applied a seemingly unrelated estimation to the models (14) and (16), the coefficient $\hat{\lambda}$ and its standard error can be computed by a linear combination post-estimation. Besides providing a gauge of the accuracy for the covariance component, the approach also allows controlling for other potentially confounding factors of productivity in a straightforward manner. Because the covariance component is computed by the intercepts, a suitable parametrization for the coefficients of the control variables is needed, for example by means of the parameter constraints. The aim is that the intercept indicates the productivity level at the sample average.

III.2 Dynamic approach

Next we are interested in the change of productivity between two periods, 0 and 1. The industry productivity level in period 1 is defined as in (5) above. The industry productivity level in period 0 is defined analogously except now the firms are classified into the following two groups; the stayer firms and the exiting firms. The former group consists of the firms that appear both in period 0 and period 1 and the latter group of those that do not appear in period 1.

Now the industry productivity level in period 0 can be written as follows

$$\tilde{\Phi}_0 = \sum_{i \in \Omega_S} s_{i0} \tilde{\varphi}_{i0} + \sum_{k \in \Omega_X} s_{k0} \tilde{\varphi}_{k0} \tag{19}$$

where $\sum_{i \in \Omega_S} s_{i0} + \sum_{k \in \Omega_X} s_{k0} = 1$.

The industry productivity level can be derived into a form that is analogous to that of (8);

$$\tilde{\Phi}_0 = \tilde{\Phi}_0^{stayer} + S_0^{exit} \left(\tilde{\Phi}_0^{exit} - \tilde{\Phi}_0^{stayer} \right) \tag{20}$$

The next task is to decompose the industry productivity change $\Delta\tilde{\Phi}_1$:

$$\begin{aligned} \Delta\tilde{\Phi}_1 &= \tilde{\Phi}_1 - \tilde{\Phi}_0 \\ &= \tilde{\Phi}_1^{stayer} - \tilde{\Phi}_0^{stayer} + S_1^{entrant} \left(\tilde{\Phi}_1^{entrant} - \tilde{\Phi}_1^{stayer} \right) + S_0^{exit} \left(\tilde{\Phi}_0^{stayer} - \tilde{\Phi}_0^{exit} \right) \end{aligned} \tag{21}$$

III.2.1 Method 2, Melitz-Polanec decomposition (dynamic Olley-Pakes)

One way to proceed from expression (21) is the one proposed by Melitz and Polanec (2009). Since productivity is measured in the log-units the components directly gives the measures for growth rates.

By noting that

$$\begin{aligned}\tilde{\Phi}_1^{stayer} &= \bar{\tilde{\varphi}}_1^{stayer} + \mathrm{cov}_1^{stayer}\left(s,\tilde{\varphi}\right) \quad \textit{and} \\ \tilde{\Phi}_0^{stayer} &= \bar{\tilde{\varphi}}_0^{stayer} + \mathrm{cov}_0^{stayer}\left(s,\tilde{\varphi}\right)\end{aligned}$$

the formula (21) can be derived into the following form:

$$\Leftrightarrow \Delta\tilde{\Phi}_1 = \Delta\bar{\tilde{\varphi}}_1^{stayer} + \Delta\,\mathrm{cov}_1^{stayer} + S_1^{entrant}\left(\tilde{\Phi}_1^{entrant} - \tilde{\Phi}_1^{stayer}\right) - S_0^{exit}\left(\tilde{\Phi}_0^{exit} - \tilde{\Phi}_0^{stayer}\right) \quad (22)$$

The first component is the firm component, which is the change of the unweighted productivity level of the stayer firms. The second component is the change in the covariance among the stayers in period *0* and *1*. The third component of (22) , the entry component, consists of two sub-components;

$$\begin{aligned}&S_1^{entrant}\left(\tilde{\Phi}_1^{entrant} - \tilde{\Phi}_1^{stayer}\right) \\ &= S_1^{entrant}\left(\bar{\tilde{\varphi}}_1^{entrant} - \bar{\tilde{\varphi}}_1^{stayer}\right) + S_1^{entrant}\left(\mathrm{cov}_1^{entrant}\left(s,\tilde{\varphi}\right) - \mathrm{cov}_1^{stayer}\left(s,\tilde{\varphi}\right)\right)\end{aligned} \quad (23)$$

The first sub-component in (23) is the difference between unweighted average productivity level of the new and stayer firms multiplied by the employment share of the entrants. The second sub-component is the difference between the covariance term among the new firms and stayer firms multiplied, again, by the employment share of the entrants.

Analogously, the fourth component of (22), the exit component, takes the following form;

$$\begin{aligned} &S_0^{exit}\left(\tilde{\Phi}_0^{exit}-\tilde{\Phi}_0^{stayer}\right) \\ &=S_0^{exit}\left(\bar{\tilde{\varphi}}_0^{exit}-\bar{\tilde{\varphi}}_0^{stayer}\right)+S_0^{exit}\left(\operatorname{cov}_0^{exit}\left(s,\tilde{\varphi}\right)-\operatorname{cov}_0^{exit}\left(s,\tilde{\varphi}\right)\right) \end{aligned} \tag{24}$$

III.2.2 Method 3

An alternative way is to proceed from (21) by making use of a Bennett (1920) type of decomposition for the stayer firms:

$$\begin{aligned} &\Leftrightarrow \Delta\tilde{\Phi}_1=\sum\nolimits_{i\in\Omega_S}\bar{s}_i^{stayer}\cdot\Delta\tilde{\varphi}_i+\sum\nolimits_{i\in\Omega_S}\bar{\tilde{\varphi}}_i\cdot\Delta s_i^{stayer}+ \\ &S_1^{entrant}\left(\tilde{\Phi}_1^{entrant}-\tilde{\Phi}_1^{stayer}\right)+S_0^{exit}\left(\tilde{\Phi}_0^{stayer}-\tilde{\Phi}_0^{exit}\right) \end{aligned} \tag{25}$$

where $\bar{s}_i^{stayer}=0.5\left(s_{i0}^{stayer}+s_{i1}^{stayer}\right)$ is the average share, $\Delta\tilde{\varphi}_i=\tilde{\varphi}_{i1}-\tilde{\varphi}_{i0}$ is the productivity change rate, $\bar{\tilde{\varphi}}_i=0.5\left(\tilde{\varphi}_{i0}+\tilde{\varphi}_{i1}\right)$ is the average productivity level, and $\Delta s_i^{stayer}=s_{i1}^{stayer}-s_{i0}^{stayer}$ is the share change of firm i . Note that all shares refer to the stayers only so that $\sum\nolimits_{i\in\Omega_S}\bar{s}_i^{stayers}=1$.

The first term on the right-hand side of (25) is the firm component. It is the weighted average of the productivity change of the stayer firms, i.e. among the firms for which the change concept is relevant. Hence, the firm component gauges the rate at which productivity of an average input increases over time when it stays in the same production unit. Each firm is weighted by the average input share (average over period 0 and period 1), which eliminates the bias in the measure that would appear if the firms were weighted by using only the input (or output) share in period 0 (or period 1) (see e.g. Maliranta, 1997a, page 19; Foster et al., 2001, page 317).

The second component is the between component, which measures the contribution of resource reallocation between the staying firms to industry productivity growth. Equation (25) is basically similar to the methods used by

Vainiomäki (1999), Maliranta and Ilmakunnas (2005), and Kyyrä and Maliranta (2008) but applied in different contexts. It is identical to that of Griliches and Regev (1995) when applied to a balanced panel (i.e. to the staying firms only).

The formula (25) has at least three important properties. First, the firm component is *intuitive* and easy to interpret. It eliminates such labor productivity effects that emerge when an input unit moves to another firm which may have more capital per labor input or capital embodies better technology. Consequently the firm component provides a kind of proxy for disembodied technological change. While each firm is weighted by the input share this method, unlike the dynamic Olley-Pakes method (Method 2), Method 3 takes into account the fact that the productivity growth of large firms is more important for industry productivity growth than that of smaller firms. Second, the method is *symmetric*, which means that if the roles of periods 0 and 1 are reversed then all components have opposite values (see Diewert & Fox, 2009). For example, a popular method by Foster, Haltiwanger and Krizan (2001) lacks this desirable property. For an illustrative demonstration of this, see Maliranta (2003, pages 97-8). Last but not least, Diewert (2005) has shown that this decomposition has a strong *axiomatic justification*.

The third component of formula (25) is the entry component. An important feature of it is that the productivity level of the new firms is compared to that of the staying firms in the same period 1. For example, in the Foster-Haltiwanger-Krizan method the productivity level of the new firms are compared to that of the staying firms in the past. As demonstrated by Maliranta (2003) this leads to an exaggereation of the contribution of the new firms to industry productivity growth especially when the time-window is long (e.g. 5 years) or when the general technical progress is rapid (e.g. in the manufacture of telecommunication equipment in recent years) (see also Melitz & Polanec, 2009). Contrary to the other methods, the interpretation of the entry component of formula (25) is straightforward since it provides an intuitive counterfactual. It indicates how much higher (or lower) industry productivity growth would have been if none of the new firms had made an entry between two periods. Of course, now it is assumed that new firms do not have an indirect productivity effect on other firms (see Aghion et al., 2009).

The fourth component, the exit component, is analogous to that of the entry component, which is one of the merits of the method. The productivity level of the exiting firms is compared to that the staying firms in the same period 0. The exit component shows how much higher or lower industry productivity growth between two periods would have been if none of the firms had made an exit and were able to improve their productivity as much as the staying firms (which is measured by the firm component).

The method given in (25) can be interpreted in alternative ways. The sum of the entry and exit components (i.e. net entry) is the difference in aggregate productivity change among all firms (unbalanced panel) and among the staying firms only (balanced panel) (Maliranta, 1997b). Alternatively, the difference between aggregate productivity and the firm productivity change (i.e. the firm component) indicates how well (or badly) the so-called representative firm model describes the evolution of productivity. The gap consists of three distinct micro-structural factors; entries, exits and the reallocation of resources between staying firms.

For sake comparing Method 2 and Method 3 it is useful to note the link between equations (22) and (25). The difference between these two methods is that productivity growth among the staying firms is decomposed differently whereas the entry and exit components are the same;

$$\sum_{i\in\Omega_S} \overline{s}_i^{stayer} \cdot \Delta\tilde{\varphi}_i + \sum_{i\in\Omega_S} \overline{\tilde{\varphi}}_i \cdot \Delta s_i^{stayer} = \Delta\overline{\tilde{\varphi}}_1^{stayer} + \Delta \operatorname{cov}_1^{stayer} \tag{26}$$

If the size and the productivity growth rate of the firms are perfectly uncorrelated then we have $\sum_{i\in\Omega_S} \overline{s}_i^{stayer} \cdot \Delta\tilde{\varphi}_i = \Delta\overline{\tilde{\varphi}}_1^{stayer}$. In this case the between component of expression (25) indicates that the covariance between share and productivity level has increased among the staying firms between periods 0 and 1.

III.2.3 Method 4

A problem with the Method 2 (equation (22)) and Method 3 (equation (25)) is that the aggregate productivity growth rate does not correspond to the standard industry productivity measure, and not necessarily even approximately, i.e.

$$\ln\frac{\Phi_1}{\Phi_0} \not\approx \frac{\tilde{\Phi}_1}{\tilde{\Phi}_0} \tag{27}$$

This may be a bit bothersome when one wishes to interpret the micro-level mechanisms behind the official industry productivity series, for example. To tackle this problem, Maliranta (2003) proposes a use of the following industry productivity growth as the starting point of decomposing micro-level sources of productivity growth;

$$\frac{\Phi_1 - \Phi_0}{\overline{\Phi}} \tag{28}$$

which is a close approximation of the standard measure of industry productivity change, i.e. $\ln\left(\Phi_1/\Phi_0\right) \cong \frac{\Phi_1 - \Phi_0}{\overline{\Phi}}$ (see Davis & Haltiwanger, 1999).

This measure can be decomposed as follows

$$\frac{\Delta\Phi_1}{\bar{\Phi}} = \sum_{i\in\Omega_S} \bar{s}_i^{stayer} \frac{\Delta\varphi_i}{\bar{\varphi}_i} + \sum_{i\in\Omega_S} \bar{s}_i^{stayer} \frac{\Delta\varphi_i}{\bar{\varphi}_i}\left(\frac{\bar{\varphi}_i}{\bar{\Phi}} - 1\right) + \sum_{i\in\Omega_S} \frac{\bar{\varphi}_i}{\bar{\Phi}} \cdot \Delta s_i^{stayer} + S_1^{entrant} \frac{\left(\Phi_1^{entrant} - \Phi_1^{stayer}\right)}{\bar{\Phi}} + S_0^{exit} \frac{\left(\Phi_0^{stayer} - \Phi_0^{exit}\right)}{\bar{\Phi}} \tag{29}$$

The first and the third components on the right-hand side of equation (29) are the firm and between components, respectively. They are approximately the same as those of Method 3, i.e.

$$\sum_{i\in\Omega_S} \bar{s}_i^{stayer} \frac{\Delta\varphi_i}{\bar{\varphi}_i} \approx \sum_{i\in\Omega_S} \bar{s}_i^{stayer} \cdot \Delta\tilde{\varphi}_i \tag{30}$$

$$\sum_{i\in\Omega_S} \frac{\bar{\varphi}_i}{\bar{\Phi}} \cdot \Delta s_i^{stayer} \approx \sum_{i\in\Omega_S} \bar{\tilde{\varphi}}_i \cdot \Delta s_i^{stayer} \tag{31}$$

The basic idea of the entry and exit components of equation (29) is the same as those of (22) and (25). Therefore one would not expect major differences between these three methods for the entry and exit components. Consequently, Method 4 shares the same desirable properties with Method 3 discussed above.

The second component of equation, which can be called the cross-component, constitutes a departure from Method 3 since it does not exist there. As the other components should be mutually reasonably similar in Method 3 and Method 4, the cross-component of Method 4 should be reasonably close to the "aggregation bias" indicated in (27). The cross-component may also have an economic interpretation. It has a resemblance with the firm component but includes an additional factor $\left(\bar{\varphi}_i / \bar{\Phi} - 1\right)$ that is negative for those firms that have had a lower than average productivity *level* in the period. The cross-component of Method 4 indicates the combined effect of a high productivity level and a high productivity growth rate on standard aggregate productivity growth. When two firms are of the same size and have the same productivity growth *rate,* then the one having a higher productivity *level* has a greater contribution to the standard industry productivity growth. On the other hand, one might expect that firms having low productivity levels have high productivity growth rates due to the catching-up potential, which may yield negative values for the cross-component of Method 4.

III.3 Contribution to the components by firm groups

Each component is the sum of the contributions of the firms involved. Accordingly, with a decomposition method one can gauge how much a certain group of firms contribute to industry productivity, and more interestingly, through which micro-level channel.

The splitting of the components by the firm group can be made with the following extension of equation (29);

$$
\begin{aligned}
\frac{\Delta\Phi_1}{\bar{\Phi}} = & \sum_g^J \left[\sum\nolimits_{i\in\Omega_{S,g}} \bar{s}_i^{stayer} \frac{\Delta\varphi_i}{\bar{\varphi}_i} \right] + \\
& \sum_g^J \left[\sum\nolimits_{i\in\Omega_{S,g}} \bar{s}_i^{stayer} \frac{\Delta\varphi_i}{\bar{\varphi}_i} \left(\frac{\bar{\varphi}_i}{\bar{\Phi}} - 1 \right) \right] + \\
& \sum_g^J \left[\sum\nolimits_{i\in\Omega_{S,g}} \left(\frac{\bar{\varphi}_i}{\bar{\Phi}} - 1 \right) \cdot \Delta s_i^{stayer} \right] + \\
& \sum_g^J \left[S_{1,g}^{entrant} \frac{\left(\Phi_{1,g}^{entrant} - \Phi_1^{stayer} \right)}{\bar{\Phi}} \right] + \\
& \sum_g^J \left[S_{0,g}^{exit} \frac{\left(\Phi_0^{stayer} - \Phi_{0,g}^{exit} \right)}{\bar{\Phi}} \right] \\
& , g = 1, \ldots, J
\end{aligned}
\qquad (32)
$$

where $\Omega_{S,g}$ denotes the group of the staying firms that belong to group g, $S_{1,g}^{entrant}$ is the input share of the new firms belonging to group g in period *1*, $S_{0,g}^{exit}$

is the input share of the exiting firms belonging to the group g in period *0*, $\Phi_{1,g}^{entrant}$ is the aggregate productivity of the new firms in period *1* belonging to the group g and $\Phi_{0,g}^{exit}$ is the aggregate productivity of the exiting firms belonging to the group g in period *0*.

Each of the five components of Method 4 is split into *J* parts by the firm type (g = 1,…,*J*). Note that the between component in the fourth row of (32) is modified by 'rescaling' the relative productivity level that is done by replacing the term $\left(\bar{\varphi}_i / \bar{\Phi}\right)$ by $\left(\bar{\varphi}_i / \bar{\Phi} - 1\right)$. The added minus 1 term is redundant for the computation of the between component over all staying firms since $\sum_{g}^{J}\left[\sum_{i \in \Omega_{S,g}} \Delta s_i^{stayer}\right] = 0$ by definition. However, the term is useful for interpreting the contribution of each firm and computing the contribution of a group of the firms to the total component. A firm that has a productivity level lower (higher) than that of the industry positively contribute to the between component if it has decreased (increased) its input share. A group of the new firms positively contributes to the entry component when their aggregate (or weighted average) productivity level exceeds that of the industry in period *1*. Finally, a group of exiting firms positively contributes to the exit component when their aggregate productivity level is lower than the industry productivity level in period *0*.

For interpreting how a certain firm group has contributed to industry productivity growth through distinct micro-level mechanisms it is useful to compare the relative productivity contribution to its input share. In cases of the firm, between and cross-components, the relevant baseline is the average input share (averaged over periods *0* and *1*) among the stayer firms, i.e.

$$S_g^{stayer} = \frac{\sum_{i\in\Omega_{S,g}} \overline{s}_i^{stayer}}{\sum_g^J \sum_{i\in\Omega_{S,g}} \overline{s}_i^{stayer}} = \sum_{i\in\Omega_{S,g}} \overline{s}_i^{stayer} \tag{33}$$

As for the entry component a relevant comparison point is the input share of the firm group in period 1 among all firms;

$$S_{1,g} = \sum_{i\in\Omega_g} s_{i1} \tag{34}$$

Analogously, a relevant comparison point for the interpretation of the exit component is the input share of the group in period 0 among all firms;

$$S_{0,g} = \sum_{i\in\Omega_g} s_{i0} \tag{35}$$

III.4 Decomposition of multi-factor productivity (*MFP*)

So far we have only considered a one-input case in the productivity measurement. All the analysis above can be generalized for a more comprehensive measure of performance that takes into account the efficiency in the use of several types of input. All that is needed is to replace input *L* by some appropriate input index *X*. In this paper we use a very simple and common alternative that is

$$X = L^{\alpha} K^{(1-\alpha)} \tag{36}$$

In the growth accounting literature it has been standard to estimate parameter α by the labor compensation (wages plus supplements) to value added ratio computed as an average of the initial and end period, i.e. the average labor income share;

$$\alpha = 0.5\left(\frac{w_{t-1} \cdot L_{t-1}}{VAL_{t-1}} + \frac{w_t \cdot L_t}{VAL_t} \right) \tag{37}$$

where w is the unit price of labor, L is labor input and VAL is the nominal value added.[5]

Now s_{i1} and φ_{i1} denote input share and multi-factor productivity, respectively;

$$s_{i1} = \frac{X_{i1}}{\sum_{i\in\Omega_1} X_{i1}} \tag{38}$$

$$\varphi_{i1} = \frac{Y_{i1}}{X_{i1}} \tag{39}$$

The relative productivity levels between different firms or productivity growth rates are independent of the units in which L or K are measured as long as α is constant over all firms (and years) that are compared. The point can be easily demonstrated more formally as follows;

$$RMFP_{ij} = \frac{Y_i \Big/ \left(L_i^{\alpha_i}\left(aK_i\right)^{1-\alpha_i}\right)}{Y_j \Big/ \left(L_j^{\alpha_j}\left(aK_j\right)^{1-\alpha_j}\right)} = \frac{Y_i \Big/ \left(L_i^{\alpha_i}\left(K_i\right)^{1-\alpha_i}\right)}{Y_j \Big/ \left(L_j^{\alpha_j}\left(K_j\right)^{1-\alpha_j}\right)} a^{\alpha_j-\alpha_i} \tag{40}$$

where $RMFP_{ij}$ is the *MFP* level of firm *i* relative to that of firm *j*, and a is the unit in which capital is measured in the data. We note that $RMFP_{ij}$ is independent of the value of a when $\alpha_i = \alpha_j$. Yet, some of studies use varying coefficients including (see e.g. Disney et al., 2003). Since the results for *MFP* are arbitrary when α vary between firms it is not surprising that labor productivity and *MFP* yield different results in such studies.

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5 Van Biesebroeck (2008) has empirically compared various alternative techniques of measuring productivity. He finds that different methods yield surprisingly similar results.

There are a number of different theoretical and empirical approaches to determine α (see e.g. Diewert & Nakamura, 2007). The approach notwithstanding, it seems natural to expect that α varies between different industries or different phases of the economic development, so it is recommendable to perform decompositions separately for the different time periods and industries (see e.g. Böckerman & Maliranta, 2007).

One should note, however, that generally

$$\begin{aligned} &\sum\nolimits_{i\in\Omega_1} X_{i1} = \sum\nolimits_{i\in\Omega_1} L_{i1}^{\alpha} K_{i1}^{(1-\alpha)} = X_1 \\ &\neq \left(\sum\nolimits_{i\in\Omega_1} L_{it}\right)^{\alpha} \left(\sum\nolimits_{i\in\Omega_1} K_{it}\right)^{1-\alpha} \end{aligned} \quad (41)$$

The inequality in the second row implies that in the multi-input case industry productivity growth obtained by the decomposition method is not equal to that obtained by using a sum-aggregate of output and input. So, in a sense Method 4 is not, using a concept of the index theory, 'consistent in aggregation' (see e.g. Theil, 1967; Vartia, 1976). It should also be noted that the use of output share instead of input shares in the decomposition method (e.g. Foster et al., 2001) does not solve this problem for it is still the case that the industry productivity change computed with a decomposition method cannot be derived from the industry level variables of output and inputs.

IV. Empirical analysis

IV.1 Data sources

The data source of the baseline analysis of this study is longitudinal data on plants in Finnish manufacturing (LDPM data). It is constructed from the annual manufacturing surveys especially for research purposes. Nowadays these data cover years 1974-2007.[6] The data have at least three important advantages for an analysis of micro-level sources productivity growth. First, data include detailed information on labor input (hours worked), capital input (capital stock estimated by perpetual inventory method) and output (value added and gross output). Second, data content and coverage is comparable over a long period of time, which is crucial for analyzing changes in trends. To improve the comparability of data over time further, only those plants are included in the sample that have at least five persons and are owned by a firm that has at least 20 persons. Third, the coverage is good. Despite removing some plants for sake of unreliable information and fine-tuning the comparability over time the sample accounts for about three quarters the total number of hours worked in the manufacturing sector, as estimated on the basis of numbers obtained from the National Accounts. More information on data and computation protocols followed in the analysis is given in Appendix 1. Maliranta (2003) provides a detailed description of the LDPM data set and its main properties.

As for a robustness check three other alternative data sources are used in this study. First of these is the Business Register data on plants (BR data) that include principally all manufacturing plants (also the smallest ones) in Finland. The disadvantages of this data set are a shorter time-span (years 1990-2007), lack of a measure for hours worked and value added. The second alternative data source is the Structural Business Statistics data (SBS data) on firms that cover years 1994-2007. In principal it covers all firms. It also includes both value added

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[6] Year 1974 is not included in the productivity analysis of this paper because of a break in the industry-specific price index series between the years 1974 and 1975.

and gross output information but not hours worked.[7] As a firm-level data set it provides an opportunity to complementary analyses to those conducted with the LDPM data source. The third alternative data source is a commercial database on firms (Asiakastieto Inc.) that is developed further in the ETLA for research purposes. This data set is substantially smaller than the SBS data set both in terms of coverage and time-span (2001-2007). The quality of the Asiakastieto data is likely to correspond to the quality of a great majority of the samples used in the economic research. Hence a robustness check with these data gives an indication of the reliability and comparability of the results made with less perfect data. The checks made with alternative data sources are useful not only for evaluating the uncertainty or comparability of the results between different countries. They also should help to identify suitable indicators of micro-level dynamics that are not only relevant but also reliable enough for conclusions.

Value added and gross output in year *t* is converted in year *t*-1 prices by using the implicit corresponding industry-level price indexes computed from the National Accounts.

IV.2 Baseline results

The baseline results of the paper are based on Method 4 and LDPM data. Later some comparisons with other methods are presented. All computations are made

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[7] The number of persons is the average during the accounting period. Hence, a person who has been employed in the firm for six months corresponds to half an employee. On the other hand, part-time employees are not converted to full-time equivalents. The number of persons engaged include workers, salaried employees and entrepreneurs. It also includes, for example, employees on sick leave or maternity leave or laid-off for a fixed period. For more detailed information on the Structural Business Statistics see http://tilastokeskus.fi/til/tetipa/kas_en.html.

at the industry level (15 industries) and separately for each pair of the successive years. The industry-level labor productivity results are aggregated to the level of the total manufacturing using input shares of the industries (the average of the initial and end year). The industry *MFP* results are aggregated by using nominal value added shares.[8] In this way comparisons between "oranges" and "apples" are avoided (see e.g. Sørensen, 2001) and the role of industry-level restructuring is eliminated. More technical details on these computations are given in Appendix 1.

Graph 3 displays the main general patterns in the development of productivity at the different levels of aggregation in the Finnish manufacturing sector by means of a productivity index.[9] The index shows the cumulative effect of the plant component[10] (solid line), the aggregate component of the industry-level computations[11] (dashed grey line) and the aggregate component of the total manufacturing computations (dashed black line).[12] The gap between the plant-level and industry-level productivity index indicates the cumulative effect of the

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[8] The use of labor hours in aggregation of the industry *MFP* results yielded quite similar results (not reported here).

[9] The productivity index is measured as follows: $IND_t = IND_{t-1} \times \left(1 + 0.5 \times at\right) \times \left(1 - 0.5 \times at\right)^{-1}$ where *at* is the component of the annual growth rate of aggregate or firm component in *t* obtained by Method 4. The starting point is set as $IND_{1975} = 100$.

[10] Note that the observation unit of LDPM data is the plant not the firm.

[11] The industry-level components are aggregated to the level of the total manufacturing by using industries' input shares as weights.

[12] These components have been computed at the total manufacturing level.

micro-level restructuring and the cross-component within industries.[13] The gap between the industry-level and the total manufacturing-level series shows the contribution of restructuring (and the cross-component) between industries. Three interesting findings emerge from the graph. First, the cumulative effect of the restructuring over the period from 1975 to 2007 is considerable; according to these estimates the level of the labor productivity would have been 41% (=(550-327)/550) lower without any productivity-enhancing restructuring during the period from 1975 to 2007. Second, the main part of productivity-enhancing restructuring has taken place within industries. Third, the gap between the plant productivity and the industry productivity development started to widen in the early 1980s.

<GRAPH 3 ABOUT HERE>

Graphs 4 and 5 showing the annual productivity growth components have two purposes; first, changes in development are more discernible and, second, the separate contributions of the different sub-components can be distinguished. Graph 4 shows the components of industry labor productivity growth and Graph 5 those of *MFP*.

A number of findings can be made from these two graphs. First, aggregate labor productivity growth computed from the LDPM sample is reasonably similar to that shown in Graph 2 that is based on the National Accounts. Though, it should be noted that some differences would not be a surprise. The effect of industry restructuring is eliminated in Graph 4 and Graph 5 but not in Graph 2.

[13] To be more precise, here the gap is the joint effect of the structural components (the between, entry and exit components) and the cross-component.

Moreover, labor productivity growth series of the National Accounts involve some imputations whereas in this analysis the main primary data is utilized without any further adjustments or corrections.

<GRAPH 4 ABOUT HERE>

<GRAPH 5 ABOUT HERE>

Second, the plant component is the most important component. Typically it constitutes 50-80 percent of industry labor and *MFP* productivity growth. On the other hand, it should be noted that this is a tremendous departure from the 100 percent that is assumed in the representative plant/firm model having still important role in the economic growth literature, for example.

Third, the micro-level restructuring has a significant contribution to industry labor productivity growth and is even more important to *MFP* growth. What is more important, the restructuring component has an important role in explaining the *acceleration* of labor and *MFP* growth after 1983. In other words, the micro-level restructuring appears to explain the increase in labor productivity growth shown in Graph 2. It seems to have driven the catching-up of the international labor productivity frontier, which is here approximated by the productivity level of the US manufacturing sector.

Fourth, some “chilling” in productivity-enhancing restructuring can be found in the mid-1990s which is about the same time when Finland almost caught up with the United States in labor productivity level. On the other hand, the productivity-enhancing restructuring has been a more important contributor of industry productivity growth in the post-transition period 1994-2007 than in the pre-transition period 1976-1983.

Fifth, as for labor productivity growth, both the exit and the between components stand out as important factors. Furthermore, these two components share similar short-run variations and trends. They started to increase after year 1983 and peaked around year 1993. The entry component is generally negative for labor productivity growth but positive for *MFP* growth. The latter finding should be interpreted somewhat cautiously since the capital measure might underrate the relative capital intensity (capital input per labor input) of the new and young establishments. For example, Maliranta (1997c) provides evidence that young plants have more rented capital per labor input than older plants, which seems to explain at least a part of the positive entry component of *MFP* growth. On the other hand, the entry component of *MFP* also has a positive slope after the late 1970s giving further support to the view that there was a significant change in the micro-level dynamics of productivity growth during the transition period 1983-1993.

Sixth, the cross-component, showed in Panel A in Graph 4 and 5, is found to play a non-negligible role in explaining variation of industry productivity growth. It has marked cyclical variation that seems to be reasonably similar for labor and *MFP* growth. The cross-component of *MFP* was clearly negative in years from 1992 to 1996. The cross-component of labor productivity growth is generally positive but had clearly negative values in 1995 and 1996.

Table 1 reports the average annual industry productivity growth and its micro-level components by the three periods at the level of industry (15 industries) and the total manufacturing for labor productivity. Table 2 presents the corresponding numbers for industry *MFP* growth and its components. The results of the total manufacturing level replicate the aforementioned general trends. The average annual restructuring component of labor productivity growth was 0.3, 1.3

and 0.8 percentage points in the periods 1976-1983, 1984-1993 and 1994-2007, respectively. The corresponding numbers for *MFP* growth were larger being 1.1, 1.7 and 1.9 percentage points.

<TABLE 1 ABOUT HERE>

<TABLE 2 ABOUT HERE>

The industry-level results indicate that similar trends can be found in several industries. On the other hand, variation between industries is considerable. An increase in the restructuring component of labor (and *MFP*) productivity between the pre-transition and the transition periods can be found in all industries apart from one out of 15 industries. The greatest increases in the restructuring component of labor productivity growth during the transition period took place in Textile (NACE 17-19), Chemicals (NACE 24), Transport equipment (NACE 34-35), and in Other (NACE 36-37), the increase being no less than 1.5 percentage points per year in each industry. According to the *MFP* measure the greatest increases in the productivity-enhancing restructuring occurred in Chemicals (NACE 24), Electrical equipment (NACE 30-31) and Other (NACE 36-37). The results for both labor productivity and *MFP* give indication that all aspects of “creative destruction”, i.e. the entry, exit and between components became more intensive during the transition period 1983-1993 in most of the industries.

To better capture the trends in restructuring by industry, the annual restructuring components of labor and *MFP* productivity growth are smoothed by Hodrick-Prescott filter ($\lambda = 6.25$). Graphical illustrations of the results by industry give further support to the view that creative destruction intensified after year 1983 in many industries and in some industries more than in others (see Appendix 2, Graph A2.2 and Graph A2.3). The analysis provides some indication of substantial creative destruction in the mid-70s but it should be noted that the both the left and right tails of the smoothed series should always be treated with caution. The manufacture of communication equipment is an industry that deserves a special attention. [14] Productivity-enhancing restructuring peaked in the mid-90s and was clearly stronger than in other industries in those days. That means that creative destruction was in operation in the industry before the Nokia-driven ICT expansion began in Finland.

IV.3 Dynamics after entry

The entry component of Method 4 (and Method 3) gauges an immediate effect of the entrants to the industry productivity level. Indirect effects aside, the entry component tells how much higher or lower industry productivity growth would have been if no entries had been taken place in the period. In what follows we look at the longer-term labor productivity dynamics of the new plants by a use of Method 4 with an extension of a break-down by the plant cohorts (see equation (32)). The results are reported in Table 3. To show how it is convenient to read the table we first focus on the plants that contributed to the entry component in the 5-year window 1985-1990, which is the cohort 1986-90.[15]

[14] Communication equipment industry witnessed a huge drop in the between and entry component of labor productivity after 2005. The decline in the smoothed series is mainly due to very negative numbers in year 2007. A closer inspection of plant-level data revealed that these negative numbers can be attributed to a few observations in that industry in that year.

[15] As earlier, all computations are made separately for each of 15 industries. The results are aggregated to the level of the total manufacturing sector by a use of the share of hours worked (the average of the initial and end year, to be more precise)

Contrary to the later cohorts, the cohort 1986-90 had a (slightly) positive entry effect (0.1 percentage points) on industry labor productivity growth. These plants accounted for 11.2% of the total number of hours worked in 1990. A proportion of these plants were disappeared by 1995 (i.e. during the next 5-year window). These plants accounted for 3.2% of the total number of hours worked in 1990. The average productivity level of these plants was (slightly) higher than those who stayed until 1995 and hence they negatively (-0.1 percentage points) contributed to industry productivity growth in the period 1990-95.

Those plants who did not make an exit before 1995 became the stayers of the period 1990-95. As Table 3 shows, these plants quite strongly increased their labor input share among all stayers from 7.2% to 8.9%. They contributed to the between component by 0.6 percentage points, which is disproportionally large effect. This is not, however, the end of the selection and restructuring mechanisms concerning the cohort 1986-1990. Some of these plants made an exit between years 1995 and 2000. As Table 3 shows, these plants contributed to the exit component of the period 1995-2000, i.e. a decade later, by 0.2 percentage points. Those who stayed increased their share from 9.1 to 10.0 percentage points and positively contributed to the between component by 1.0 percentage points. The numbers of Table 3 for the period 2000-2005 indicate that this was the peak of the life-cycle of the cohort 1986-90 (their labor input share started to decline) and the end of the productivity-enhancing selection (in fact, the exit component became negative) and restructuring process among the stayers (the between component turned to zero).

Table 3 also shows how the cohort 1986-1990 has contributed to industry productivity growth through the plant component (i.e. having a high productivity growth rate). The labor input weighted average productivity growth rate of the stayers was 26.8% (not shown in the table),[16] which contributed, as can be read from Table 3, to the plant component by 2.2 percentage points in the period 1990-1995. In the next period, i.e. the period 1995-2000, the average productivity growth rate was accelerated to 30.1% (not shown in the table) and its contribution increased to 2.9 percentage points. All in all, the results suggest that the cohort 1986-90 not only had a relatively high productivity level but also a high productivity growth rate. As Table 3 indicates, the cohort still had an important contribution to industry productivity growth in the period 2000-2005 through the plant component.

A high productivity level and a high productivity growth rate is a combination that is particularly advantageous to industry productivity. This seems to be reflected in a relatively large cross-component contribution of the cohort 1986-1990 in the period 1990-1995 and 1995-2000.[17]

More generally, as Table 3 indicates, a proportion of the new plants immediately makes an exit. If these plants have a lower-than-average productivity level (as usually is the case) they positively contribute to industry productivity growth through the exit component in the next period. Table 3 shows that the exit component has had a positive contribution and it was the largest in the period

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[16] This is obtained by dividing the cohort's contribution by its average labor input share, i.e. 26.8%=2.2%/(0.5x(7.2%+8.9%))

[17] When two plants are of the same size (in terms of labor input) and have the same productivity growth rate then the one who has a higher productivity level contribute more to the standard aggregate industry productivity rate. The difference can be read from the plants' contribution through the cross-component.

1995-2000. By looking at the contribution of the different cohorts it can be conclude that the oldest cohorts account for the main part of the exit component. However, in the early 1980s and since the mid-1990s, also the newest cohort has had a significant and disproportionally large contribution to the exit component. So, a more detailed examination of the entry and exit components with a break-down by cohorts gives a clear indication of a “revolving door phenomenon” or a kind of experimentation that has been prevalent especially since 1990s.

So, those of the new plants that do not make immediately an exit become stayers. Table 3 points out the general tendency that younger staying (i.e. surviving) plant cohorts increase their labor input share at the cost of older cohorts. Both younger and older cohorts positively contribute to the between component, the former by creating high productivity jobs and the latter by destroying low productivity jobs. To sum up, Method 4 seems be a useful tool for investigating micro-level dynamics of productivity growth involving incessant experimentation, selection and restructuring.

IV.4 Analysis with alternative decomposition methods

IV.4.1 Method 1, static Olley-Pakes decomposition method

The static Olley-Pakes decomposition for the labor productivity has been computed by a use of the regression approach represented in Section III.1. Two regression models explaining the log labor productivity of a plant is estimated[18];

$$\tilde{\varphi}_i = \alpha^U + \sum_{j=1}^{j=15} \beta_j^U \cdot D_j + \varepsilon_i, \tag{42}$$

[18] I thank Pekka Ilmakunnas for useful suggestions concerning these estimations.

$$\sqrt{L_i}\tilde{\varphi}_i = \sqrt{L_i}\alpha^W + \sum_{j=1}^{j=15}\beta_j^W \cdot \sqrt{L_i}D_j + \sqrt{L_i}\varepsilon_i, \qquad (43)$$

Model (42) is unweighted (i.e. untransformed) and Model (43) is labor input weighted (i.e. transformed) regression. The both models include an intercept term and dummies for 15 industries.

In order to estimate these models and to have a suitable interpretation for the intercepts, the following constraints to industry coefficients have been imposed for the both regression models

$$\sum_{j=1}^{j=15} share_j \beta_j^X = 0, \quad X = \{U, W\} \qquad (44)$$

where $share_j$ is the labor input share of the industry j in the total plant-panel ($\sum_{j=1}^{j=15} share_j = 1$).

A seemingly unrelated estimation is applied to these models.[19] As shown in equation (18), the covariance component is obtained as a difference of the intercept of Model (43) and Model (42). This is done by a linear combination estimator, which also provides a robust standard error for the covariance component of the static Olley-Pakes decomposition. This procedure has been performed separately for each year from 1975 to 2007 (but using the same industry weight constraints).

The collected results are shown in Graph 6. It represents the covariance component gauging the contribution of allocation within industries and its 95%

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[19] This is performed by *suest* postestimation command of Stata Statistical Software package (Release 10).

confidence interval. The graph provides evidence on a substantial increase in the role of micro-level allocation as a determinant of the industry productivity level during the 1980s. The latter part of the 1990s witnessed a further increase in its effect. However, a plateau is discerned since the late 1990s which gives indication on a chilling in the micro-level dynamics of productivity growth. All in all, the analysis with the static Olley-Pakes method gives a picture on the development of micro-level dynamics that is broadly similar to that obtained with Method 4 above.

It should be noted that since the industry coefficient *constraints* are held constant over all years the effect of the changes in the industry structures are eliminated in the graph. As a robustness check the analysis has also been performed by using year-specific (i.e. current) industry coefficient constraints, which yields more or less similar picture.[20]

<GRAPH 6 ABOUT HERE>

IV.4.2 Method 2, dynamic Olley-Pakes (Melitz-Polanec)

Decomposition analysis with Method 2 is conducted in a manner analogous to that made with Method 4 above. Computations are performed separately for each pairs of the consecutive years and for each of 15 manufacturing years. The industry-level results are aggregated to the level of the total manufacturing by using the industry labor input shares. The main results are presented in Graph 7. Panel A shows aggregate productivity growth and how it is split between the unweighted

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[20] The Olley-Pakes decomposition analysis has been performed as a traditional accounting exercise by year and industry. As expected, these unreported computations give a similar picture on the evolution of the allocation component in the Finnish manufacturing industries.

plant component and the restructuring component, which includes the covariance change, entry and exit component.

The unweighted plant component dominates but occasionally the restructuring component has both absolutely and relatively a quite large contribution, for instance, in years 1984, 1992 and 2003. When compared to the restructuring component of Method 4 showed in Graph 4, the restructuring component of Method 2 exhibits less stable patterns over time. Panel B of Graph 7 indicates that the variability of the restructuring component can largely be attributed to the covariance change component. The other sub-components of the restructuring component, that is say the entry and exit components, clearly have smoother patterns. In fact, they are quite similar to those of Method 4, as expected.

As shown in equations (22) and (24), Method 2 allows spliting the entry and exit components further into two parts; unweighted average and covariance change effect. The results for labor productivity are shown in Table 4.a (the entry) and Table 4.b (the exit). Generally the both sub-components of the entry effect negatively contribute to industry productivity growth (the unweighted average effect in the period 2002-20007 is an exception but it is mostly due to one single industry that is the manufacture of communication equipment). So, on average, new plants have a productivity level lower to that of the stayers. Moreover, the results imply that covariance between the productivity level and the size is smaller among the new plants than among the stayers. Broadly speaking, the latter observation seems to be in line with the earlier conjecture concerning productivity-enhancing restructuring by plant cohorts made with Method 4. It was then found that generally it is the youngest cohorts where the restructuring is the most effective in relative terms.

The break-down of the exit component by the dynamic O-P method shown in Table 4.b reveals a deeper anatomy of the increasing exit component since the 1970s. The main driver of this trend is a sustained increase in the covariance change effect of the exits. During the pre-transition period (i.e. 1978-1983) it was negative in most industries but become gradually positive. This finding suggests that a change has taken place especially among the larger plants: their propensity to exit has become increasingly sensitive to their productivity level. As a consequence, when large and low productivity plants make an exit the relationship between the productivity level and the size (i.e. covariance component) among the remaining plants becomes stronger. The unweighted average effect of the exits has been positive all the time. A considerable increase can be found between the pre-transition and transition periods (i.e. from the period 1978-83 to the period 1984-1989) but this component has been relatively stable since the early 1990s.

<GRAPH 7 ABOUT HERE>

< TABLE 4.a-b ABOUT HERE>

< TABLE 4.b ABOUT HERE>

IV.4.3 Method 3

As argued in Section *III.2.3* the plant, between, entry and exit components of Method 3 can be expected to be close to those of Method 4. An empirical comparison of the plant and the restructuring components between the methods validates the proposition (see Appendix 2, Graph A2.4).

Another remark concerning Method 3 is that industry productivity growth rate obtained from it may not even approximately correspond to the standard industry productivity growth rates computed from aggregate industry data. An empirical investigation with labor productivity and *MFP* reveals that the absolute value of the "log-bias" often is non-negligible (as for results concerning *MFP*, see Appendix 2, Graph A2.5). Furthermore, since Method 4 is expected to provide a close approximation to the standard industry productivity growth rate, this implies that the cross-component of Method 4 should be close to the "log-bias" in Method 3. Indeed, empirical results give support to this (as for results concerning *MFP*, see Appendix 2, Graph A2.5).[21] The bias (and the cross-component) has been substantial and have had some striking time patterns. The early 1990s witnessed clearly negative and at the turn of the 2000s positive values of the cross-component. The absolute values of these numbers are large enough to be essential in the analysis of cycles and trends in industry productivity growth, for example.

IV.5 Robustness analysis

A number of further robustness checks have been made for two main purposes: 1) to examine the robustness of the empirical findings of this paper made with Method 4, and 2) to compare the robustness (and thus usefulness) of the alternative methods to Method 4. Here we focus on the between component of labor productivity growth of Method 4 which was found to be a solid gauge of productivity-enhancing restructuring.

IV.5.1 Robustness of Method 4

As documented, for instance, by Ali-Yrkkö et al. (2000), the manufacture of communication equipment industry (i.e. NACE 32-33) with Nokia-company and its hundreds of the subcontractors has had an exceptionally decisive role to play in

[21] The corresponding picture on labor productivity growth is not reported but is broadly similar although trends of the cross-component (and log-bias) are not as pronounced as for *MFP* growth shown in Appendix 2.

the development of the Finnish economy especially since the latter part of the 1990s. Hence, it is of a great interest to know how it is reflected in the micro-level dynamics of productivity growth in the Finnish manufacturing. This is examined by looking at how the restructuring component of productivity growth changes when the manufacture of communication equipment industry is excluded from the analysis. The results indicates a minor role for the “Nokia-industry” in explaining the acceleration of the between component in the latter part of the 1980s while it has had a significant contribution in the period from 1994 to 2001 (Appendix A2.6).

In addition, a number of other robustness checks have been made with Method 4. The between component of labor productivity growth is robust to using gross output measure instead of value added (see top-left panel in Graph 8). Firm-level data (SBS) give results partly different from those obtained with the plant data (LDPM). However, it should be noted that, contrary to the use of plant data, the decomposition made with the firm data does not capture the productivity-enhancing restructuring between plants within multi-plant firms which in an important part of the micro-level renewal (see e.g. Disney et al., 2003; Kyyrä & Maliranta, 2008). Yet, both the plant and firm data give the same basic message; on the basis of the between component, productivity-enhancing restructuring has been an important source of productivity growth during the post-transition period. The main discrepancies in the results pertain to years 2000 and 2001 which seem to be exceptional anyway (see top-right panel in Graph 8). The alternative plant-level data source (i.e. Business Register) gives some further support to main conclusions (see bottom-left panel in Graph 8). Finally, the results obtained with alternative firm-data (Asiakastieto-data) are consistent with those obtained with the SBS data (see bottom-right panel in Graph 8).

<GRAPH 8 ABOUT HERE>

Further robustness checks of Method 4 with LDPM data include a use of an alternative threshold for the inclusion to the sample (plants employing at least 20 persons), an alternative measure of labor input (the number of persons) and a longer time-window (5-year windows). The results of these experiments are not reported here but they in no way challenge the basic results.

IV.5.2 Robustness of the alternative methods

An important property of a good method is that the results are not easily driven by some peculiarities of data. For sake of comparing the methods in this respect, a host of sensitivity checks has been performed with the alternative methods as well. While Method 3 was found to be quite similar to Method 4, except for the cross-component, this exploration focuses on the static as well as dynamic Olley-Pakes decomposition method (i.e. Method 1 and Method 2).

In the following, the main findings of these experiments are briefly described. An analysis of the static O-P method with LDPM plant-data indicated that neither the level nor the time pattern of the covariance component is not very sensitive to the inclusion or exclusion of small (5-19 persons) or very small (1-4 persons) plants. Neither are the results very sensitive to measuring the labor input with the number of persons instead of hours worked.

However, the *level* of the covariance component is very sensitive to the *measure of productivity*. The covariance-component of the *MFP* is roughly 10%-points lower than that of labor productivity (not reported here). Moreover, the covariance component turns out to be very sensitive to the use of plant or firm as a unit of observation. With a use of SBS firm data over the period from 1995 to 2007, the average cross component is 34.6 percentage points when all manufacturing firms employing at least one person are included (see Table 5). However, the covariance component drops steeply with an increase in the size threshold. In a sample covering all manufacturing firms employing at least 5 persons, the covariance component is 25.2 percentage points that is more than 10 percentage points lower than with no threshold. The difference is considerable given that the firms employing less than 5 persons account for only 4.0 percent of the employment (but 61.6 percent of the number of firms) in our data and consequently have a minor contribution to industry employment and productivity in manufacturing. This may not be a problem only from the point of view of validity but of reliability as well. One could suspect that the quality of data is poorer for the smaller than larger firms. On the other hand, the standard error of the covariance component exhibits just a moderate decline with the increase in the threshold (see Table 5).

<TABLE 5 ABOUT HERE>

Graph 9 presents the comparisons of the results with the dynamic O-P method (i.e. Method 2) analogous to those given in Graph 8 for Method 4. We again see that the covariance change effect, the novelty of Method 2, has annual variation which is far greater than that of the between component of Method 4 shown earlier. Further, as with the static O-P method, it is found that the use of plant or firm as the unit makes a difference (see top-right panel in Graph 9). The covariance change component has particularly strong annual variation when data also include very small plants as it is the case with the Business Register data (see bottom-left panel). Finally, due to the great variability in the covariance change component it does not seem to be able to yield a reliable picture on the development of micro-dynamics with short firm-level panel data (see e.g. bottom-right panel). On the other hand, with longer panels and a use of wider time-windows (e.g. 5-year windows) it seems possible to capture important changes in the micro-level dynamics. For instance, the covariance change component computed with LDPM plant-data and using 5-year windows clearly indicate an important change in the mid-80s as well as in the mid-90s that which is in keeping with the picture that has obtained in this study (not reported here).

<GRAPH 9 ABOUT HERE>

V. Conclusions

This paper has sought suitable methods for analyzing the micro-level dynamics underlying the great leap in productivity of the Finnish manufacturing industries before and after the great depression of the early 1990s.

A useful method (called Method 4 in this study) with several theoretical and empirical advantages is proposed. It gives an unbiased view on the role of entries and exits as well as the reallocation between staying firms in industry productivity growth. The firm (or plant) component indicates the rate at which productivity of an average input increases when it stays at the same production unit. The restructuring component consists of the entry, exit and between components. The fifth component of the method is called the cross-component. It essentially captures the difference between the standard measure of the industry productivity growth, based on the aggregates of output and inputs, and the measure of industry productivity growth computed by aggregating log-productivity numbers of the firms, as typically done in the micro-level productivity decompositions.

By a use of plant level data covering a long period of time, a preferred method is shown to be useful tool in detecting longer run effects of the entries and the underlying micro-level mechanisms. As usual, the initial entry effect on industry labor productivity is found to be negative. However, in the next period the newly born plants have a disproportionally large contribution to the positive exit component. The remaining new plants become stayers and contribute to industry productivity growth through the plant component, between component and the cross-component. Splitting these components further by plant cohorts reveals that young plants have a disproportionally large contribution to the between component, indicating that the entry is only a part of broader and longer restructuring process that is time-consuming and gradual, and to the plant component, indicating that younger plants are able to achieve greater-than-average productivity growth due to learning-by-doing, for instance.

The preferred method is analytically and empirically compared with some interesting alternatives. The first of these is the popular static productivity decomposition proposed by Olley and Pakes (1996). For computing it, a novel regression approach is represented which provides the standard error estimate of the covariance (allocation) component as well as an opportunity to control other factors of productivity in a flexible manner.

The method, however, ignores the entries and exits and, for that matter, it is not fully compatible with the view, emphasized by the modern economic growth literature, that incessant restructuring is an essential element of growth. This shortcoming is corrected in the second method of comparison, which is the so-called dynamic Olley-Pakes decomposition (Method 2 in this paper) recently proposed by Melitz and Polanec (2009). The method is shown to have some important analytical and empirical similarities to the preferred method. Though, the preferred method appears to give a somewhat more robust picture on the productivity-enhancing restructuring. This is found with ample empirical robustness checks made with alternative data sets, measures of input or output, units of observations (firm or plant), size thresholds and time-windows. These experiments are also helpful in search of suitable methods for international comparisons with micro-data that are potentially plagued by data differences due to varying statistical, administrative or legal systems.

However, the dynamic Olley-Pakes method provides an interesting angle to the role of entries and exits in the micro-level dynamics of productivity growth. Empirical results of this paper show that emergence of new plants incessantly lowers the relationship between the productivity level and the size of the plants and thus decreases the covariance (i.e. allocation) component of the productivity level in industries. At the same time, however, the relationship becomes stronger among the staying plants (due to reallocation of resources between low and high productivity plants). Furthermore, the exit of plants appears to have a positive effect on the covariance component of the industry productivity level. So, as it was with the preferred method, empirical findings of the dynamic Olley-Pakes method suggest that the entrants contribute negatively and the staying plants and the exiting plants positively to the reallocation component of industry productivity growth.

As for the empirical contribution of this study, with suitable methods and with exceptionally rich and long panel data on plants a number of important aspects in the micro-level dynamics of rapid industry productivity growth in Finnish manufacturing industries are unveiled. Three periods can be distinguished in the development; 1) the pre-transition period (from 1976 to 1983), 2) the transition period (from 1984 to 1993) and 3) the post-transition period (after 1994). The average annual restructuring component of labor productivity growth in these three periods was 0.3, 1.3 and 0.8 percentage points, respectively. The corresponding numbers for *MFP* growth were larger being 1.1, 1.7 and 1.9 percentage points. Both the productivity-enhancing restructuring between the stayers (i.e. the between component) and the exit component positively contributed to industry labor productivity growth. The results with a *MFP* measure suggest that the entrants have a positive impact on industry productivity growth. However, the results should be treated with cautious due to the problems in measuring capital input accurately especially for the new plants.

Evidence suggests that the collapse of the trade to the former Soviet Union after 1983 triggered "creative destruction" in the Finnish manufacturing industries that paved the way for a climb to the international productivity frontier by the mid-90s. On the other hand, the results are at least broadly consistent with the view emphasized in the modern economic growth literature that micro-level restructuring is more important for such economies and industries that are on the international technology frontier than those far away from it.

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Appendix 1. Data

Longitudinal data on plants in Finnish manufacturing (LDPM) is constructed from annual manufacturing surveys especially for research purposes. Nowadays the data cover years 1975-2007.

In principle, the plant is defined as a local kind-of-activity unit. In other words, 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.

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.

To ensure the comparability of the results over time plants employing less than five persons and plants owned by a firm employing less than 20 persons are dropped from the sample.

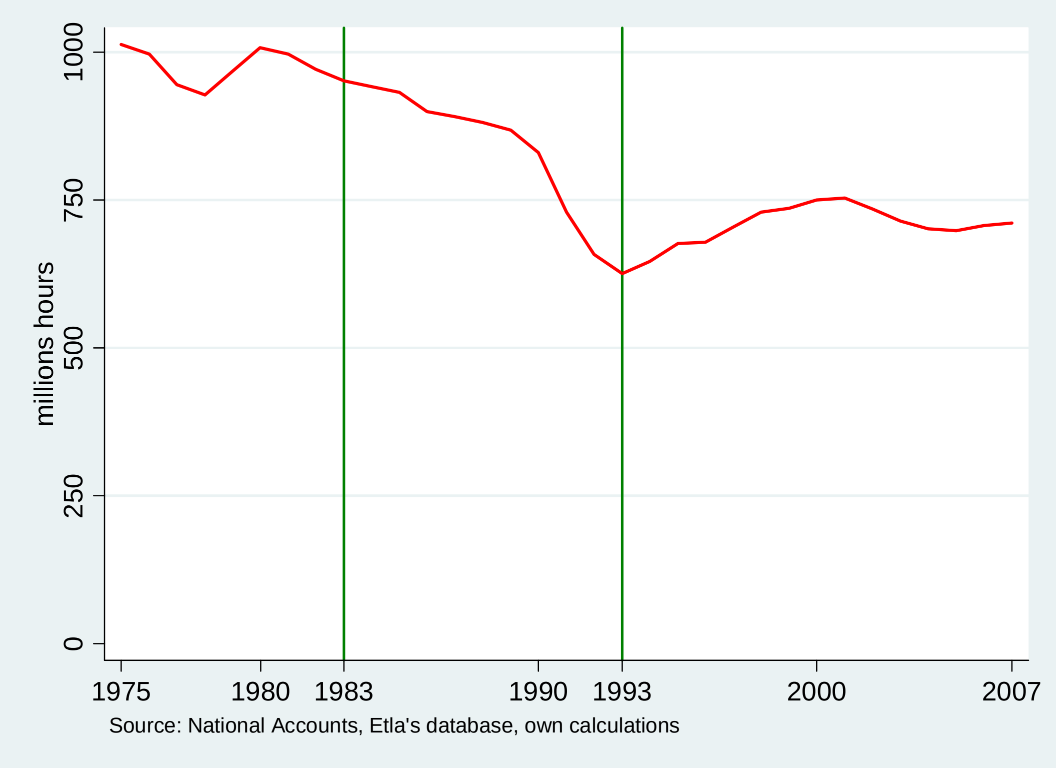
As always with these kinds of data, the LDPM data include outliers that might be influential in an economic analysis. A transparent procedure is needed to clean the data. An approach similar to that of Mairesse and Kremp (1993) is adopted. Those observations are deemed as outliers whose log of labor productivity differs by more than 4.4 standard deviations from the input-weighted industry average (15 industries) in that year. The decompositions are performed separately for each pairs of consecutive years. If a plant is classified as an outlier in either an initial (i.e. t-1) or an end year (i.e. in year t) it is not included in this computation (but is possibly included in earlier and later periods). Thanks to this procedure no artificial entries or exits are created by removing outliers. Sometimes a single plant might have an impact on one of the micro-level components that is simply unbelievable. A more detailed inspection of these cases reveals that the changes in value added or labor input are sometimes erroneous beyond reasonable doubt. Since, on certain occasions, these errors are quite influential in decomposition calculations, further cleaning in needed to obtain reliable results. For this reason, the decompositions are made in two rounds. If the absolute value of the between component of Method 2 is greater than 2 percentage points, the plant is classified as an outlier in the first round. A similar procedure is performed for entries and exits, too. These are conservative criteria since they lead to exclusions of a couple of plants per year on average.

Table A1.1. Descriptive statistics on LDPM sample

	Observations						Hours worked, millions					
Year	1980	1985	1989	1995	2000	2005	1980	1985	1989	1995	2000	2005
Industry												
15a6	696	697	677	542	418	358	87.8	84.1	77.5	54.5	50.4	42.5
17t9	812	743	640	381	201	171	111.1	85.7	54.4	21.3	16.7	13.1
20	458	474	430	350	290	298	74.6	53.9	47.8	32.7	34.9	32.0
21	160	181	179	165	170	132	72.2	72.3	65.0	52.9	56.4	41.6
22	300	421	444	400	324	339	37.4	54.5	52.4	33.8	34.5	32.6
24	132	163	168	172	165	154	26.1	31.0	31.2	27.4	27.4	23.5
25	141	145	178	178	179	180	25.8	23.2	21.0	19.0	24.6	21.4
26	203	301	313	302	214	233	22.8	31.2	31.1	16.1	20.7	20.8
27	78	82	70	76	80	80	32.5	30.9	27.6	23.6	24.8	24.4
28	366	376	409	393	425	573	41.8	36.8	35.3	24.8	37.7	44.2
29	559	590	610	565	500	553	108.0	93.8	86.7	69.0	80.7	79.7
30a1	136	141	177	166	142	153	36.8	37.6	30.5	25.9	24.8	21.4
32a3	90	120	127	152	180	201	21.4	25.4	30.6	40.5	58.4	68.6
34a5	202	212	207	152	133	144	60.8	58.6	44.0	30.9	28.7	24.7
36a7	291	285	279	231	176	184	32.8	27.6	24.3	14.6	16.0	13.8
Manufacturing	4624	4931	4908	4225	3597	3753	791.8	746.6	659.2	487.1	536.8	504.2

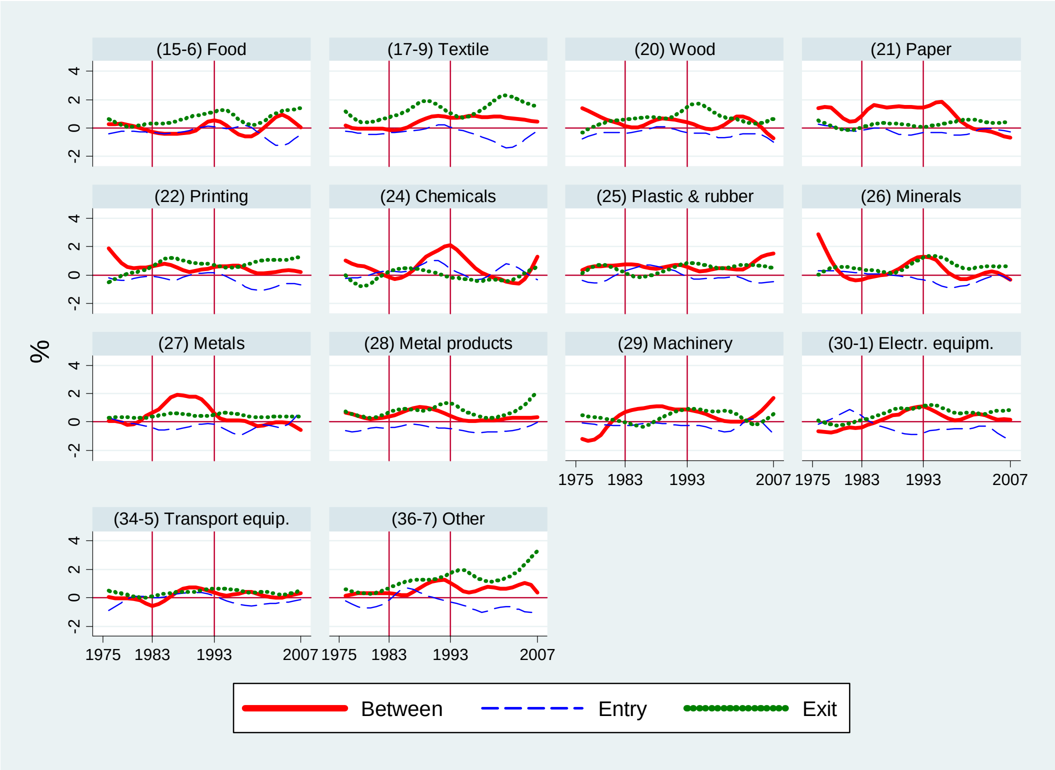
Appendix 2. Robustness checks and additional analysis

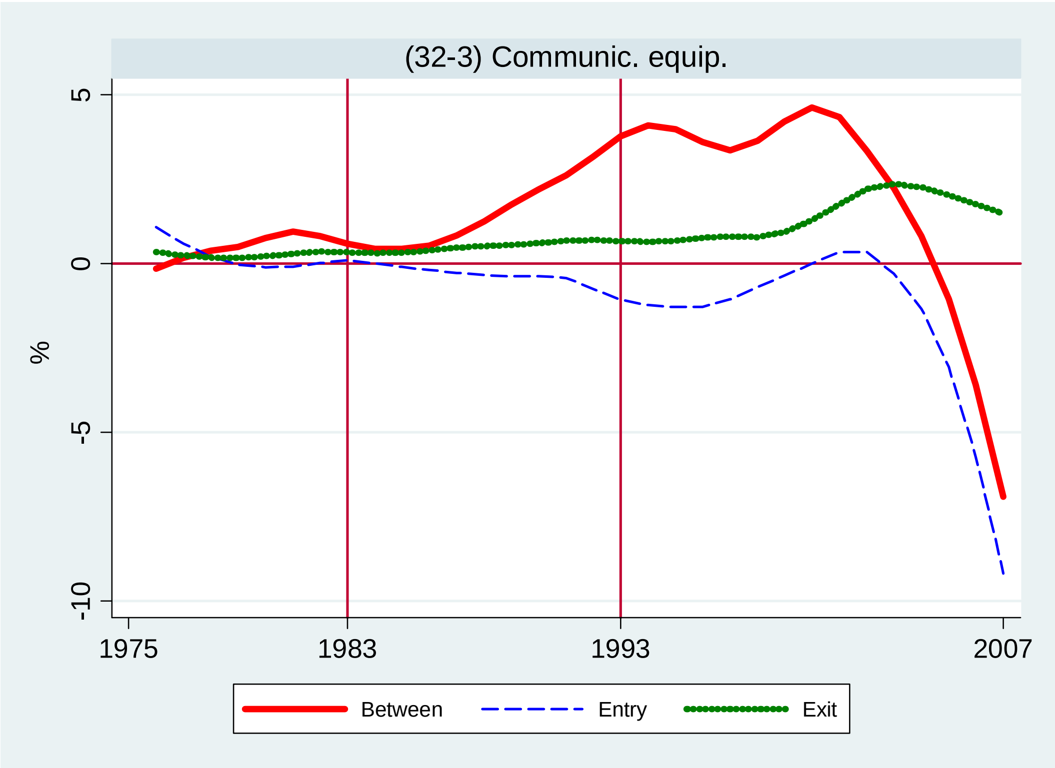
GRAPH A2.1. Development of hours worked in the manufacturing sector



Note: For details, see text.

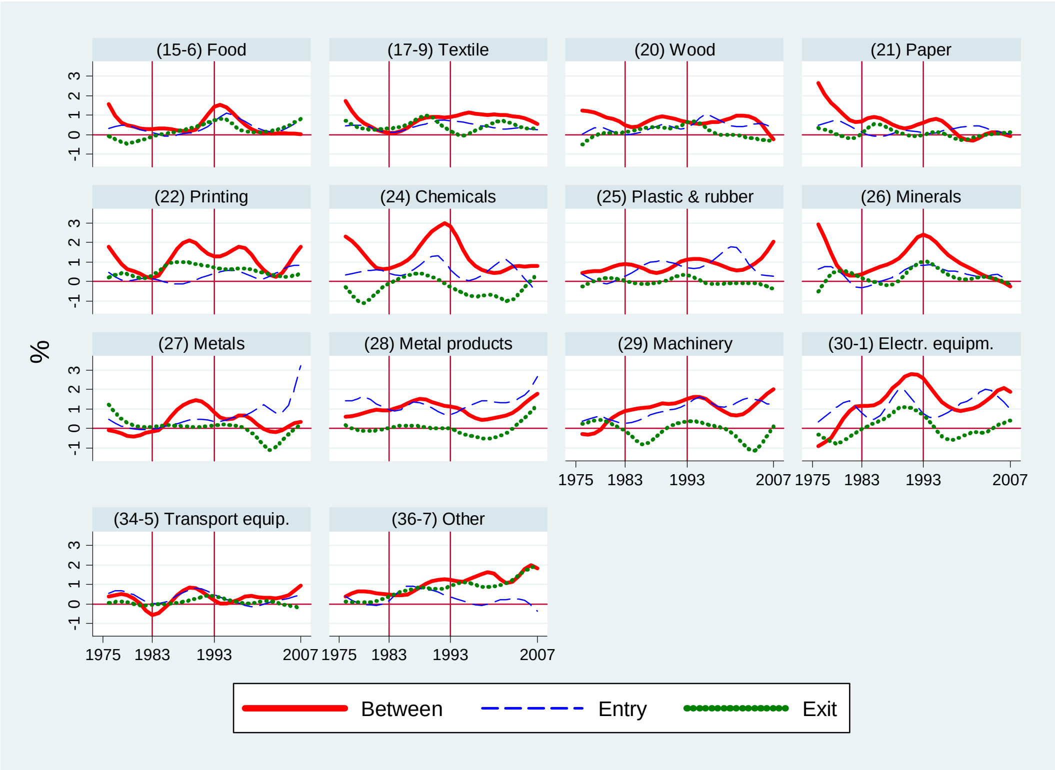
Graph A2.2. Restructuring components of labor productivity growth by industries, Method 4

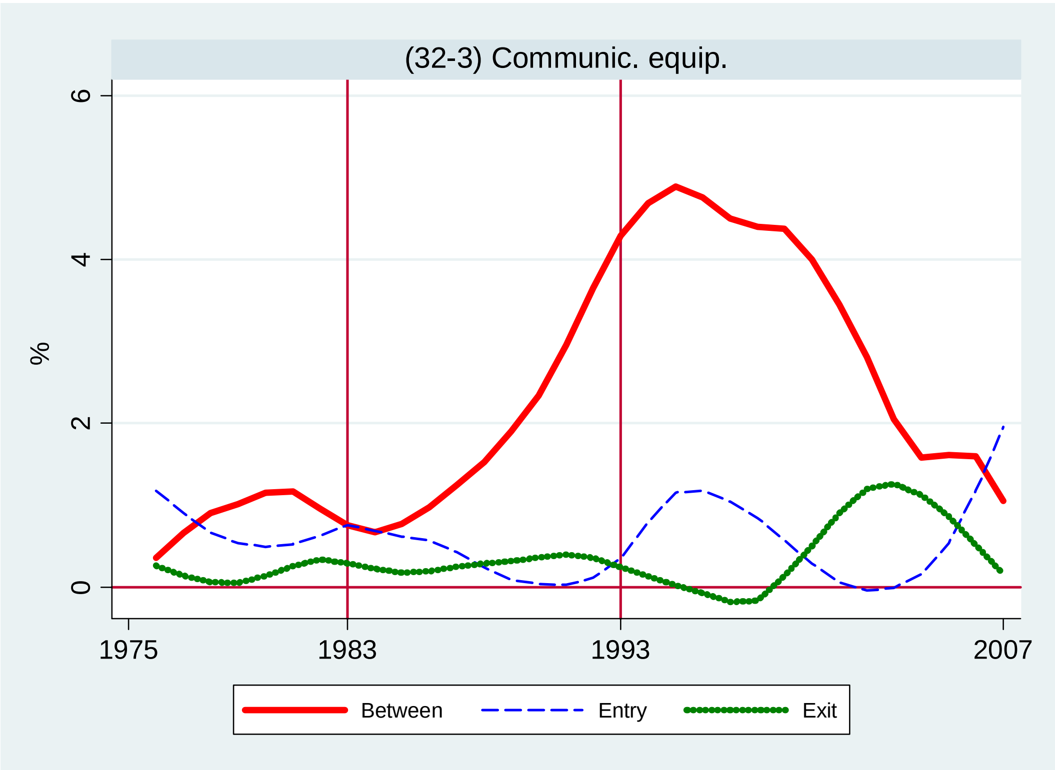




Notes: For details, see text.

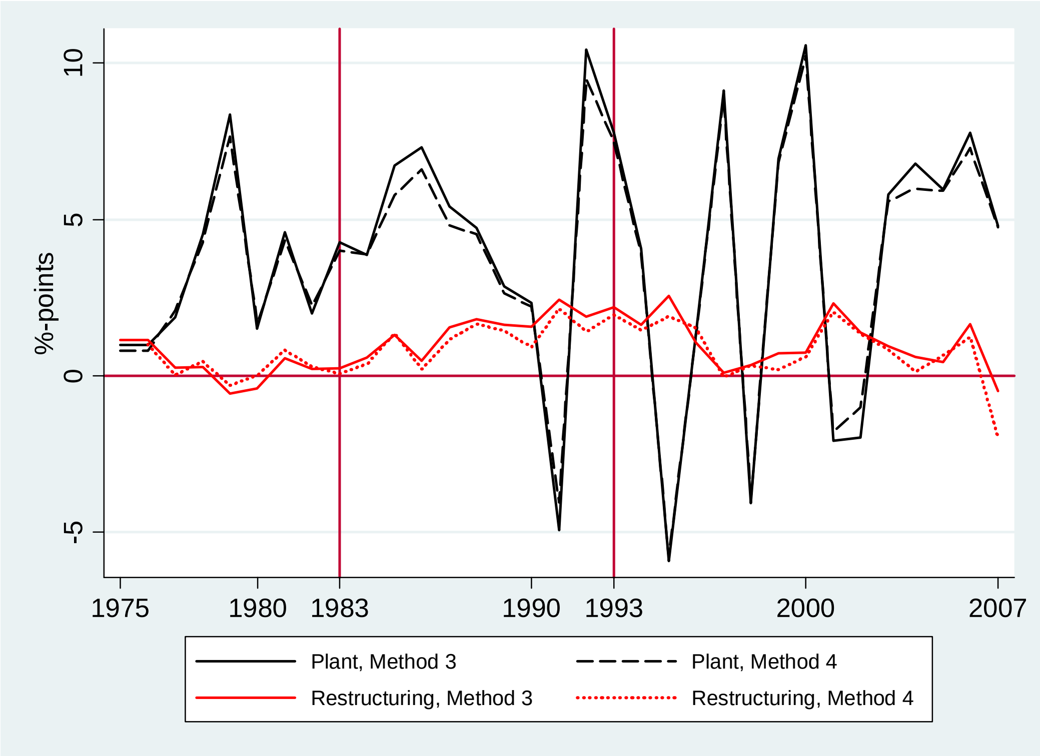
Graph A2.3. Restructuring components of *MFP* growth by industries, Method 4





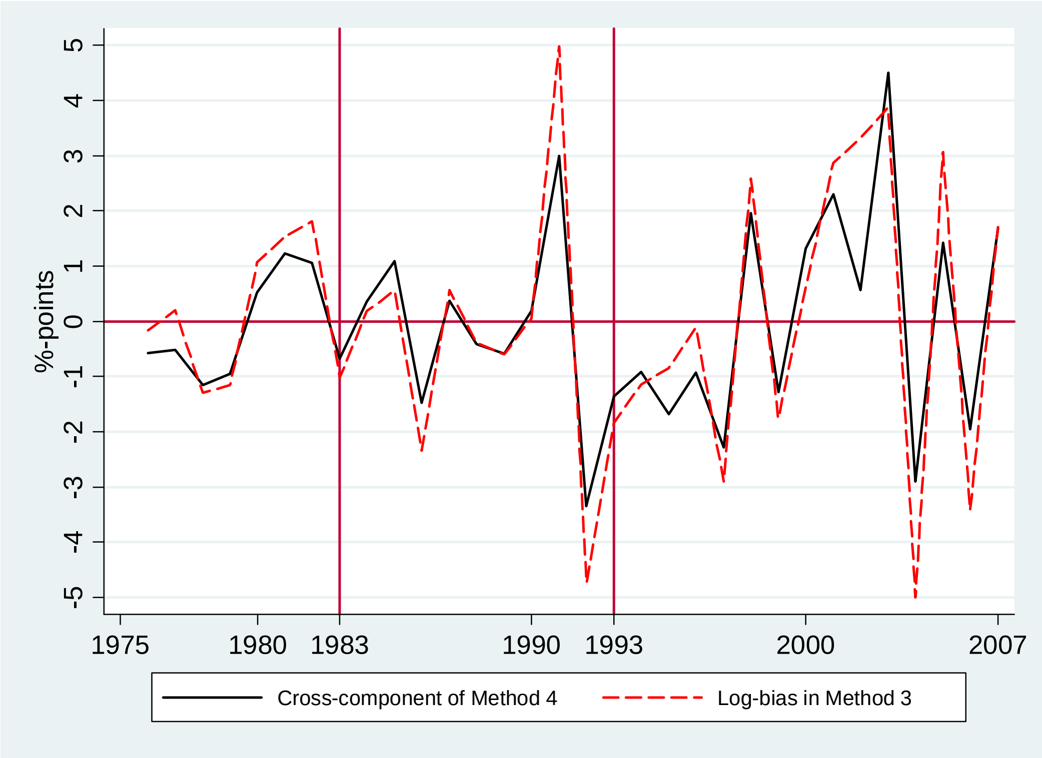
Notes: for details, see text.

GRAPH A2.4. Comparisons of Method 3 and Method 4, labor productivity growth



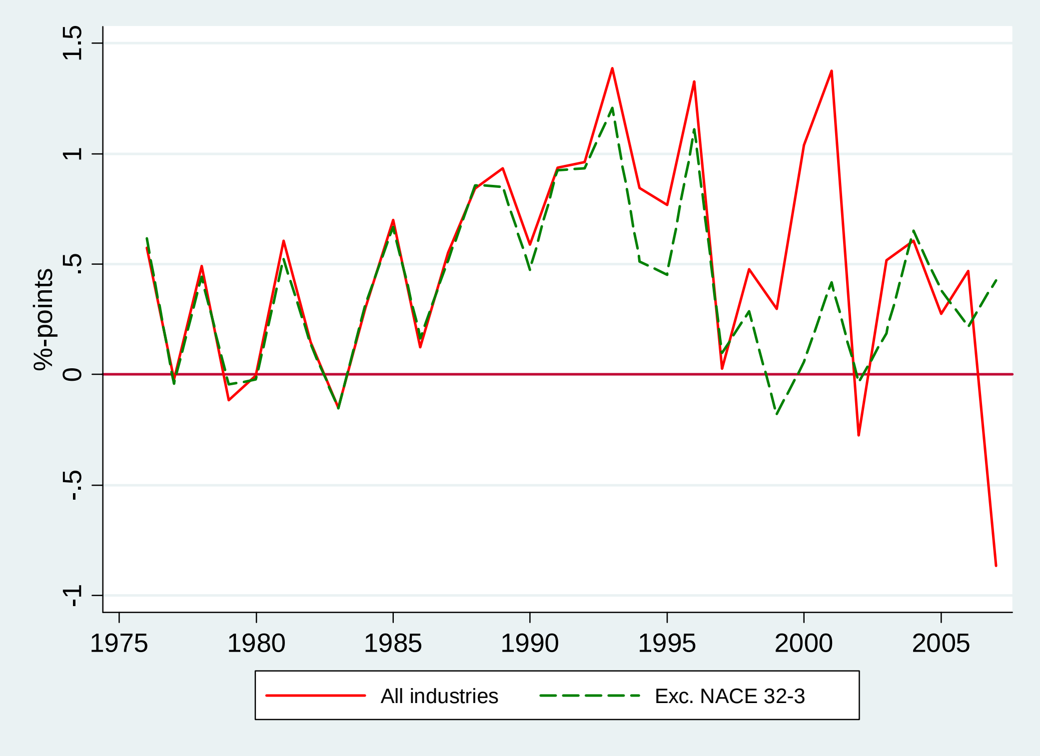
Note: For details, see text.

GRAPH A2.5. Comparison of log-bias in Method 3 with the cross-component of Method 4, *MFP* growth



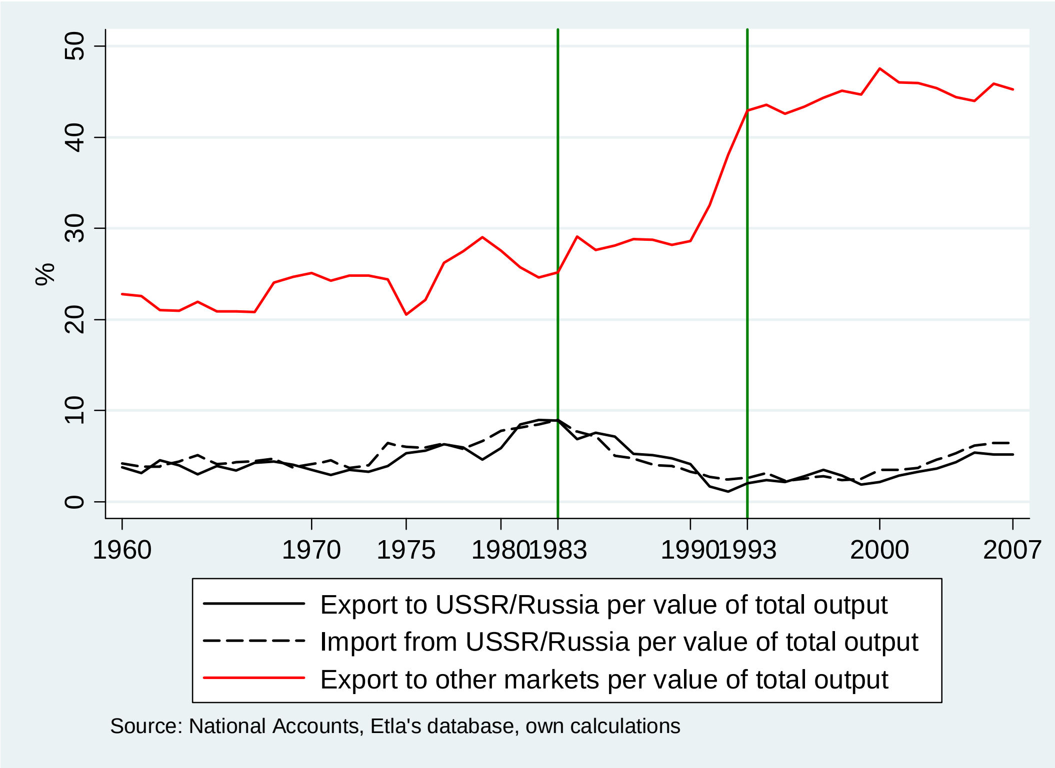
Note: For details, see text.

GRAPH A2.6. The annual between component of labor productivity growth in all industries and excluding the manufacture of communication equipment



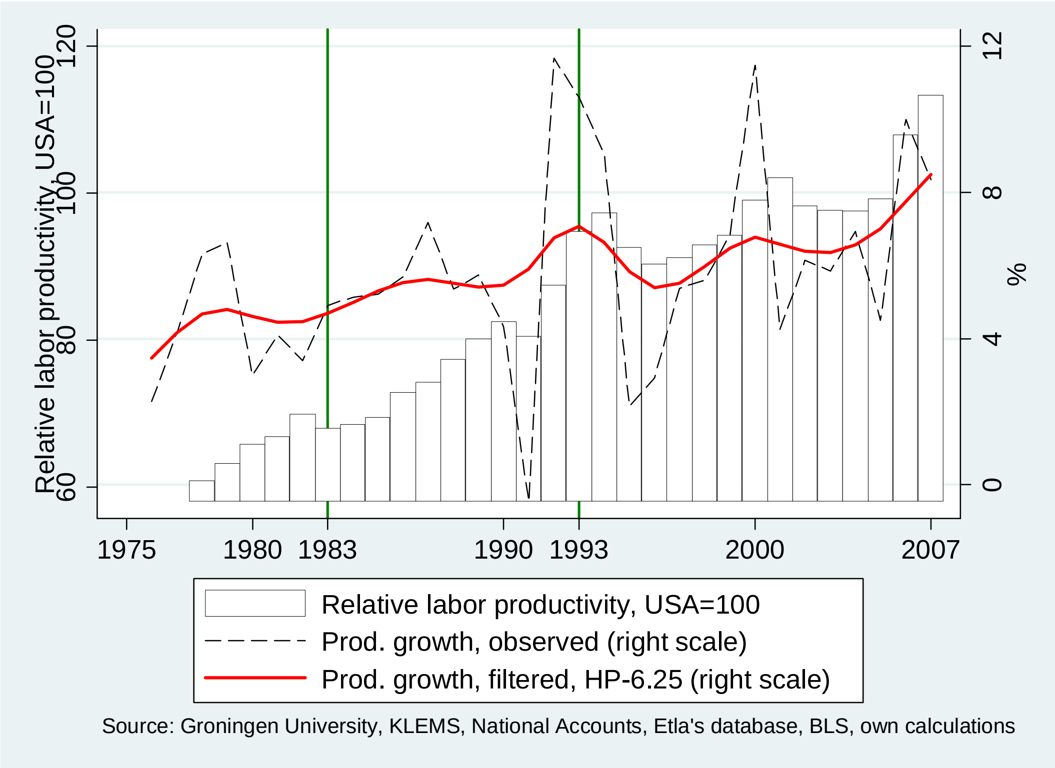
Note: For details, see text.

GRAPH 1. Phases in the trade of the manufacturing sector



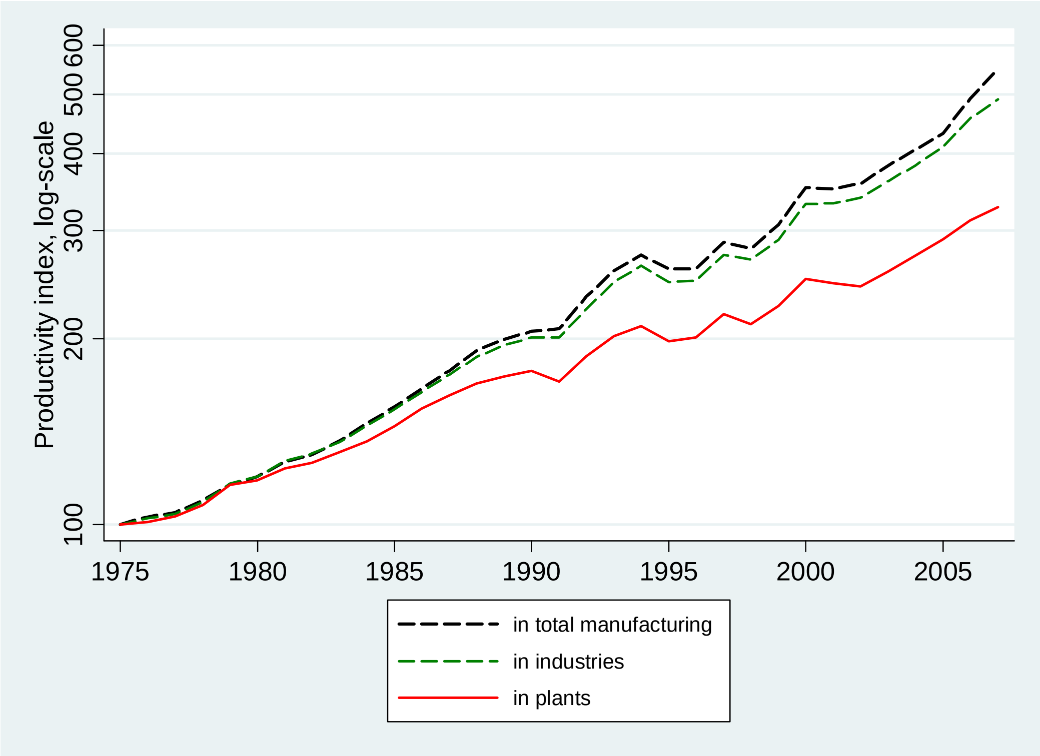
Note: For details, see text.

GRAPH 2. Development of labor productivity in the manufacturing sector



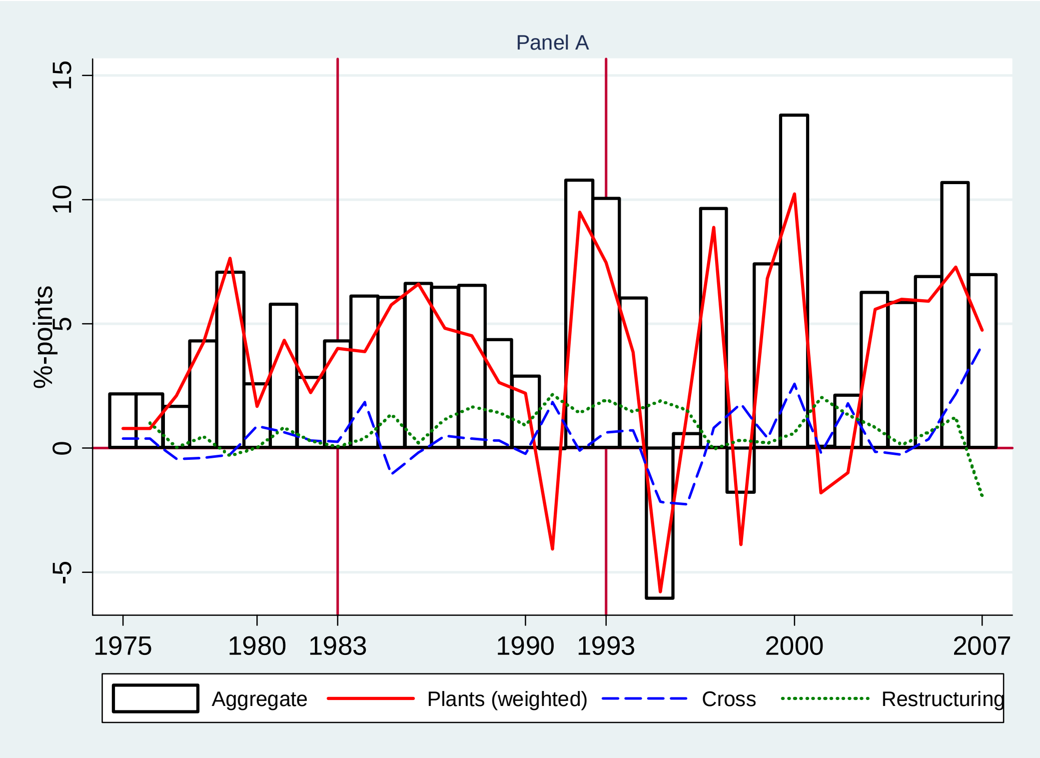
Note: The relative labor productivity level (that is 74.3%) for year 1987 is obtained from ICOP Industrial Database (1987 Benchmark), Groningen Growth and Development Centre. The other years until 2005 are extrapolated by using the productivity series of the EU-KLEMS-database and years 2006-2007 by using National Accounts (for Finland) and the Bureau of Labor Statistics (for USA). For further details, see text.

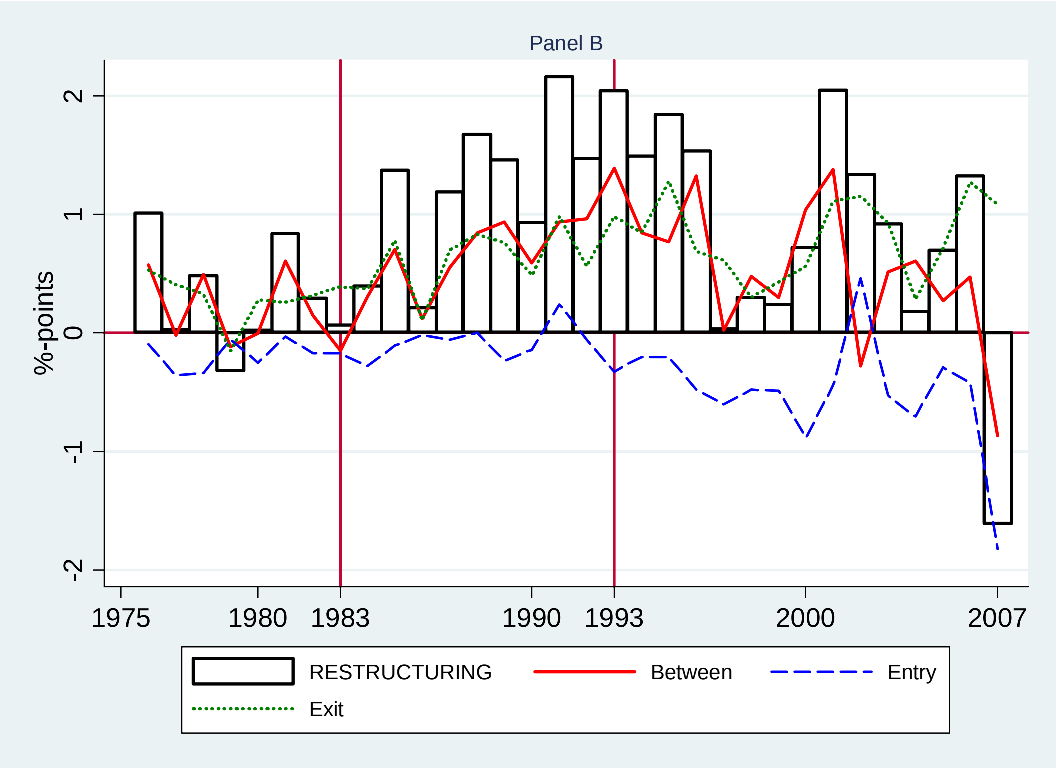
GRAPH 3. Labor productivity development at the different levels of the aggregation, Method 4



Note: For details, see text.

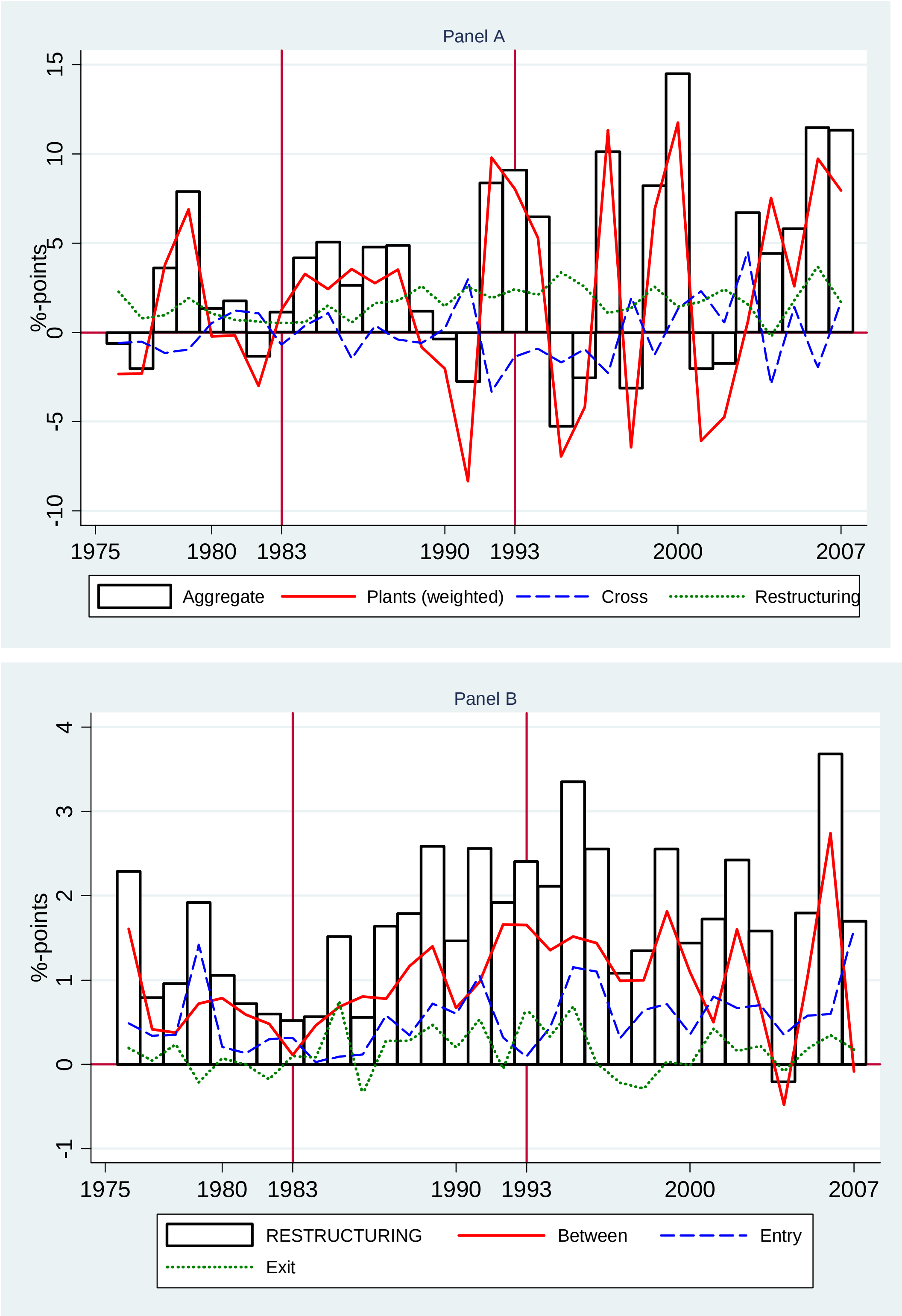
GRAPH 4. Micro-level sources of labor productivity growth in Finnish manufacturing industries, Method 4





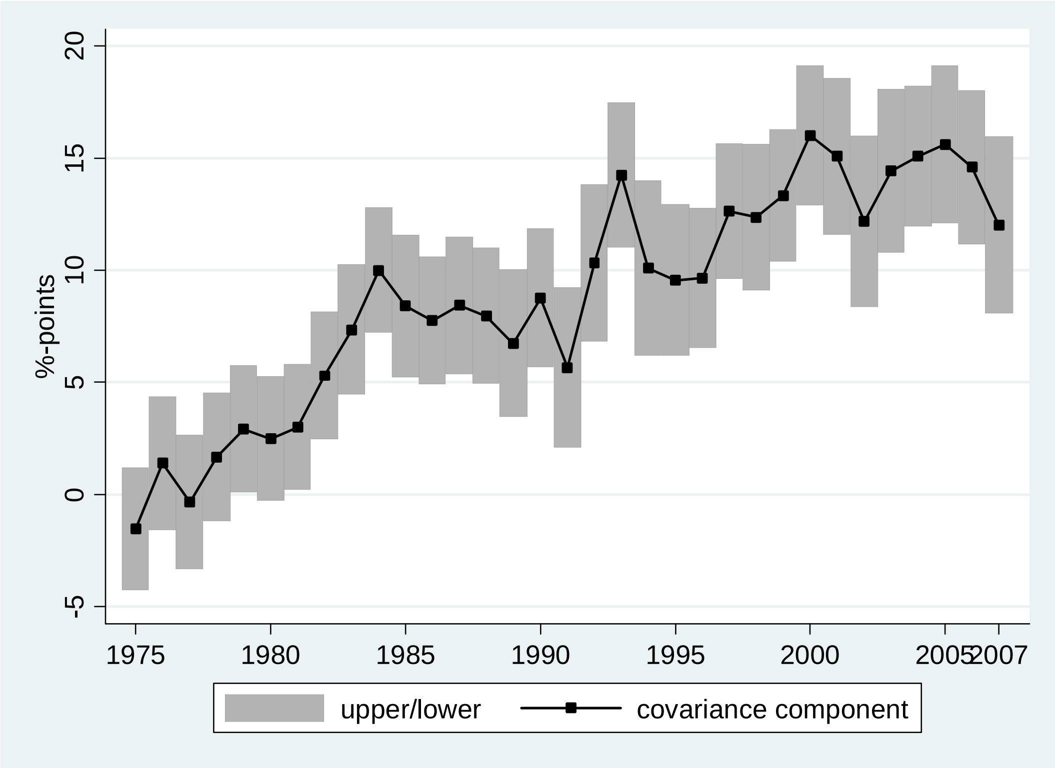
Note: Panel A presents the annual aggregate labor productivity growth and its three main components; the plant component, cross-component and restructuring component. Panel B presents the annual restructuring component and its three sub-components; the between component, entry component and exit component.

GRAPH 5. Micro-level sources of *MFP* growth in Finnish manufacturing industries, Method 4



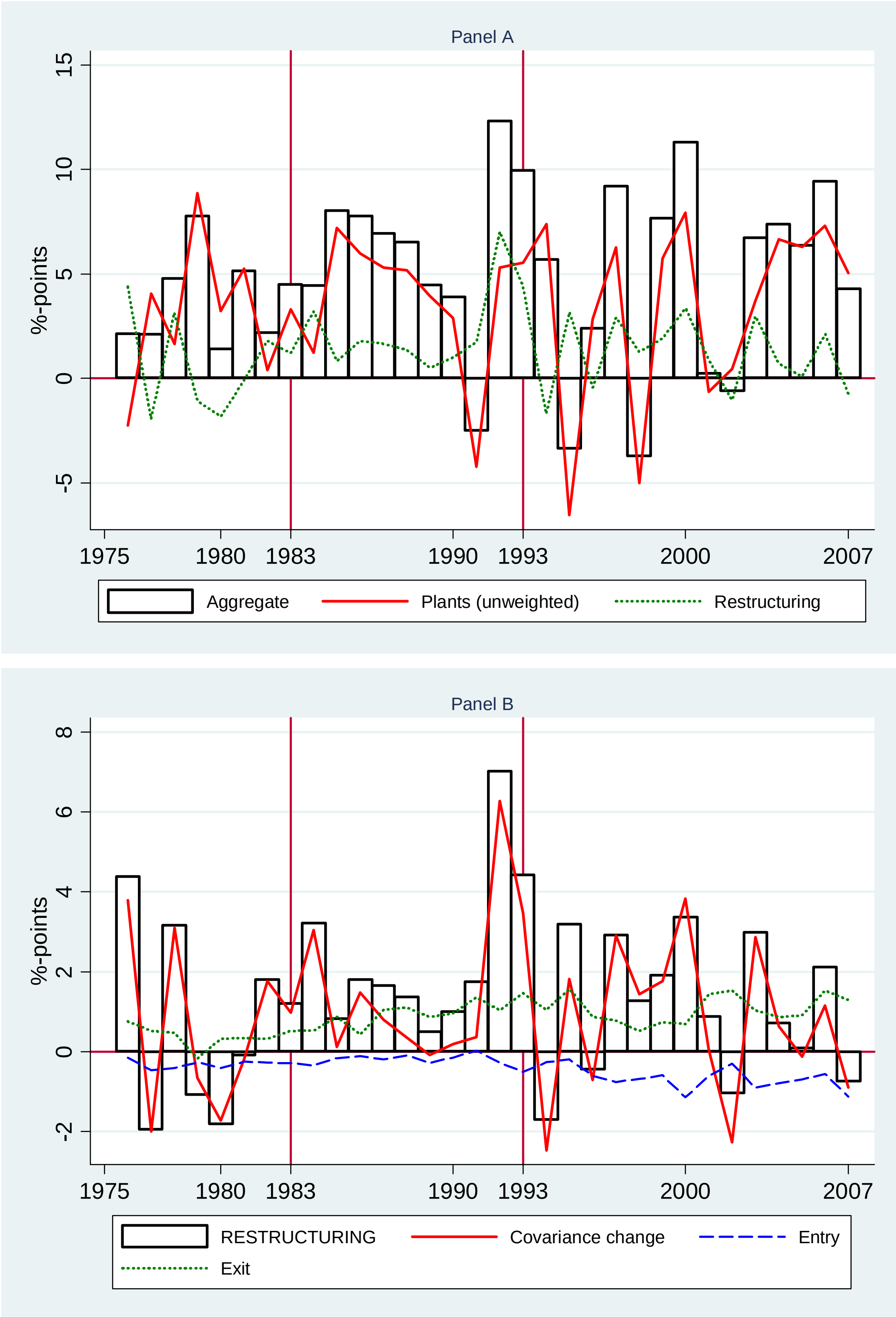
Panel A presents the annual aggregate *MFP* growth and its three main components; the plant component, cross-component and restructuring component. Panel B presents the annual restructuring component and its three sub-components; the between component, entry component and exit component.

GRAPH 6. Static allocation (i.e. covariance) component of the Olley-Pakes decomposition and its 95% confidence interval



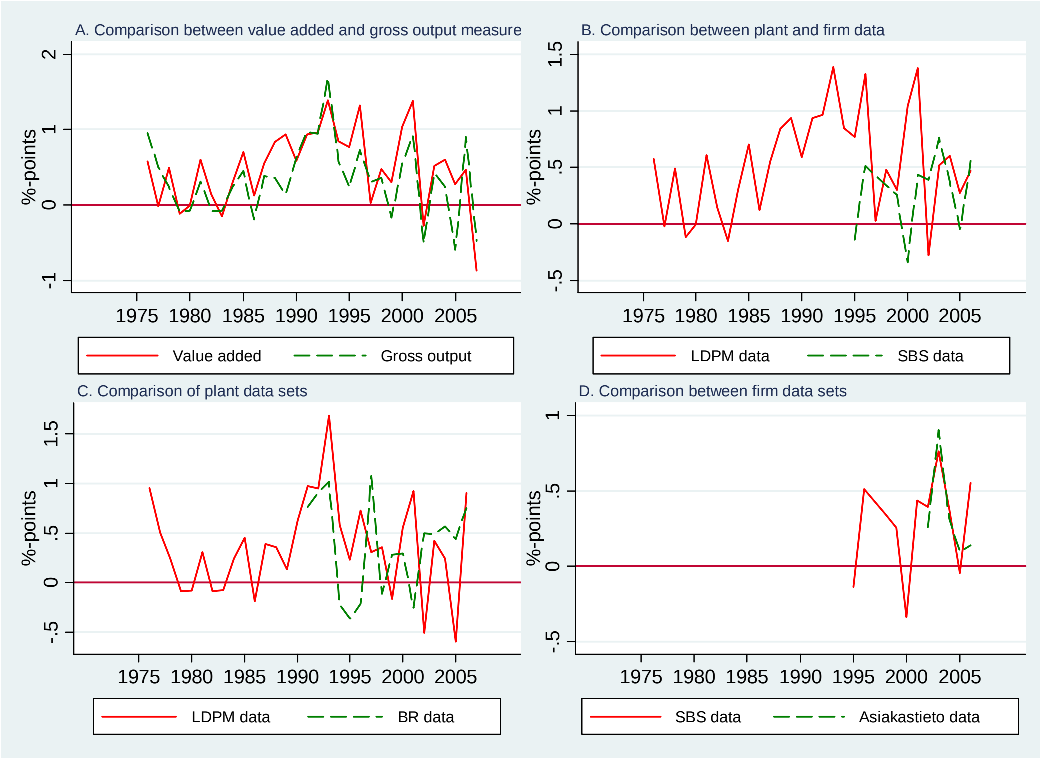
Note: The covariance component and its robust standard error are computed by a use of a regression approach. For further details, see text.

GRAPH 7. Dynamic Olley-Pakes (Melitz-Polanec) decomposition, Method 2



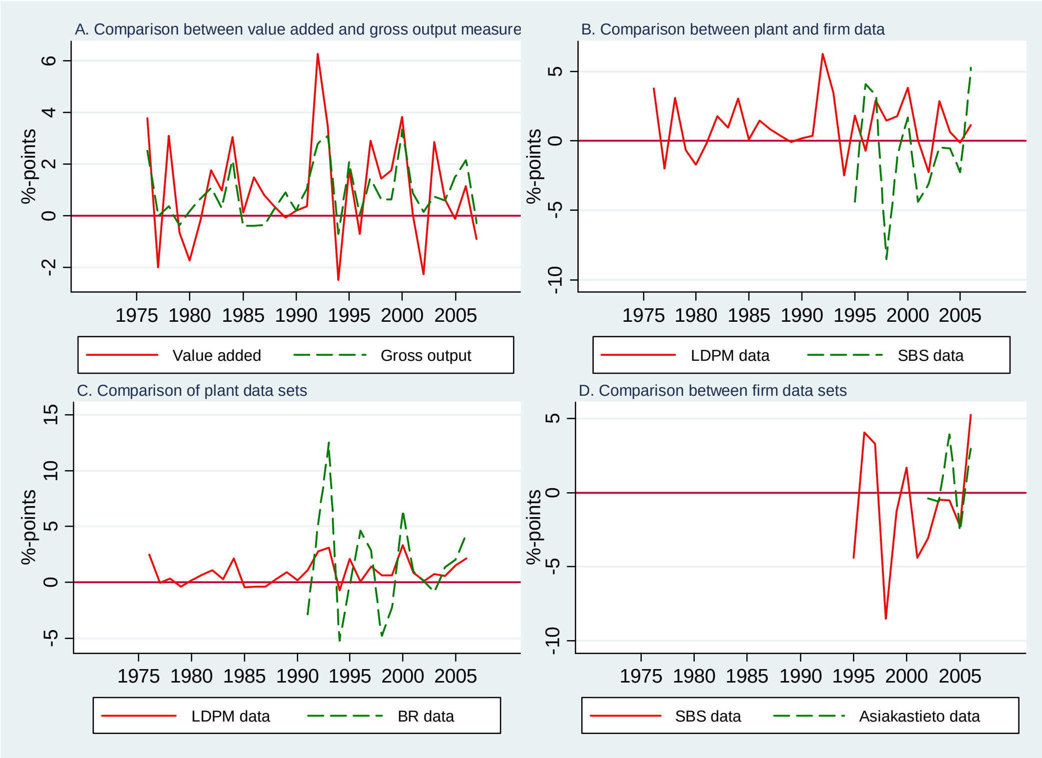
Note: see text.

GRAPH 8. Comparisons of the between component of Method 4



Note: see text.

GRAPH 9. Robustness of the covariance change component of the dynamic Olley-Pakes method (Method 2)



Note: see text.

TABLE 1. Micro-level sources of industry labor productivity growth, the annual average, Method 4

INDUSTRY	Agg.	Plant	Cross	Restr.	Betw.	Entry	Exit
Pre-transition period: 1976–1983							
(15-6) Food	2.2	2.4	-0.3	0.2	0.1	-0.2	0.3
(17-9) Textile	2.6	2.3	0.0	0.4	0.0	-0.4	0.7
(20) Wood	4.6	5.4	-1.4	0.6	0.8	-0.4	0.2
(21) Paper	7.0	5.7	0.6	0.8	0.8	-0.1	0.1
(22) Printing	2.7	1.5	0.6	0.7	0.8	-0.2	0.1
(24) Chemicals	3.0	3.6	-0.9	0.3	0.7	0.0	-0.4
(25) Plastic & rubber	5.3	4.7	-0.2	0.9	0.6	-0.2	0.5
(26) Minerals	4.3	3.2	-0.2	1.2	0.6	0.2	0.4
(27) Metals	9.8	7.4	1.8	0.6	0.3	0.0	0.3
(28) Metal products	5.5	5.0	0.1	0.4	0.4	-0.5	0.4
(29) Machinery	3.5	3.3	0.6	-0.4	-0.5	-0.2	0.3
(30-1) Electr. equipm.	0.6	0.7	0.2	-0.3	-0.7	0.4	0.0
(32-3) Communic. equip.	6.7	2.5	3.0	1.2	0.6	0.3	0.3
(34-5) Transport equip.	2.2	2.3	0.2	-0.4	-0.3	-0.2	0.2
(36-7) Other	3.0	2.8	-0.1	0.2	0.3	-0.6	0.5
MANUFACTURING	3.9	3.4	0.2	0.3	0.2	-0.2	0.3
Transition period: 1984–1993							
(15-6) Food	5.9	4.9	0.6	0.4	-0.1	-0.1	0.6
(17-9) Textile	5.3	2.8	0.6	1.9	0.4	0.0	1.5
(20) Wood	6.7	4.5	1.0	1.2	0.4	-0.1	0.9
(21) Paper	6.9	5.2	0.1	1.7	1.7	-0.2	0.2
(22) Printing	2.5	2.2	-1.2	1.4	0.5	-0.1	1.0
(24) Chemicals	5.0	3.6	-0.5	1.8	1.0	0.5	0.2
(25) Plastic & rubber	8.3	6.9	-0.1	1.5	0.7	0.5	0.2
(26) Minerals	4.1	2.6	0.6	0.9	0.6	-0.2	0.5
(27) Metals	7.2	6.3	-0.6	1.5	1.4	-0.4	0.5
(28) Metal products	6.3	3.9	0.8	1.6	0.7	-0.3	1.2
(29) Machinery	5.1	3.3	0.8	1.0	1.0	-0.2	0.2
(30-1) Electr. equipm.	13.5	11.8	0.8	0.9	0.7	-0.6	0.7
(32-3) Communic. equip.	11.7	9.0	1.1	1.6	1.5	-0.5	0.5
(34-5) Transport equip.	4.4	2.5	0.7	1.2	0.5	0.2	0.5
(36-7) Other	4.1	1.3	0.6	2.3	0.8	0.2	1.3
MANUFACTURING	6.0	4.3	0.4	1.3	0.7	-0.1	0.7
Post-transition period: 1994–2007							
(15-6) Food	5.1	4.1	0.3	0.6	0.2	-0.5	0.9
(17-9) Textile	3.1	1.1	0.4	1.5	0.7	-0.7	1.6
(20) Wood	2.7	1.7	0.6	0.5	0.2	-0.5	0.9
(21) Paper	4.2	3.2	0.4	0.6	0.4	-0.3	0.5
(22) Printing	2.0	1.2	0.1	0.6	0.4	-0.6	0.9
(24) Chemicals	3.3	2.0	1.1	0.2	0.1	0.2	-0.1
(25) Plastic & rubber	0.7	0.0	-0.2	0.9	0.6	-0.4	0.6
(26) Minerals	2.6	1.9	0.1	0.5	0.2	-0.4	0.8
(27) Metals	4.3	3.1	1.0	0.1	-0.1	-0.3	0.5
(28) Metal products	0.7	0.2	0.1	0.4	0.2	-0.6	0.7
(29) Machinery	4.5	3.6	0.2	0.7	0.5	-0.3	0.5
(30-1) Electr. equipm.	8.5	7.6	0.2	0.6	0.3	-0.5	0.8
(32-3) Communic. equip.	16.7	11.0	3.7	2.0	2.0	-1.5	1.5
(34-5) Transport equip.	1.2	0.0	1.0	0.2	0.2	-0.4	0.4
(36-7) Other	2.8	1.1	0.0	1.7	0.6	-0.8	1.9
MANUFACTURING	4.9	3.4	0.7	0.8	0.5	-0.5	0.8

Note: See text.

TABLE 2. Micro-level sources of industry *MFP* growth, the annual average, Method 4

INDUSTRY	Agg.	Plant	Cross	Restr.	Betw.	Entry	Exit
Pre-transition period: 1976-1983							
(15-6) Food	-1.9	-1.6	-1.0	0.7	0.6	0.4	-0.3
(17-9) Textile	0.5	-0.8	-0.1	1.4	0.7	0.3	0.4
(20) Wood	3.7	4.4	-1.8	1.1	1.0	0.2	-0.1
(21) Paper	4.1	3.1	-0.7	1.7	1.2	0.5	-0.1
(22) Printing	0.9	-1.9	1.5	1.3	0.8	0.2	0.3
(24) Chemicals	0.8	-0.4	-0.1	1.4	1.3	0.6	-0.6
(25) Plastic & rubber	1.4	1.3	-0.7	0.8	0.6	0.1	0.1
(26) Minerals	1.7	1.0	-0.9	1.6	1.1	0.2	0.2
(27) Metals	9.0	7.6	1.1	0.4	-0.1	0.1	0.4
(28) Metal products	4.2	2.6	-0.5	2.1	0.8	1.4	-0.1
(29) Machinery	1.7	0.7	0.0	0.9	0.2	0.4	0.3
(30-1) Electr. equipm.	-0.9	-1.6	-0.1	0.9	0.3	1.0	-0.4
(32-3) Communic. equip.	3.5	-2.0	3.5	2.0	0.9	0.9	0.2
(34-5) Transport equip.	1.3	0.5	0.4	0.4	0.0	0.4	0.0
(36-7) Other	0.7	0.3	-0.3	0.7	0.6	0.0	0.1
MANUFACTURING	1.5	0.5	-0.1	1.1	0.6	0.4	0.0
Transition period: 1984–1993							
(15-6) Food	3.6	3.2	-0.5	0.9	0.5	0.1	0.3
(17-9) Textile	4.1	2.1	0.2	1.7	0.6	0.5	0.6
(20) Wood	4.9	3.0	0.6	1.3	0.7	0.3	0.4
(21) Paper	3.7	3.5	-0.8	1.0	0.7	0.1	0.2
(22) Printing	0.8	-0.9	-0.7	2.3	1.4	0.0	0.9
(24) Chemicals	2.5	1.6	-2.0	3.0	2.1	0.7	0.2
(25) Plastic & rubber	6.2	4.8	-0.2	1.7	0.8	0.8	0.1
(26) Minerals	1.3	-0.8	0.1	2.0	1.4	0.3	0.3
(27) Metals	4.8	4.8	-1.2	1.2	0.8	0.3	0.1
(28) Metal products	4.6	2.0	0.2	2.3	1.2	0.9	0.2
(29) Machinery	3.4	1.3	0.5	1.6	1.2	0.7	-0.3
(30-1) Electr. equipm.	12.3	8.2	0.2	3.9	2.1	1.1	0.7
(32-3) Communic. equip.	7.3	3.4	1.6	2.3	2.0	0.0	0.3
(34-5) Transport equip.	2.9	1.4	0.3	1.2	0.5	0.5	0.2
(36-7) Other	1.4	-1.5	0.5	2.4	0.9	0.7	0.7
MANUFACTURING	3.7	2.2	-0.2	1.7	1.0	0.4	0.3
Post-transition period: 1994–2007							
(15-6) Food	4.3	2.7	0.1	1.5	0.5	0.6	0.4
(17-9) Textile	2.5	0.6	0.1	1.7	1.0	0.4	0.3
(20) Wood	2.4	1.0	0.1	1.3	0.6	0.6	0.1
(21) Paper	3.8	3.9	-0.5	0.4	0.2	0.2	0.0
(22) Printing	2.1	0.4	-0.5	2.1	1.1	0.5	0.5
(24) Chemicals	1.8	1.1	0.1	0.6	0.8	0.4	-0.6
(25) Plastic & rubber	0.1	-1.4	-0.4	1.9	1.0	1.0	-0.1
(26) Minerals	2.4	1.6	-0.6	1.5	0.8	0.5	0.3
(27) Metals	3.3	0.7	1.5	1.0	0.2	1.0	-0.3
(28) Metal products	0.7	-1.0	-0.6	2.3	0.9	1.5	-0.1
(29) Machinery	5.1	3.1	-0.5	2.5	1.3	1.4	-0.2
(30-1) Electr. equipm.	8.1	7.0	-1.4	2.5	1.4	1.3	-0.2
(32-3) Communic. equip.	13.5	7.3	1.7	4.5	3.2	0.8	0.5
(34-5) Transport equip.	1.1	-0.4	1.0	0.5	0.3	0.1	0.1
(36-7) Other	1.7	-0.6	-0.5	2.8	1.4	0.1	1.3
MANUFACTURING	4.6	2.5	0.1	1.9	1.1	0.7	0.1

Note: See text.

TABLE 3. Decomposing the contributions of plant cohorts to industry labor productivity growth, Method 4

Period		1980-1985			1985-1990			1990-1995			1995-2000			2000-2005		
		Comp-nent	Share of hours		Comp-nent	Share of hours		Comp-nent	Share of hours		Comp-nent	Share of hours		Comp-nent	Share of hours	
			1980	1985		1985	1990		1990	1995		1995	2000		2000	2001
TOTAL		24.5			26.2			20.5			26.0			16.9		
ENTRY		0.9		8.0	0.1		11.2	-0.9		11.8	-1.7		13.5	-1.4		10.8
EXIT		1.1	9.9		1.6	15.3		1.5	21.3		1.9	11.7		0.6	15.1	
Cohort	-1975	0.7	7.6		1.4	10.8		1.4	13.0		0.9	5.3		0.7	3.9	
	1976-80	0.4	2.3		0.2	2.6		0.1	2.8		0.2	1.2		0.2	1.1	
	1981-85				0.0	1.8		0.1	2.3		0.2	0.9		0.1	0.8	
	1986-90							-0.1	3.2		0.2	1.6		-0.3	2.7	
	1991-95										0.3	2.7		-0.6	3.6	
	1996-00													0.4	3.0	
BETWEEN		0.5	100.0	100.0	2.0	100.0	100.0	2.1	100.0	100.0	2.9	100.0	100.0	0.4	100.0	100.0
Cohort	-1975	0.6	90.1	88.9	1.5	84.3	82.5	0.9	77.0	74.1	1.5	66.6	64.5	-0.3	59.7	58.4
	1976-80	-0.1	9.9	11.1	0.4	10.7	11.5	0.4	10.1	10.8	0.5	10.3	10.6	0.2	10.5	10.8
	1981-85				0.1	5.0	6.0	0.1	5.7	6.2	0.1	6.0	6.1	0.0	6.1	6.4
	1986-90							0.6	7.2	8.9	1.0	9.1	10.0	0.0	10.4	9.9
	1991-95										0.0	8.1	8.8	0.6	7.8	8.5
	1996-00													-0.1	5.6	6.1
PLANT		18.9	100.0	100.0	21.6	100.0	100.0	17.6	100.0	100.0	20.1	100.0	100.0	16.5	100.0	100.0
Cohort	-1975	17.1	90.1	88.9	18.0	84.3	82.5	11.9	77.0	74.1	13.4	66.6	64.5	8.0	59.7	58.4
	1976-80	1.8	9.9	11.1	2.6	10.7	11.5	2.1	10.1	10.8	1.7	10.3	10.6	2.1	10.5	10.8
	1981-85				1.0	5.0	6.0	1.5	5.7	6.2	0.9	6.0	6.1	1.3	6.1	6.4
	1986-90							2.2	7.2	8.9	2.9	9.1	10.0	3.2	10.4	9.9
	1991-95										1.2	8.1	8.8	0.9	7.8	8.5
	1996-00													1.0	5.6	6.1
CROSS		3.1	100.0	100.0	1.0	100.0	100.0	0.2	100.0	100.0	2.9	100.0	100.0	0.9	100.0	100.0
Cohort	-1975	2.9	90.1	88.9	1.1	84.3	82.5	-0.5	77.0	74.1	0.8	66.6	64.5	1.3	59.7	58.4
	1976-80	0.2	9.9	11.1	0.1	10.7	11.5	-0.1	10.1	10.8	-0.1	10.3	10.6	-0.1	10.5	10.8
	1981-85				-0.2	5.0	6.0	0.1	5.7	6.2	0.1	6.0	6.1	-0.1	6.1	6.4
	1986-90							0.7	7.2	8.9	2.0	9.1	10.0	0.1	10.4	9.9
	1991-95										0.1	8.1	8.8	-0.4	7.8	8.5
	1996-00													0.0	5.6	6.1

Notes: See text.

TABLE 4.a Decomposing entry component of labor productivity growth by dynamic O-P (Method 2), selected 5-year windows

	Unweighted average effect					Covariance effect				
Period	1978-83	1984-89	1993-98	1997-02	2002-07	1978-83	1984-89	1993-98	1997-02	2002-07
Industry										
(15-6) Food	-1.9	-0.8	-1.1	-2.7	-1.3	0.3	0.3	-0.5	0.0	0.2
(17-9) Textile	-1.0	-1.2	-0.2	-1.2	-0.1	0.4	1.1	-1.9	-1.3	-0.7
(20) Wood	-0.8	1.0	-2.3	-1.7	-2.6	1.0	-1.0	0.0	0.9	-0.4
(21) Paper	0.2	0.7	-1.4	0.5	-0.3	-0.4	1.4	0.1	-1.8	-0.1
(22) Printing	0.4	-0.1	-0.7	-1.8	-1.2	0.1	0.2	-2.3	-2.3	-0.5
(24) Chemicals	0.5	1.4	-0.7	-1.1	-0.2	0.8	-0.1	-3.6	2.5	-2.1
(25) Plastic & rubber	6.2	0.7	-0.5	1.0	0.0	-9.4	-2.2	-0.2	-1.6	0.1
(26) Minerals	0.3	0.4	-1.6	-2.5	0.2	-1.3	-0.9	0.6	-0.9	-0.5
(27) Metals	-3.8	-1.1	-1.8	-0.9	0.7	2.7	-0.9	-1.6	-1.0	-1.9
(28) Metal products	-1.9	0.6	-1.7	-3.5	-1.7	0.3	-2.4	-0.5	-1.9	0.8
(29) Machinery	-0.8	1.7	0.7	-1.0	0.3	-3.7	-1.4	-1.0	0.9	-1.1
(30-1) Electr. equipm.	0.0	-1.7	1.7	0.4	0.5	-3.5	1.0	1.0	-0.4	-1.2
(32-3) Comm. equip.	-2.4	-0.7	-3.1	1.7	8.1	-1.0	-3.3	-2.6	-8.5	-25.7
(34-5) Transp. equip.	-0.3	0.6	0.2	-1.3	-0.5	-0.5	0.4	0.7	-0.5	1.5
(36-7) Other	-1.0	2.0	-0.3	0.4	1.7	-2.0	-1.9	-3.0	0.4	-5.8
Weighted average	-0.6	0.2	-0.8	-0.9	0.7	-0.8	-0.3	-0.9	-1.3	-3.9
Unweighted average	-0.4	0.2	-0.9	-0.9	0.2	-1.1	-0.6	-1.0	-1.0	-2.5

Notes: see text.

TABLE 4.b. Decomposing exit component of labor productivity growth by dynamic O-P (Method 2), selected 5-year windows

	Unweighted average effect					Covariance effect				
Period	1978-83	1984-89	1993-98	1997-02	2002-07	1978-83	1984-89	1993-98	1997-02	2002-07
Industry										
(15-6) Food	2.3	1.3	4.7	2.9	4.1	-1.3	-1.1	-2.9	0.1	-1.9
(17-9) Textile	2.4	5.3	3.5	5.0	5.2	-0.6	0.9	-0.7	1.8	2.5
(20) Wood	1.4	3.8	4.3	1.4	1.7	-1.4	2.8	1.8	0.4	-1.8
(21) Paper	-0.2	7.0	3.9	2.6	3.8	-1.8	-1.1	4.0	1.1	3.8
(22) Printing	0.7	4.7	2.0	1.1	4.9	0.4	3.9	-0.3	0.4	0.5
(24) Chemicals	0.4	3.8	-0.9	1.8	3.1	-1.2	-0.4	0.4	-2.5	-1.8
(25) Plastic & rubber	1.5	-1.0	0.4	1.5	1.9	-0.3	-1.0	-0.3	-0.3	0.5
(26) Minerals	0.3	1.0	5.5	-0.2	2.1	1.9	0.6	1.6	0.5	1.4
(27) Metals	0.7	3.0	1.5	-1.5	0.1	0.3	-0.2	0.3	-1.3	-0.5
(28) Metal products	0.2	6.4	0.6	1.4	2.8	0.6	-0.5	1.5	0.2	0.7
(29) Machinery	1.1	3.4	2.2	1.3	0.1	-2.1	-0.7	1.7	0.4	-3.2
(30-1) Electr. equipm.	1.5	2.8	-1.4	1.7	0.4	-2.0	-10.0	4.2	2.0	-4.8
(32-3) Comm. equip.	1.4	0.5	3.2	4.1	2.3	-0.3	-0.8	0.3	10.4	12.0
(34-5) Transp. equip.	-0.2	3.9	-0.1	1.0	0.5	0.6	4.1	1.0	0.4	0.4
(36-7) Other	3.1	3.5	8.9	2.7	7.2	0.7	1.1	-2.1	-0.1	5.2
Weighted average	1.2	3.6	2.6	1.9	2.3	-0.7	0.0	0.8	1.4	1.2
Unweighted average	1.1	3.3	2.6	1.8	2.7	-0.4	-0.2	0.7	0.9	0.9

Notes: see text.

TABLE 5. Covariance component of the static O-P method and the size threshold for the inclusion to the sample, the SBS firm-panel, average over the period from 1995 to 2007

Size threshold, number of persons	***none***	***1***	***2***	***3***	***4***	***5***	***10***	***15***	***20***
Covariance component	36.2	34.6	30.1	27.7	26.2	25.2	22.4	21.4	20.7
Standard error	3.50	3.49	3.47	3.45	3.44	3.43	3.40	3.38	3.36

Notes: see text.