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## On the Evolution of Size and Productivity in Transition: Evidence from Slovenian Manufacturing Firms

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# LICOS

## Centre for Transition Economics

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#### **On the Evolution of Size and Productivity in Transition: Evidence from Slovenian Manufacturing Firms**

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# On the Evolution of Size and Productivity in Transition: Evidence from Slovenian Manufacturing Firms

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## Abstract

This paper compiles a set of stylized facts on the evolution of firm size and labor and total factor productivity distributions during the process of transition. These facts are based on the data for all Slovenian manufacturing firms active between 1994 and 2003. Stylized picture of transition can be summarized as follows. Initially, we can distinguish between two types of firms: small and on average more productive and large and on average less productive firms. Removal of institutional restrictions has spurred growth of small firms and entry of new firms on one hand and decline and exit of large firms on the other. These simultaneous shifts have transformed the shape of firm size distribution from bimodal into unimodal. While labor and total factor productivity distributions exhibit large right-hand shifts and lower heterogeneity over time, firm productivity rankings changed substantially. Smaller firms, which were initially more productive, exhibited lower productivity growth rates and thus gradually lost their advantage. Commonly held view of transition as a process of reallocation of resources from inefficient state to efficient private firms is at odds with our results of aggregate labor and total factor productivity decompositions. Almost half of aggregate labor productivity growth can be explained by within firm growth and the rest by reallocation. Our evidence suggests that within firm growth seems to be related to the process of technological catching up of less productive large firms. These stylized facts may give a wrong impression of transition being a deterministic process, while it is not. The process is stochastic and thus similar to those found for established market economies. Hence theoretical models of transition should reflect deterministic features that we outlined and preserve stochastic elements introduced in now standard models of industrial dynamics.

*JEL* codes: L11, L16, L60,

KeyWords: manufacturing, size, labor productivity, total factor productivity, catching up, distributions, transition.

## 1 Introduction

Firm size and productivity are tightly related in industrial organization literature. Theoretical models of industrial dynamics that allow for heterogeneity in firm productivity levels predict that more productive firms should also be larger (e.g. Jovanovic, 1982; Ericson and Pakes, 1995; Kortum and Klette, 2002; Rossi-Hansberg and Wright, 2004), which is consistent with abundant empirical evidence (see surveys by Caves, 1998; Bartelsman and Doms, 2000; Ahn, 2001). Besides productivity, there is a number of factors that affect firm size distributions (FSD), ranging from preferences and production functions for different products to financial, institutional and regulatory factors. For example, Cooley and Quadrini (2001) and Cabral and Mata (2003) argue that financing constraints affect both evolution and stationary FSD, while Schivardi and Torrini (2001) argue that employment protection legislation has small, but noticeable effect on FSD in Italy. Distortions to FSD in market economies are, however, modest when compared to distortions that were generated by institutional restrictions in ex-socialist countries. For example, even ex-Yugoslavia, a disintegrated country with the most liberal institutional setup among all ex-socialist countries, imposed effective constraints on employment in private firms. This and many other institutional constraints combined with direct political interference in allocation of resources generated bimodal FSD

(see Newberry and Kattuman, 1992; Vahcic and Petrin, 1989). Transition process removed many of these binding constraints and triggered the process of restoration of positive relationship between firm size and productivity.

This paper studies the evolution of firm size and productivity distributions during the process of transition and our aim is to compile a set of facts that should motivate any realistic model of industrial dynamics in transition. While during early transition, researchers built some theoretical models in order to provide some guidance to governments in choosing the optimal speed of reforms (see Aghion and Blanchard, 1994; Castanheira and Roland, 2000), these models focused primarily on reallocation of production inputs and outputs from inefficient state firms to efficient state firms, while assumed that productivity of private and state firms remained unchanged. In these models, small private firms should grow, while large state firms should disappear and size and productivity relationship would restore primarily through reallocation. However, recent evidence surveyed in Djankov and Murrell (2002) shows that productivity growth was substantial during transition process and one cannot only focus on reallocation in explaining shifts in FSD and FPD, a point already made by Blanchard (1997). What are relative contributions of reallocation and restructuring is an empirical issue that is addressed in this paper. In fact, our aim is to provide a comprehensive overview of industrial dynamics during the process of transition. For that purpose, we use the data for Slovenian manufacturing firms active in the period 1994-2003. While Slovenia is the most advanced transition country in terms of per capita income, we believe that qualitative features should be very similar to those of other countries with less favorable initial conditions. Our main findings on FSD can be summarized as follows.

First, over the course of transition the shape of FSD changed, from initially bimodal into unimodal. In spite of this, FSD at the end 2003 cannot (yet) be described by any often used standard parametric family of distributions, such as log-normal or generalized gamma. Second, the average size and dispersion have both been decreasing monotonically. According to the legal classification of size of firms, the shares of employees in micro, small and medium size firms increased, while the share of employees in large firms decreased. Total number of firms increased substantially, while the share of small firms increased at the expense of all other firms. Third, using both non-parametric (transition matrices, stochastic kernels) and parametric techniques, we observe both substantial persistence combined with important shifts in FSD. While growth of firms is naturally stochastic, the key shifts that transformed FSD are the following. Micro and small firms grow, while medium and large firms reduce size. Net entry is also important, primarily entry of micro and small firms and exit of large firms. Fourth, while exit of smaller firms is more likely, in terms of labor flows these are much less important than exit of large firms. Entering firms are on average smaller than surviving firms, while hazard rates for these decline with age. Exiting firms are smaller on average, although in the early transition, the difference in size was smaller, suggesting of strong exit of large firms in the early transition. Similarly, exit of new entrants in the early transition is smaller and increases over time. Fifth, FSD of surviving and exiting entrants is not much different in a year of entry, which confirms results of Cabral and Mata (2003) for Portugal and suggests that it is not survival bias that leads to shifts in FSD of surviving new firms. Sixth, in line with non-parametric evidence, we find a negative (and non-linear) relation between initial size and subsequent growth even after correcting for survival bias, which is now a standard feature in the literature (see Evans, 1987 and Hall, 1987). We also find that in the early transition, this relationship is more negative than in later transition.

The evolution of FPD is closely related to that of FSD with the following features. First, labor and total factor productivity are both growing at high rates over the entire period. Growth in labor productivity is only modestly explained by growth in capital intensity and thus a large part of labor productivity growth is ascribed to total factor productivity. Second, according to Olley and Pakes (1996) cross-sectional decomposition, we find that in the early transition more productive firms did not employ more disproportionately more workers and vice versa. However, by the end of transition period, this has changed. Third, we find that larger firms exhibit faster growth in productivity, which resulted in change of productivity rankings for firms in different size classes. While at the outset of transition, micro firms were the most productive ones, by the end of transition, large firms took the lead. Fourth, different decompositions of aggregate labor and total productivity growth show that within firm growth was just as important as reallocation, which is very similar to results for U.S. manufacturing firms (Foster, Haltiwanger and Krizan, 1998). We find that larger firms contribute more to aggregate growth. For smaller firms, between effect is particularly important, which suggests that smaller, more productive firms gained their employment share. We also find large and negative cross or covariance effect, particularly for large firms, which implies that these firms increased productivity by downsizing. Fifth, we find that less productive firms are more likely to exit. Thus, the average productivity of exiting firms is lower than that of surviving firms. Similarly, entering firms are less productive than surviving firms. In relation to

this, we find that while surviving new firms are more productive than exiting new firms, surviving firms increase their productivity over subsequent period, which suggests that learning is much more important for new firms than survival bias. Sixth, we find that a large part of aggregate labor and total factor productivity growth is generated in firms that were initially lagging behind. While this evidence is subject to survival bias, even after correcting for it, we find a negative relationship between initial productivity and subsequent growth, which also suggest that learning or catching up of large firms is of great importance in explaining growth during transition process.

The paper is organized as follows. In the second section, we describe the basic features of Slovenian economy and provide an overview of the data. The third section contains the stylized facts on the evolution of firm size distributions, while in the fourth section, we provide evidence about the evolution of capital intensity and labor and total factor productivity distributions. The last section concludes.

## 2 The data

### 2.1 Some facts on Slovenian economy

Recently, the accounting data for Slovenian manufacturing firms has been used extensively. Some of the more recent examples are Damijan et al. (2002), Hutchinson and Xavier (2003), Orazem and Vodopivec (2003) and de Loecker and Konings (2004). The main reason for this is comprehensive coverage of firms and relatively high measurement quality of variables, especially when compared to other transition countries.<sup>1</sup> Therefore, Slovenian economy does not need a lengthy introduction as it can be found in Orazem and Vodopivec (2003). For the purpose of our analysis, it is useful to summarize its main macroeconomic indicators and institutional features.

In 2003, the per capita income was around 70 percent of EU-15 average, which makes Slovenia the most advanced transition country. The population is stable, around 2 million inhabitants, which makes it a small economy. As part of enlarged EU, it is open to trade and total exports account for 2/3 of gross domestic product. Our sample is available for the period between 1994 and 2003, which is a period of stable, but gradually declining, growth and the average growth rate of GDP was 3.8 percent. The employment dynamics is U-shaped, declining until 1997 and growing until 2001 and leveling off since then. In Table 1, we show aggregate statistics for the manufacturing sector for the period between 1994 and 2003. The aggregate value added (in constant 1994 prices) has been gradually increasing at the average annual growth rate of 7 percent. The aggregate employment has declined from 220 to 204 thousand workers, a 7.5 percent decline, while the aggregate capital (in constant 1994 prices) has increased by 7 percent, the main increase being in the period between 2000 and 2003.

Until the collapse of socialism, the institutional system of Slovenia, until 1991 part of the former Yugoslavia, was characterized by social ownership, worker management of firms, substantial political interference in firm decisions on investment, employment, prices and wages. In order to meet these restrictions, government introduced a massive system of discretionary taxes and transfers. In addition, private firms were not allowed to employ more than 10 employees, which influenced the initial size distribution of firms. The distribution was bimodal, with modi of micro and large firms. The small and medium size firms were largely missing, which Petrin and Vahcic (1989) graphically described as a "black hole" in the size distribution. The main institutional change relevant for the evolution of size and productivity distribution happened in 1988, when government allowed setting up of new firms by introducing a Company Law. The law was very much ineffective and in 1993, it was amended. These institutional changes freed institutional constraints on entry of new firms, capital allocation and growth of firms. The law on privatization of state firms was passed in 1992, although privatization did not start until 1994. The main method of privatization was distribution of vouchers which could be used in firms that initiated the process of privatization. The owners of privatized firms are mainly insiders, while government still plays important role through state pension and endowment (restitution) funds. According to EBRD's transition indicators, Slovenia was a gradual and slower reformer than many less developed transition countries (EBRD, 2003). While the main progress in price and trade liberalization was achieved before 1994, labor markets are still strongly unionized and labor policies were the most restrictive of the formerly planned economies and all EU-15 countries but Portugal (Riboud et al., 2001).

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<sup>1</sup>For example, the available manufacturing data for Czech Republic contain rounded estimates of employment, while for countries such as Estonia, only a small fraction of all firms are included in the data set.

## 2.2 Description of the data set

Our empirical investigation is based on accounting data for all Slovene manufacturing firms (NACE 2-digit sectors 15-37) active in the period between 1994 and 2003, provided by the Slovenian Agency for Public Evidence (CHECK). Although the data are also available for 1992 and 1993, extensive changes in accounting standards, reporting rules and company law in 1993 make these earlier data incomparable. In addition, high inflation rates in this period makes the real data heavily distorted. Thus, by using the data from 1994 onwards, we lose insight on dynamics during the period of output decline. Nevertheless, we maintain that qualitative features of dynamics of early transition period can also be traced in our sample.

The total number of firms in our data set is 9350, although we limit our attention only to 7218 firms for which data on employment, capital and value added are available and positive. The dynamics of number of firms that comply with this condition is summarized in Table 1. The total number of active firms increased from 3288 in 1994 to 4662 in 2003, while the total number of firms that survived over the entire period is 1917. The entry of new firms was particularly active in the early years of our sample, but gradually declined to rates found in other studies. Hence, the average entry rate<sup>2</sup> was almost 12 percent, a number comparable only to values for Portugal in the early eighties (Cable and Schwalbach, 1991), but much higher than in other developed or developing countries. Cable and Schwalbach (1991) report average annual entry rates around 7 percent for UK and US, while among developing countries Morocco with 5 percent had the highest entry rates (Clerides, Lach and Tybout, 1998). Note that our entry rates are much higher than those reported by de Loecker and Konings (2004), who also report entry rates for Slovenian manufacturing. This is partly due to a surge in entry (and exit) rates in 2002 spurred by a change in accounting standards and capital ravalorization rules, which resulted in extraordinarily large simultaneous exit and entry rates. In addition, we also have slightly more restrictive definition of entry and exit.<sup>3</sup> The average exit rates have also started at lower values, around 5 percent and increased to 9 percent and leveled off around 7 percent. The average exit rate is 8.4 percent, a number comparable to Norway (8.7 percent) and lower than in Portugal (9.5 percent) in the eighties (Cable and Schwalbach, 1991), but much higher than those in developing countries. Clerides, Lach and Tybout (1998) report exit rates for Morocco, Mexico and Colombia that are below 4 percent.

**Table 1: Dynamics and aggregate characteristics of manufacturing firms**

Year	Number of firms				All active firms		
	All	Entry	Exit	Survivors	Employment	Capital	Value added
1994	3288	-	-	-	220,610	791	401
1995	4029	911 (0.22)	170 (0.05)	3118	235,813	814	427
1996	4246	554 (0.13)	337 (0.08)	3692	222,610	776	458
1997	4356	474 (0.10)	364 (0.08)	3882	214,317	805	521
1998	4406	410 (0.09)	360 (0.09)	3996	211,793	799	525
1999	4431	386 (0.09)	361 (0.08)	4045	205,320	800	574
2000	4446	337 (0.08)	322 (0.07)	4109	200,202	798	603
2001	4479	343 (0.08)	310 (0.07)	4136	201,898	815	635
2002	4616	788 (0.17)	650 (0.15)	3828	209,126	817	688
2003	4662	456 (0.10)	410 (0.09)	4206	204,212	837	729

Source: Author's calculations.

Notes: i) The numbers refer to the end of each year.

ii) Capital and value added are given in constant 1994 billion SIT.

iii) The entry and exit rates are given in parentheses. The entry rates are calculated relative to the number of active firms in the year of entry, while the exit rates are calculated relative to the number of active firms in the year prior to exit.

<sup>2</sup>The entry rate is defined as the number of entrants divided by the total number of active (entrants and continuing) firms in a given year; the exit rate is defined as the number of firms exiting the market in a given year divided by the number of active firms in the previous year.

<sup>3</sup>The key difference in results is in definition of an active firm, for which we require positive employment, value added and capital, while they only require positive employment. We do so in order to have consistent sample also for productivity analysis, which cannot be done for firms with negative value added and capital. Different definitions generate differences primarily for firms that have negative value added in one year and are thus counted as permanent exit and entry. Although there is a positive bias in entry and exit rates (these are 1 to 2 percentage points higher using our definition of an active firm), qualitative features of entry dynamics are preserved.

All nominal variables (sales, value added, material costs and capital) that are used in analysis are deflated. Sales, value added and material costs are deflated using two-digit NACE producer price indices, while capital is deflated using consumer price index. The difference is a consequence of mandatory revaluation of assets using consumer price index until 2002.<sup>4</sup> The calculation of the capital series in constant prices for 2002 and 2003 requires only deflation for the old capital to the base year, disregarding inflation in 2002 and 2003, while for investments we deflate values for the whole cumulative inflation. Since we use price deflators that are at best at two-digit NACE level and not firm specific, within industry price differences are embodied in output and productivity measures. Prices can reflect idiosyncratic demand shifts and variation in market power rather than quality or productivity differences between firms. As a consequence, the estimates of productivity may be misleading.

### 3 The evolution of firm size distributions (FSD)

In this section, we analyze the dynamics of firm size distributions by combining three different methods: graphical method based on stochastic kernels, transition matrices and standard parametric estimation techniques. First, we explore the evolution of shape of size distribution. Second, we look at transition matrices which convey information on surviving firms. Third, we explore relevance of entry and exit and fourth, we look at relationships using parametric estimation methods.

#### 3.1 The shape of FSD

In this section, we identify the first set of stylized facts that stems from the evolution of firm size distributions (FSD). We first discuss the transformation of shape of FSD during the transition process. In the previous section, we noted that in ex-Yugoslavia, but also in other socialist countries, effective constraints on capital accumulation and employment growth were in place preventing small firms to either enter or grow. Petrin and Vahcic (1989) and Newbury and Kattuman (1992) document this fact for majority of transition countries, which resulted in a bimodal FSD at the end of socialist period. In Figure 1, we plot FSD for employment as a measure of size for three different time periods using the method of stochastic kernels.<sup>5</sup> Even though transition process started already in 1988, the FSD for 1994 is still bimodal, although the mass of small firms is already large (see Figure 1 below). Over time, the shape of size distribution has changed and by the end of 2003, the only remnant of bimodality is greater mass of larger firms. Such evolution can also be traced using measures of size, such as capital, sales or value added. In the interest of brevity, the size distribution for log of capital is shown in Figure A1 in Appendix.

The FSD were often approximated by parametric distributions, in particular by lognormal, but also Yule or Pareto distributions (e.g. Ijiri and Simon, 1964). Cabral and Mata (2003), however, show that log-normality may have been a result of rather incomplete samples and FSD for all firms are more skewed to the right. They also suggest that a generalized gamma distribution may be a better parametric description of FSD.<sup>6</sup> Visual inspection indicates that FSD for Slovenian manufacturing cannot be approximated by log-normal distribution. This is confirmed by Jarque-Bera (JB) and Kolmogorov-Smirnov (KS) tests of normality given in Table 2. There we also show the measures of dispersion (standard deviation, denoted SD) asymmetry of distribution (skewness) and thickness of tails of distribution (kurtosis). Note that dispersion has been declining, while measures of skewness and kurtosis exhibit less clear trend. The reference values of skewness and kurtosis for the standard normal distribution are 0 and 3, respectively. The reason for failure of normality test is asymmetry (skewness to the right) of FSD, which is implied by the values of skewness much above the reference values. We have also tried to fit the generalized gamma distribution and provide parametric characterization of dynamics of FSD. However, the estimated parameters for generalized gamma distribution are not close to those obtained by Cabral and Mata (2003) and are thus omitted from the text.

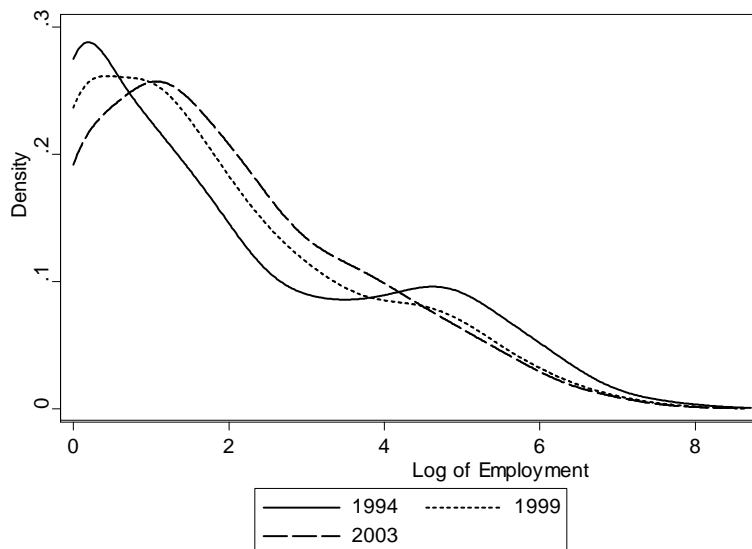
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<sup>4</sup>De Loecker and Konings (2004) use producer price indices also for capital. This, however, introduces bias in the real values of capital.

<sup>5</sup>The method of stochastic kernels is convenient when total number of observations is not large. This nonparametric method for plotting size distributions generates smooth graphs. The method evaluates each point of the estimated density as a weighted sum of the data frequencies in the neighborhood of the point being estimated. In our case the weighting is a normal (gaussian) density. The size of bandwidth around the point of evaluation is 0.45, which is used throughout this paper. The larger is the bandwidth, the smoother is the estimated density. However, for our data, the qualitative features of the data are largely independent of selected bandwidth.

<sup>6</sup>The generalized gamma distribution contains three parameters instead of two, where the first two are mean and standard deviation and the third is a shape parameter. Note that this distribution nests normal distribution. Cabral and Mata (2003) track surviving new firms over time and find that with age shape appears more and more like lognormal.

**Figure 1: Evolution of firm size distribution**



Source: Author's calculations.

Note: The data are smoothed using gaussian kernel and bandwidth 0.45.

**Table 2: Summary statistics and normality tests for log of employment**

Year	SD	Skewness	Kurtosis	JB (p)	KS (p)
1994	1.98	0.78	2.49	371.9 (0.00)	0.15 (0.00)
1999	1.75	0.87	2.96	562.3 (0.00)	0.14 (0.00)
2003	1.67	0.79	2.99	492.0 (0.00)	0.11 (0.00)

Source: Author's calculations.

Notes: i) JB denotes Jarque and Bera parametric test of normality, while KS denotes

ii) p denotes the level of statistical significance.

iii) SD denotes standard deviation.

iv) The measures of skewness and kurtosis are standard third and fourth central moments.

While nonparametric plots of size distributions depict change in size distributions, they do not convey much about the underlying shifts. For that purpose, Markov chain models are convenient. They have been used fruitfully ever since Adelman (1958) analyzed firm size distribution in the U.S. steel industry. Some recent examples of use of Markov chain models are Konings (1995) for UK, Biesebroeck (2002) for sub-Saharan African countries and Schivardi and Torrini (2003) for Italy.

Before we can use these models, we need to group firms into size classes. Several different classification are used in the literature, for example, Konings (1995) grouped firms in classes that were determined relative to the average size in a given time period. However, this approach eliminates the average shift in size and mainly focuses on shifts within size distributions. Hence, we use a classification that specifies size classes in terms of absolute number of employees. In particular, we chose the standard legal classification as it allows us to make international comparisons. The legal classification groups firms into four size classes: micro (1-9 employees), small (10-49), medium (50-249) and large firms (250 and more).

Before we turn to analysis of transitions of firms, we show in Table 3 the shifts in FSD. There we show percentage shares of firms in a given class relative to total for number of firms and employees (in parentheses). In line with the FSD shift depicted in Figure 1, the structure of firms in 2003 is quite different from that in 1994. The shares of micro, medium and large firms have decreased, the share of small firms increased from 15 to 22 percent. While medium and large firms were gradually losing their importance, micro firms initially gained, but lost in subsequent periods.

The shifts of employment shares are equally revealing. Micro and small firms gained shares from 2.5 and 5.2 percent to 4.8 and 11.5 percent, respectively. Large firms, on the other hand, lost almost



ten percentage points, falling from a 65 percent share to 54 percent. Medium size firms have gained couple percentage points, although the dynamics is not monotone. Since there is a number of factors (e.g. industrial structure, regulatory framework, taxation, size of a country, etc.) that determine the FSD in a given country, we can gain only little by making inter-country comparisons. Nevertheless, the fact that Slovenian manufacturing structure is far from that for EU-15 countries or Estonia, which is of similar size as Slovenia is revealing of limitations to growth micro and small firms. Micro and small firms are still under-represented in Slovenia, while the only country with fairly similar size structure is another transition country - Romania.

**Table 3: Firm size distribution in time and average firm size**

Year	Micro	Small	Medium	Large	Average size
1994	63.5 (2.5)	14.7 (5.2)	15.0 (27.1)	6.7 (65.1)	67.1
1997	66.3 (3.8)	17.1 (7.6)	12.1 (28.9)	4.5 (59.7)	49.2
2000	65.1 (4.3)	19.2 (9.4)	11.7 (30.4)	4.0 (55.9)	45.0
2003	62.9 (4.8)	21.8 (11.5)	11.5 (29.5)	3.8 (54.2)	43.8
EU-15	- (13.1)	- (21.6)	- (23.4)	- (41.9)	-
Estonia	- (7.9)	- (24.0)	- (34.6)	- (33.5)	-
Romania	- (4.3)	- (11.0)	- (23.1)	- (61.6)	-

Source: Author's calculations and Eurostat (2004).

Notes: i) The numbers in columns 2 to 5 denote percentage shares of firms in respective size classes.

ii) In parentheses, there are shares of these firms in total employment.

iii) Average size of firms is calculated as unweighted average of employment.

iv) The data for EU, Romania and Estonia show the structure of employment in 2001.

In the Appendix, Table A1, we show FSD at a finer grid of size classes, closely following those used in Schivardi and Torrini (2003). We can see that the decline in micro firms was largely due to decline of share of one-employee firms. While size classes that employ less than 50 employees have all increased their importance, firms employing more than 50 employees have all reduced their share in employment. Similar conclusions can be drawn for employment shares, although the margin stands at 100 employees. Note that firms that employ more than 1000 workers suffered most in terms of employment.

### 3.2 The evolution of FSD analyzed with transition matrices

Now we turn to the estimation of transition matrices, which allow us to gain insights into underlying shifts of FSD. The methodology of transition matrices is described in Appendix B. The shifts in FSD may be a result of reallocation of labor between firms of different productivity levels or due to growth of productivity within existing firms. Technology is the key factor emphasized in virtually all theoretical models of industrial dynamics (see Jovanovic, 1982; Ericson and Pakes 1995, Rossi-Hansberg and Wright, 2004 etc.) There are, however, numerous other factors at work, such as financial constraints (Cooley and Quadrini, 2001; Cabral and Mata, 2003), regulation or even business cycles. Since the transition process is itself itself cyclical and consists of many simultaneous institutional changes, we should expect some variation in transition matrices.

The transition probabilities depend on time span over which they are calculated. The shorter is the difference between periods over which we calculate them, the greater is persistence of size and the lower are the exit rates. Moreover, the transition probabilities over a shorter period of time are more prone to idiosyncratic phenomena. In order to avoid this, we shall follow the approach in the literature (see for example Schivardi and Torrini, 2003) and average transition probabilities. The additional advantage of this approach is that we avoid the problem of selection of initial year. Following Anderson and Goodman (1957) we also calculate likelihood ratio tests for time invariance (homogeneity) of transition matrices. If transition matrices are time invariant, calculation of ergodic size distribution is justified.<sup>7</sup>

In Table 4, we provide the likelihood ratio tests of time homogeneity. We provide two sets of statistics for deviations of individual transition matrices from three and nine year averages. Surprisingly, for most of annual transition matrices, we cannot reject the hypothesis of homogeneity. However, transition matrices

<sup>7</sup>In principle, we can calculate the ergodic distribution for any regular transition matrix (one with all elements positive). However, whether this makes sense depends on time homogeneity of annual transition matrices.

for 1994/95 and 2001/02 deviate substantially. The first year transition matrix is different due to considerable entry and low exit rates, while the 2001/02 transition matrix is related to institutional changes that we discussed above. Since deviations from three year averages are smaller and there are some time specific features of transition matrices, we show the average transition matrices for three year periods.

**Table 4: Tests of time homogeneity for transition matrices**

Year	3 year	9 year
1994/95	55.7*	84.2*
1995/96	21.1	37.3*
1996/97	16.4	11.7
1997/98	13.8	18.5
1998/99	17.7	21.6
1999/00	22.8	38.1*
2000/01	77.6*	30.4
2001/02	121.7*	282.9*
2002/03	23.5	28.0

Source: Author's calculations.

Notes: The value of theoretical  $\chi^2_{20}$  for  $\alpha = 0.05$  is 31.41.

Table 5 shows these average annual transition matrices over the following periods: 1994-1997, 1997-2000 and 2000-2003. These matrices reveal several interesting features about the process of transition. First, note that the diagonal elements of transition matrices, which correspond to probabilities that firms remain in the same size class also after a year, are above 85 percent, which is fairly large. High persistence was observed also for UK, although size class definitions were different to ours and thus incomparable (see Konings, 1995). Although we observe differences in persistence rates for different size classes, they are largely due to selected width of size classes. Intertemporal comparison, however, reveals that persistence rates increased for larger firms and decreased for micro firms, while the direction of change is not clear for the remaining two classes. These changes of persistence rates are by definition reflected also in off-diagonal terms. A particular feature of transition process was relatively low productivity of large firms, which on one hand implied an opportunity for entry and growth of small firms and downsizing of large firms. Table 1 we saw high entry and low exit rates in the early years of our sample. Table 5 now shows that in the early transition exit rates were particularly low for micro firms (only 6 percent in 1995) and later increased, while probability that a micro firm grew into a small firm declined over time. On the other hand, large firms were more likely to shrink in the early transition period than in the subsequent periods. This evidence is complementary to what we show below for productivity. Namely, labor and total factor productivity of large firms were lagging behind that of smaller firms, but by the end of our sample, ended up being the most productive. Thus, there is less scope for downsizing of these firms.

A feature that is regularly observed and has been found in virtually all studies of exit (see Dunne, Samuelson and Roberts, 1988) is a negative relationship between exit rates and size. These are also confirmed in regression analysis of survival probabilities. At last, comparison of size structure of entering firms with size structure of surviving firms given in Table 3, reveals that entering firms are much smaller than incumbents, having much smaller shares of medium and large firms in FSD. Again, we do not emphasize differences in transition probabilities for the last period as they are subject to turnover that is related to institutional changes that took place in 2002.

**Table 5: Three year average transition matrices**

1994-1997					
$t \setminus t - 1$	Micro	Small	Medium	Large	Entry
Micro	88.2	4.8	0.3	0.1	82.8
Small	3.5	84.9	3.9	0.3	10.8
Medium	0.0	3.5	88.3	7.0	5.2
Large	0.0	0.1	1.6	88.8	1.2
Exit	8.2	6.7	5.9	3.7	-
1997-2000					
$t \setminus t - 1$	Micro	Small	Medium	Large	Entry
Micro	87.9	4.7	0.1	0.0	83.7
Small	2.9	86.9	3.1	0.0	10.4
Medium	0.0	3.0	89.6	5.6	4.9
Large	0.0	0.0	1.5	90.2	1.0
Exit	9.2	5.3	5.8	4.2	-
2000-2003					
$t \setminus t - 1$	Micro	Small	Medium	Large	Entry
Micro	84.8	6.3	0.3	0.2	76.9
Small	2.6	85.0	4.5	0.0	15.3
Medium	0.0	2.2	88.9	5.0	6.3
Large	0.0	0.0	1.2	91.5	1.5
Exit	12.6	6.5	5.2	3.3	-

Source: Author's calculations.

Notes: Transition probabilities are given in percent.

Despite rejection of time invariance of annual transition matrices, the general message conveyed by a long-term (9 year) transition matrix, given in Table 6, is more or less the same. Naturally, the persistence rates are much lower for longer time span. Exit rates are also much higher, where these decrease with size, although there is nonlinearity as micro firms have lower exit rates than small firms. The key flows in shift of underlying size distribution are related to growth of micro firms into small firms and a downward shift of medium size and large firms. Further, the entering firms distribution is much more concentrated on the lower end and thus helps to fill the initial gap in the FSD. Transition matrix also reveals that micro firms have negligible probability to grow into large firm in a period of 9 years, while only modest share of small firms actually made it. The literature on financing constraints often emphasizes these as key limitations to growth of small firms (Cabral and Mata, 2003). Konings and Xavier (2003) compare financing constraints for Slovenian and Belgium firms and find that these are much more important in Slovenia.

In Table 6, we also calculate the stationary or ergodic FSD. Clearly, this is not yet justified as there were important shifts in annual transition matrices and entry and exit rates are not the same. Nevertheless, the ergodic distribution made on the basis of a nine year transition matrix gives a reasonable prediction. The share of small firms should increase even further, while micro and large firms should decrease. This is in line with the observed trend of filling the gap in the size distribution.

**Table 6: Transition matrix 1994-2003**

$t \setminus t - 9$	Micro	Small	Medium	Large	Entry	Ergodic
Micro	45.9	9.33	1.22	0.90	70.9	60.9
Small	10.9	35.8	9.18	0.90	19.6	25.0
Medium	0.72	7.78	46.3	18.1	7.87	11.5
Large	0.00	0.67	4.49	48.4	1.60	2.65
Exit	42.6	46.4	38.8	31.7	0	-

Source: Author's calculations.

The transition probabilities have a limitation that they do not convey the relative importance of flows for firms in different size classes. For example, while transition probabilities for shifts of firms between micro and small in both directions are fairly similar, this does not imply that these flows cancel out. The

difference is initial shares of different size classes to which transition probabilities apply. In order to correct for this, we calculate the probabilities relative to total number of firms in 2003 and show them in Table 7 for the period 1994-2003. This table further shows that shifts in size distribution were to a large extent related to growth of micro firms into small firms, entry process and also decline of medium and large firms.

**Table 7: Shifts in number of firms 1994-2003**

$t \setminus t - 9$	Micro	Small	Medium	Large	Entry	Total
Micro	958 (20.5)	49 (1.1)	6 (0.1)	2 (0.0)	1919 (41.2)	2980 (62.9)
Small	227 (4.9)	177 (3.8)	45 (1.0)	2 (0.0)	564 (12.1)	976 (21.8)
Medium	15 (0.3)	36 (0.8)	228 (4.9)	40 (0.9)	218 (4.7)	532 (11.5)
Large	0 (0.0)	2 (0.0)	23 (0.5)	107 (2.3)	44 (0.9)	176 (3.8)
Exit	889 (19.1)	220 (4.7)	192 (4.1)	70 (1.5)	-	1370 (29.4)
Total	2089 (44.8)	484 (10.4)	492 (10.6)	221 (4.7)	2745 (58.9)	-

Source: Author's calculations.

Notes: Percentages in parentheses are calculated relative to end 2003 number of firms, that is 4664.

In order to complement the evidence given so far, we also look at labor turnover. Table 8 contains employment shifts over entire transition period relative to aggregate employment change for all active firms in manufacturing. In Table 1, we have summarized aggregate employment and the change over the course of 9 years amounted to 16 thousand workers. This number is a denominator for labor flows in Table 8.

The largest flows of labor are related to declining share of large firms, which was almost 2.6 times the aggregate employment decline. This consists of both decline in employment of surviving firms and net entry. While medium size firms also experienced net decline, some medium size firms actually grew into large firms. Aggregate growth of employment in micro and small firms was positive, both due to growth of surviving firms and net entry. The actual transition dynamics is in accord with predicted transition dynamics, although the net aggregate effect was still negative. This, however, may also be a result of generous early retirement schemes, unemployment benefits and returns to participation in informal economy (see Polanec, 2004).

**Table 8: Relative labor flows, 1994-2003**

$t \setminus t - 9$	Micro	Small	Medium	Large	Entry
Micro	0.06	-0.03	-0.04	-0.05	0.38
Small	0.19	0.05	-0.10	-0.03	0.78
Medium	0.07	0.12	-0.15	-0.48	1.38
Large	0.00	0.38	0.45	-1.16	1.39
Exit	-0.14	-0.34	-1.42	-2.29	-

Source: Author's calculations.

Notes: The shares are calculated relative to aggregate labor flows.

### 3.3 Entry and exit

In previous analysis, we have seen that net entry process played important role in transition. We have learned that entry rates were particularly high (low) in the early transition years and leveled off in the later transition. Table 9 compares the average size of surviving, entering and exiting firms in three different years: 1995, 1998 and 2001. The average employment of surviving firms is much higher than the average employment of both entering and exiting firms in all these years. We further note that the average size of all of these groups of firms have been decreasing. This is again consistent with early exit of larger firms, which has decreased in the later transition. The decline in average size is, however, modest and dependent on the choice of year.<sup>8</sup>

<sup>8</sup>In 2002, the average entrants size is again 23 employees.

**Table 9: Size distribution of surviving and entering firms**

Year	Type	Micro	Small	Medium	Large	Average employment
1995	surviving	64.7	15.9	13.6	5.7	60.7
1995	entering	80.1	12.1	6.5	1.3	22.0
1995	exiting	66.8	16.0	14.5	2.7	34.1
1998	surviving	64.0	18.4	13.0	4.7	50.5
1998	entering	82.7	11.7	4.2	1.5	20.5
1998	exiting	78.1	12.7	7.2	1.9	21.4
2001	surviving	63.0	20.5	12.4	4.1	50.3
2001	entering	84.6	9.0	4.7	1.8	16.9
2001	exiting	81.3	13.1	4.8	0.9	14.5

Source: Author's calculations.

A complete characterization of evolution of FSD requires also investigation of survival patterns of entering firms. It is now standard evidence that hazard rates are more or less monotonically declining with age. For example, Baldwin (1995) has shown for Canadian manufacturing firms that first year exit rate is 10 percent and irregularly declines with age, while Mata et al. (1995) report hazard rates for Portuguese manufacturing firms, which monotonically decline. These are 25, 16 and 13 percent hazard rates in the first, second and third year after entry. The hazard rates in relation to age of firms for cohorts entering between 1995 and 1999 are shown in Table 10. Note first that these rates are somewhere in between those reported for Canada and Portugal and more or less regularly decline with age. A transition specific pattern can also be traced in hazard rates for different cohorts. We already know that entry rates were much higher in the early transition, which is an indication of opportunity for entry of new firms that would provide new products. Table 10 shows that exit rate in the first year of existence, firms in 1995 cohort were much less likely to exit. While for later cohorts, first year hazard rates are not monotonically increasing, hazard rates after two years confirm this pattern and give indication of gradual market saturation. Consistent with this hypothesis are also declining employment and output shares of younger cohorts, which are not shown here.

**Table 10: Hazard rates and age of entering firms**

Year \ Age	1	2	3	4	5	6
1995	10.2	7.3	5.7	5.5	3.9	5.1
1996	15.3	6.4	6.2	4.6	4.6	-
1997	15.0	7.9	7.3	7.8	-	-
1998	19.0	6.0	4.8	-	-	-
1999	14.2	8.8	-	-	-	-

Source: Author's own calculations.

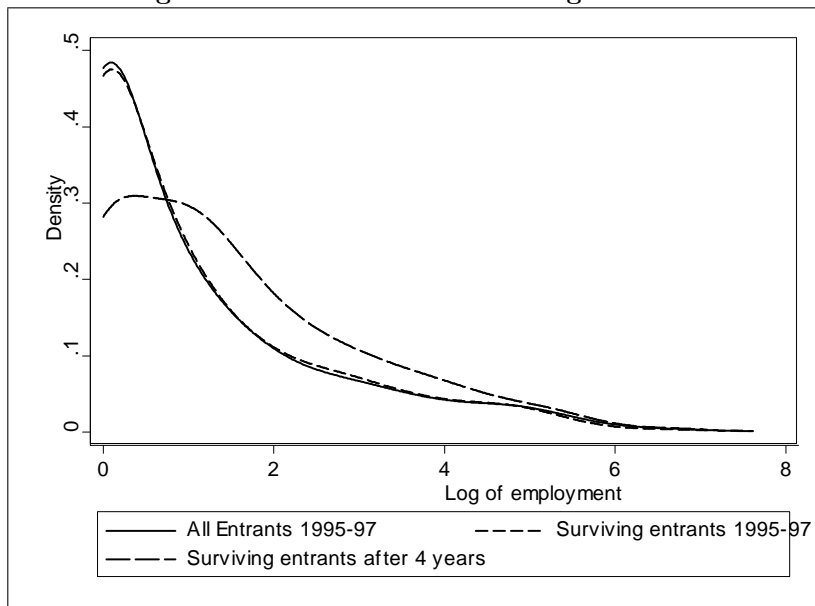
Notes: Since 2002 exit rates are high due to institutional changes and are incomparable, we do not report these.

Dunne, Roberts and Samuelson (1988) and Cabral and Mata (2003) have also tracked FSD for surviving entrants and found that average size of these firms increases with age. Such evolution could be either a result of growth of surviving firms or selection bias. Dunne et al. (1989a) found correlation between initial size of entrants and size after several periods, while Cabral and Mata (2003) have, however, compared initial FSD for entrants that survived and those that exit and found negligible size advantage for surviving entrants. The idea of dependence of size in given period to size at entry features in Jovanovic's (1982) model of industrial dynamics, where firms' managers do not know their productivity and learn about it using Bayesian updating techniques. A consequence of this assumption is serial dependence of size with all previous sizes (which reflect technology). Cabral and Mata (2003) conclude upon their evidence that selection upon initial size is not determining the evolution of FSD. Instead they argue in favor of liquidity constraints.

In Figure 2, we show evolution of FSD for 1995-97 cohorts of entrants, which exhibits a clear shift to the right. We provide additional details for the 1995 cohort of entrants in Table 11, which shows that share of micro firms decreased, while shares of larger firms increased. In addition, size distribution exhibits lower dispersion and skewness. All of these features are also documented in Cabral and Mata (2003). Turning

back to Figure 2, we confirm the finding by Cabral and Mata (2003) of negligible difference in initial size between all and only surviving entrants. Again, this can be interpreted against Jovanovic's (1982) model of industry dynamics and the key assumption of passive learning of managers about their firms' productivity levels. In the section exploring evolution of labor productivity distribution, we find that also productivity levels of entrants that survive are not much different from all other firms. Furthermore, we also find that FSD for surviving and exiting firms, active in 1994 were not much different in 1994 (see Figure 3).

**Figure 2: Size distribution and age of firms**



Source: Author's calculations.

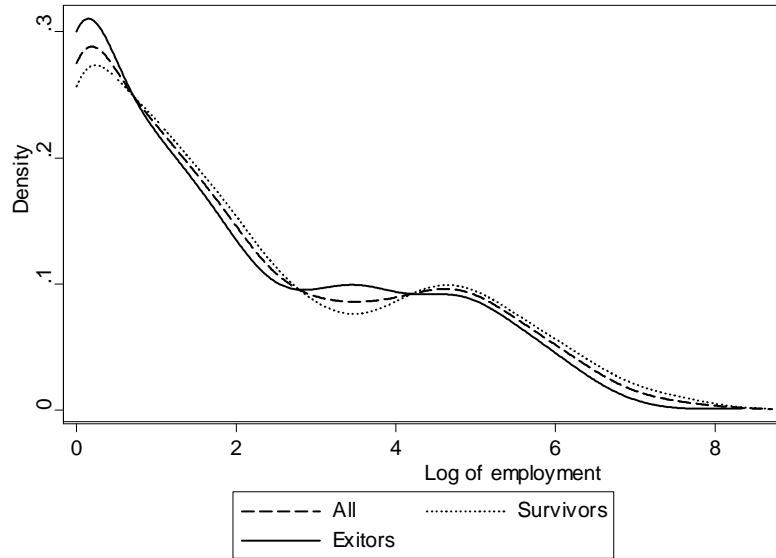
Notes: 1995 denotes firm size distribution at birth, 1999 and 2003 denote distributions of surviving firms at age of four and eight, respectively.

**Table 11: Size distribution and age for firms entering in 1995**

Year	Micro	Small	Medium	Large	Firms	Mean	St. Dev.	Skewness	Kurtosis
Entry	81.6	10.8	6.4	1.3	911	1.13	1.51	1.52	4.56
4	75.0	16.1	7.5	1.3	676	1.56	1.49	1.04	3.64
8	71.1	19.8	6.9	2.2	506	1.76	1.47	0.91	3.50

Source: Author's calculations.

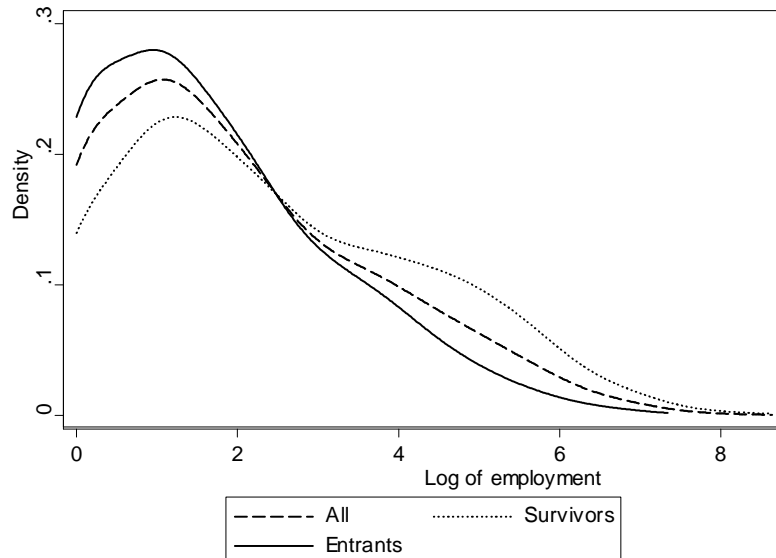
**Figure 3: Size distributions of surviving and exiting firms in 1994**



Source: Author's calculations.

At the end of this section, we conclude with evidence on relative contributions of different types of firms. While Figure 4 suggests that FSD of surviving and exiting firms were not much different, bimodality of FSD must be either a result of evolution of surviving firms and entry of new firms. Figure 4 compares FSD in 2003 for surviving and entering firms between 1994 and 2003. While we have already seen that entrants are smaller on average, we can also see that surviving firms have greater concentration of large firms than entrants. Thus disappearance of bimodality is partly caused by entry of new firms.

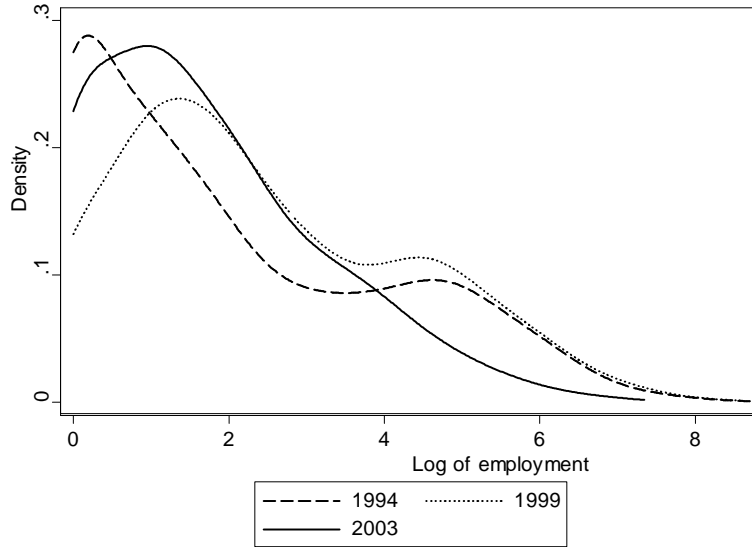
**Figure 4: Size distributions of surviving and entering firms in 2003**



Source: Author's calculations.

Nevertheless, the evolution of FSD for surviving firms only, given in Figure 5, shows that bimodality has also disappeared for surviving firms. Combined with evidence on exiting firms, this is primarily due to evolution of FSD for surviving firms and not by selection bias.

Figure 5: Size distributions for surviving firms



Source: Author's calculations.

### 3.4 Parametric analysis

Economists have often investigated a relationship between growth of firms and initial size. The early investigations concluded that there is no relationship between size and growth, which is known as a law of proportionate effect or Gibrat's law (see Gibrat, 1931; Ijiri and Simon, 1964; Mansfield, 1962). However, more recent studies have concluded that even after correction for survival bias there is a negative relationship between size and growth (see Evans, 1987; Hall, 1987; Dunne, Roberts and Samuelson; 1989). This finding is consistent with observation of Cabral and Mata (2003) that FSD is not quite log-normal, which would have been the case if growth of firms was indeed independent of initial size. This literature has also observed a negative relationship between variance of growth rates and initial size. Thus, while growth rates of smaller firms are larger, they are also more variable.

In a very recent study, Konings and Xavier (2003) studied the relationship between firm size and firm growth for a sample of Slovenian manufacturing firms active in the period between 1994 and 1998 and also found a negative relation. In this section, we investigate this relationship in line with approach outlined by Evans (1987). A modified equation that postulates the relationship between growth and size is

$$S_{it+\tau} = G(S_{it}, a_{it}, y_{it})^\tau S_{it} e_{it}, \quad (1)$$

where  $S_{it}$  and  $a_{it}$  denote initial firm size and age, and  $y_{it}$  denotes labor productivity defined as a ratio between value added and employment. Taking logarithm of (1) and dividing through by  $\tau$ , we obtain

$$\frac{\ln S_{it+\tau} - \ln S_{it}}{\tau} = \ln G(S_{it}, a_{it}, y_{it}) + \varepsilon_{it},$$

where  $\frac{\ln S_{it+\tau} - \ln S_{it}}{\tau}$  denotes the average growth rate of firm  $i$  between  $t$  and  $t+\tau$ . First order approximation of  $\ln G(S_{it}, \hat{A}_{it})$  is  $\alpha_0 + \alpha_1 \ln S_{it} + \alpha_2 \ln a_{it} + \alpha_3 \ln y_{it}$ , and estimation equation is

$$\frac{\ln S_{it+\tau} - \ln S_{it}}{\tau} = \alpha_0 + \alpha_1 \ln S_{it} + \alpha_2 \ln a_{it} + \alpha_3 \ln y_{it} + \varepsilon_t. \quad (2)$$

Since we do not observe growth rates for firms that decided to exit, the average growth rate is subject to sample selection bias. Dunne et. al. (1989) showed that exit rates are not independent of the right-hand side variables in (2) and as a consequence the estimates obtained by OLS are biased. Table 5 confirms this for size of firms as large firms are less likely to exit, although the relationship between probability of exit



and size was non-linear. As the relationship between size and exit is negative, we expect to see a negative bias in the relationship between size and its subsequent growth. That is, we may conclude that small firms grow faster than large firms not only due to actual negative relationship, but also due to self-selection bias. Nevertheless, Konings and Xavier (2003) find no selection bias for the period from 1994-1998.

In order to eliminate potential bias in our estimates, we jointly estimate the equation for growth of firms (2) and survival equation (sample selection equation) using partial maximum likelihood model<sup>9</sup>, as suggested by Heckman (1979). This procedure is more efficient than two stage least squares under the assumption of joint normality of errors  $\varepsilon_t$  and  $\xi_t$  in the selection equation

$$\Pr(\text{Survival} = 1) = \beta_0 + \beta_1 \ln S_{it} + \beta_2 \ln a_{it} + \ln y_{it} + \xi_t. \quad (3)$$

We further need to assume that error terms have zero mean and variances 1 and  $\sigma$ , respectively. The selection bias is only relevant in estimation of (2) when there is correlation between error terms, which we denote by  $\rho$ . Therefore the key test of presence of selection bias is in  $\rho$  being different from 0.

Table 12 provides estimates of growth equations. Clearly, assumption of homoskedasticity is not justified due to negative relationship between variance of growth rates and initial size (see Dunne et al., 1989). Hence for inference we use heteroskedasticity-robust (Huber-White) standard errors. In addition, we also allow for heterogeneity of growth rates and survival probability in different sectors and include sectoral dummies for NACE 2 digit industries in both estimation equations.

**Table 12: Relationship between growth, size and productivity**

Equation	Period					
	1994-1997		1997-2000		2000-2003	
	(1)	(2)	(3)	(4)	(5)	(6)
Growth						
$\ln S_0$	-0.04 (-21.0)*	-0.09 (-7.5)*	-0.02 (-13.3)*	-0.10 (-9.8)*	-0.02 (-9.8)*	-0.08 (-8.6)*
$\ln^2 S_0$	-	0.01 (2.8)*	-	0.03 (7.3)*	-	0.02 (5.8)*
$\ln^3 S_0$	-	$-10^{-3}$ (-1.5)	-	$-2 \cdot 10^{-2}$ (-6.4)*	-	$-2 \cdot 10^{-2}$ (-4.5)*
$\ln(\frac{y}{l})_0$	0.07 (10.6)*	0.08 (10.4)*	0.08 (9.6)*	0.06 (10.1)*	0.08 (10.6)*	0.07 (9.5)*
<i>Cons</i>	-0.38 (-6.8)*	-0.37 (-6.0)*	-0.52 (-7.6)*	-0.36 (-7.4)*	-0.53 (-9.1)*	-0.40 (-7.3)*
Survival						
$\ln S_0$	-0.01 (-0.6)	0.14 (1.3)	0.05 (3.3)*	0.51 (6.5)*	0.15 (10.0)*	0.57 (7.5)*
$\ln^2 S_0$	-	-0.08 (-1.7)	-	-0.19 (-5.6)*	-	-0.17 (-4.8)*
$\ln^3 S_0$	-	0.01 (1.8)	-	0.02 (5.0)*	-	0.03 (4.0)*
$\ln(\frac{y}{l})_0$	0.31 (8.8)*	0.31 (8.7)*	0.36 (10.5)*	0.35 (10.6)*	0.39 (12.4)*	0.35 (11.4)*
<i>Cons</i>	-1.0 (3.6)*	-1.0 (-3.6)*	-1.8 (-6.9)*	-1.8 (-7.3)*	-2.7 (-11.0)*	-2.5 (-10.6)*
$\rho$ (s.e.)	0.22 (0.2)	0.24 (0.20)	0.48 (0.13)	-0.04 (0.14)	0.32 (0.06)	0.21 (0.05)
$\chi^2(1)$	1.66 (0.2)	1.3 (0.25)	9.3 (0.00)*	0.07 (0.80)	26.9 (0.00)*	15.6 (0.00)*
Log L	-917.96	-897.60	-638.25	-596.38	-791.67	-738.05
N	3288	3288	4320	4320	4428	4428

Source: Author's calculations.

Notes: i) Dummies for 2 digit NACE sectors included in both equations.

Asterisk denotes 5 percent significance level.

The standard errors of estimates are heteroskedasticity robust, based on Huber-White estimator of variance.

In columns (1), (3) and (5) of Table 12, we show the estimates of equations (2) and (3) for three subperiods. We find statistically significant negative relationship between size and subsequent growth for all subperiods. The coefficient for initial size is twice as large (in absolute terms) for the early transition period, an indication of larger growth differential between small and large firms. This is in line with many theoretical contexts, where less competition implies faster growth rates for relatively small firms. In line with our expectations, the results also suggest that initially more productive firms grew faster than less productive. In columns (2), (4) and (6), we have included higher order terms for initial size and confirmed

<sup>9</sup>Note that the reason why we cannot perform full conditional maximum likelihood model is that we can observe the average growth of firms,  $\frac{\ln S_{it+\tau} - \ln S_{it}}{\tau}$ , only for firms that survive. Thus, while we can use full the full density of *Survival* given conditioning variables, we can only use the density for average growth when *Survival* = 1. This approach has an advantage over that used by Dunne, Roberts and Samuelson (1989) as it avoids arbitrary assumption of growth -1 for firms that exit in calculation of average response.

results by others. There is a nonlinear relationship between growth and size, although always monotone. The results for labor productivity are robust to inclusion of these higher order terms.

The results in the lower part of columns (1), (3) and (5) confirm the importance of initial size as a determinant of survival. For the periods 1997-2000 and 2000-2003, we find that larger firms are more likely to survive. On the other hand, for the early transition process, we find a negative, but statistically significant sign. The  $\chi^2$  test for hypothesis of no survivor bias,  $\rho = 0$ , is also rejected for this early period, which suggests that probability of exit for large firms was just as high as for small firms. This finding, however, contrasts that of Tables 5 and 6 above, where we have shown that a negative relationship can be found for all subperiods. Nevertheless, we have found that smaller firms are increasingly likely to exit over time and in the early transition these rates were lower and much closer to those for larger firms. The solution to these puzzling results may be in non-linear relationship between probability of survival and size. Therefore, we show results with higher order terms in columns (2), (4) and (6). Note that these terms are highly statistically significant for the later transition periods. Again, we find that none of right-hand side variables are significant for the early period. Nevertheless, plotting the third order polynomial for this early period shows that there is indeed weak relationship between survival and size for employment below 150 workers, while above that the relationship is strongly positive. This finding is more or less consistent with results stemming from transition matrices in Table 5. In all estimated survival equations, we also include initial labor productivity. We find that more productive firms are more likely to survive, which is across all time periods.

Note that since we do not have information on age of firms that have entered prior to 1994, we did include age in the estimation equations so far. Hence, we estimate equations (2) and (3) for new firms only for the period 2000-2003. Table 13 shows that older firms are growing in size with lower rates, while their survival is more likely. However, this last result is not very robust as inclusion of higher order terms renders it statistically insignificant. Note also, that all the remaining coefficients that are common to Tables 12 and 13 are consistent both in direction of relationship and size.

In order to relate these results to theoretical models, note that age is only relevant in Jovanovic's (1982) model, while in the model of Ericson and Pakes (1995), age is irrelevant for subsequent growth. This consistency with Jovanovic model should not, however, be interpreted as confirmation of passive learning model as there are other reasons why age could be relevant for growth in size. A simpler hypothesis not related to Bayesian updating, but also consistent with relationship between growth and age may be already learning by doing.

**Table 13: Relationship between growth, size, age and productivity**

Growth	Equation	
	(1)	(2)
$\ln S_{it}$	-0.02 (-5.9)*	-0.08 (-4.6)*
$(\ln S_{it})^2$	-	0.03 (2.8)*
$(\ln S_{it})^3$	-	-0.003 (-2.1)*
$\ln \frac{y}{l}$	0.07 (8.6)*	0.07 (8.3)*
$\ln a$	-0.02 (-2.7)*	-0.02 (-2.3)*
<i>Cons</i>	-0.40 (-6.3)*	-0.42 (-5.6)*
Survival		
$\ln S_{it}$	0.10 (4.0)*	0.65 (4.6)*
$(\ln S_{it})^2$	-	-0.24 (-3.24)*
$(\ln S_{it})^3$	-	0.03 (2.6)*
$\ln \frac{y}{l}$	0.38 (7.4)*	0.37 (7.2)*
$\ln a$	0.12 (2.0)*	0.09 (1.5)
<i>Cons</i>	-2.63 (-6.8)*	-2.74 (-7.0)*
$\rho(s.e.)$	0.13 (0.04)	0.24 (0.14)
$\chi^2(1)$	8.00 (0.005)*	2.72 (0.10)
Log <i>L</i>	-327.92	-307.00
N	1669	1669

Source: Author's calculations.

Notes: i) Dummies for 2 digit NACE sectors included in both equations.

Asterisk denotes 5 percent significance level.

The standard errors of estimates are heteroskedasticity robust, based on Huber-White estimator of variance.

## 4 The evolution of labor productivity

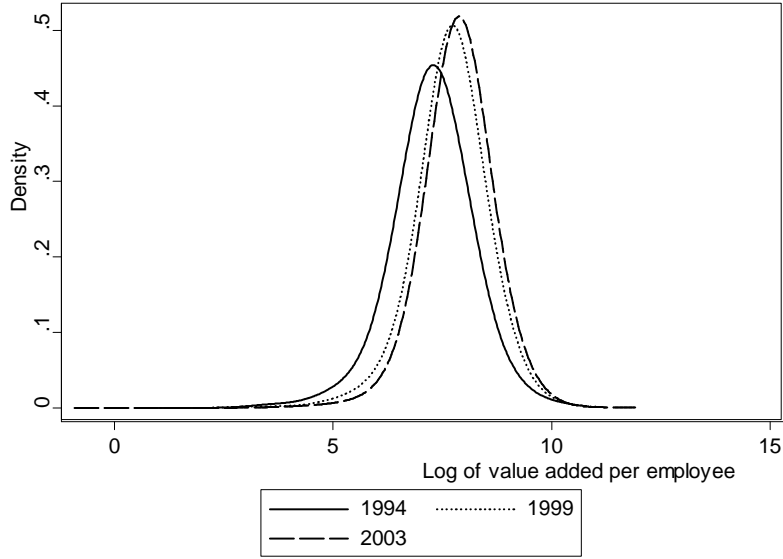
Virtually all theoretical models of industrial dynamics predict that FSD should reflect primarily firm productivity distribution (see Jovanovic, 1982; Ericson and Pakes, 1995; Klette and Kortum, 2002; Rossi-Hansberg and Wright, 2004), although in reality many other factors, such as financial constraints, institutions and regulations, are also important. Restrictions imposed on firm behavior during socialism and corresponding bimodal size distribution is the best example of how institutions and regulations can disconnect this correspondence between size and productivity. On the contrary, removal of these restrictions should restore this relationship. Hence, in this section, we explore the dynamics of labor productivity distributions and relate it to the dynamics of size and underlying factors of growth, such as capital deepening and total factor productivity catch up.

### 4.1 Basic statistics on labor productivity

Figure 6 below shows the evolution of distribution for logarithm of labor productivity, defined as a ratio between value added and total employment, for all active firms.<sup>10</sup> Note first substantial heterogeneity in labor productivity of firms, which is a well established fact also for all other countries (see survey in Bartelsman and Doms, 2000). More importantly, Figure 6 shows that labor productivity has been gradually increasing over the entire transition period.

<sup>10</sup>In fact, the data are normalized numbers of employees, corrected for the number of hours worked. Thus, used measure of productivity is close to labor productivity per hour worked (apart from scale adjustment).

**Figure 6: Evolution of labor productivity distribution**



Source: Author's calculations.

Notes: <sup>1</sup> The labor productivity distributions are calculated using gaussian stochastic kernels with smoothing parameter equal to 0.45.

Tables 14 and 15 provide some descriptive statistics on the evolution of labor productivity distribution. Table 14 shows that the average logarithm of labor productivity increased by almost 0.60, while dispersion has decreased. There is an increase in skewness in direction of higher concentration of below average productivity firms and an increase in thickness of tails. The values for standard measures of skewness and kurtosis suggest that the bell-shaped densities do not belong to normal distributions, which is also confirmed by omitted normality tests.

**Table 14: Descriptive statistics for labor productivity in 1994 and 2003**

Statistic \ Year	1994	2003
Mean	7.27	7.86
Standard Deviation	0.91	0.76
Skewness	-0.52	-0.98
Kurtosis	5.85	11.3
p10	6.24	7.04
p25	6.80	7.46
p50	7.28	7.87
p75	7.79	8.28
p90	8.29	8.71

Source: Author's calculations.

Table 15 summarizes evolution of average and aggregate labor productivity in time, expressed in constant 1994 prices, where these two productivity measures differ in the choice of weights. In calculation of the average labor productivity, we use equal weights for all firms and in calculation of the aggregate labor productivity, we use employment shares as weights. A cross-sectional decomposition of aggregate labor productivity, proposed by Olley and Pakes (1996), relates these two measures and shows whether economic activity (here measured by employment) is disproportionately located in high productivity plants. This decomposition for the period  $t$  can be written as follows

$$y_t = \bar{y}_t + \sum_{i \in Active} (\theta_{it} - \bar{\theta}_t)(y_{it} - \bar{y}_t), \quad (4)$$

where  $y_t$  and  $\bar{y}_t$  denote aggregate and average labor productivity, respectively,  $y_{it}$  and  $\theta_{it}$  denote labor productivity and labor share in firm  $i$ , respectively and  $\bar{\theta}_t$  denotes the average labor share. If difference between aggregate and average labor productivity is positive, the cross term is also positive, implying that firms with above average productivity employ disproportionately more workers and vice versa.

Turning now to results, Table 15 reveals that the average labor productivity exceeded the aggregate labor productivity in all years but 2003. In 1994, the average labor productivity exceeded the aggregate labor productivity by as much as 18 percent. Consequently, the cross product term in (4) is negative, which suggests that labor was disproportionately allocated in less productive firms.<sup>11</sup> However, this difference has been decreasing gradually and in 2003 the rankings reversed. Therefore, the cross-sectional allocation of employment (and gross output) is more and more in line with productivity.

The evolution of this change is reflected in the last four columns of Table 15, which contain the aggregate labor productivity for firms in different size classes. In the early transition years, larger firms were still less productive than smaller firms and combined with larger employment shares for larger firms this resulted in average labor productivity exceeding aggregate labor productivity. However, faster growth of productivity in larger firms has caused that the aggregate labor productivity exceeds the average labor productivity in 2003. Note that the rankings of firms in different size classes according to the aggregate labor productivity in 2003 is still different from that observed in majority of European countries<sup>12</sup> (see Eurostat, 2004), where larger firms are on average more productive. Nevertheless, if the growth rates of the aggregate labor productivity of larger firms continues to exceed the growth rates in smaller firms, such rankings should be soon achieved. Note that in parentheses of the last four columns of Table 15, we also show labor productivities relative to average 2 digit NACE sectors in order to eliminate potential structural shifts. However, the dynamics of relative labor productivity is in line with that for absolute values, which confirms described patterns.

**Table 15: Evolution of labor productivity  
[in thousand SIT, constant base in 1994]**

Year	Average <sup>1</sup>	Aggregate <sup>2</sup> (Relative <sup>3</sup> )				
	All (S.D. <sup>4</sup> )	All	Micro	Small	Medium	Large
1994	2153 (2890)	1818	2262 (1.06)	1889 (0.94)	1687 (0.84)	1848 (0.87)
1995	2147 (2641)	1808	2244 (1.04)	1958 (0.96)	1713 (0.85)	1825 (0.88)
1996	2359 (2860)	2057	2412 (1.02)	2320 (1.03)	1942 (0.87)	2095 (0.88)
1997	2670 (3791)	2430	2779 (1.03)	2506 (0.99)	2183 (0.85)	2539 (0.92)
1998	2748 (4587)	2480	2768 (1.03)	2664 (1.02)	2233 (0.83)	2594 (0.92)
1999	2983 (3310)	2794	3104 (1.02)	2908 (1.03)	2389 (0.84)	2979 (0.97)
2000	3067 (3672)	3010	3154 (1.01)	3128 (1.05)	2558 (0.87)	3226 (0.99)
2001	3184 (3804)	3145	3308 (1.01)	3236 (1.02)	2739 (0.90)	3337 (0.98)
2002	3337 (4525)	3290	3379 (1.01)	3166 (1.01)	2891 (0.92)	3553 (1.04)
2003	3528 (4770)	3570	3559 (1.02)	3353 (0.99)	3060 (0.92)	3893 (1.02)
Aver. growth	5.64	7.79	5.16	6.58	6.84	8.63

Source: Author's calculations.

Notes: <sup>1</sup> The average value added per employee is calculated as a simple (unweighted) average of individual productivities.

<sup>2</sup> The aggregate value added per employee is calculated as weighted average of individual productivities, where weights used are respective labor shares.

<sup>3</sup> Relative labor productivity is calculated as an unweighted average of ratios of firms' labor productivities and their sectoral (2 digit Nace) unweighted averages.

<sup>4</sup> Standard deviations of labor productivity.

<sup>11</sup>Note that we could calculate the aggregate labor productivity also using gross output shares instead of labor shares. In that case aggregate labor productivity exceeded average labor productivity in all years and the difference has been increasing, suggesting that more productive firms had ever increasing share in aggregate sales. Although initial values suggest disproportional allocation of output in more productive firms, which is contrary to results with labor productivity, the change in allocation of output is in line with that of labor.

<sup>12</sup>Also for transition countries like Czech Republic, Hungary and Estonia, rankings in productivity are in line with size rankings. The only exception is Lithuania, where small firms are the least productive of all.

### 4.1.1 Decomposition of labor productivity growth

So far we have established that larger firms grow faster, which leads to correspondence between productivity and size rankings. In the industrial organization literature, authors proposed a variety of decompositions of aggregate (labor or total factor) productivity growth (see Baily, Hulten and Campbell, 1992; Griliches and Regev, 1995; Olley and Pakes, 1996 and Foster, Haltiwanger and Krizan, 1998). These decompositions allow one to understand how growth in productivity has come about. Following Foster, Haltiwanger and Krizan (1998, henceforth FHK), we use two decompositions proposed by FHK and Griliches and Regev (1995, henceforth GR) as both of these have advantages and disadvantages. Before we turn to results, we shortly outline these methods.

The decomposition proposed by FHK is a modification of a method by Baily, Hulten and Campbell (1992).<sup>13</sup> The basic equation for a change in labor productivity is the following<sup>14</sup>

$$y_t - y_{t-\tau} = \sum_{i \in S} (\theta_{it-\tau} (y_{it} - y_{it-\tau}) + \sum_{i \in S} (\theta_{it} - \theta_{it-\tau}) (y_{it-\tau} - y_{t-\tau}) + \sum_{i \in S} (\theta_{it} - \theta_{it-\tau}) (y_{it} - y_{it-\tau}) + \sum_{i \in E} \theta_{it} (y_{it} - y_{t-\tau}) - \sum_{i \in X} \theta_{it-\tau} (y_{it-\tau} - y_{t-\tau}), \quad (5)$$

where  $y_t - y_{t-\tau}$  denotes the cumulative change in labor productivity over a period  $\tau$ ,  $y_t$  and  $y_{it}$  denote aggregate and individual labor productivity, respectively, and  $\theta_{it}$  denotes labor or gross output share of firm  $i$ .  $S$ ,  $E$  and  $X$  denote sets of surviving, entering and exiting firms, respectively.

The first term of the right-hand side of equation (5) is a "within component" and measures the contribution of changes in labor productivity weighted by the fixed initial shares in the aggregate employment (or gross output). The second term is a "between component" and measures the contribution of changing shares in the aggregate employment (or output), weighted by the difference between initial individual and initial aggregate labor productivity. Thus, an increase in its share contributes positively to aggregate productivity growth only if the firm has higher than initial aggregate labor productivity for the entire manufacturing. The third term is a "cross or covariance component", which measures the covariance between the changes in employment (or output) shares and the changes in the labor productivity. This term is positive if employment and productivity changes move in the same direction and vice versa. The fourth term measures the contribution of entering firms and the fifth term the contribution of exiting firms. Note that these last two terms are positive only if labor productivities of these firms exceed the initial aggregate labor productivity.

FHK emphasize two important features that distinguish their decomposition from others. First, their decomposition treats surviving, entering and exiting firms in an integrated manner and second, it separates within and between effects from cross or covariance effects. Alternatively, GR decomposition uses the average labor (or gross output) shares as weights in calculation of within component and thus it partly reflects also the cross effect. Hence, FHK prefer their method, although they admit that it suffers when data are plagued by measurement errors, particularly for employment.

The GR decomposition has the following structure

$$y_t - y_{t-\tau} = \sum_{i \in S} \bar{\theta}_i (y_{it} - y_{it-\tau}) + \sum_{i \in S} (\bar{y}_i - \bar{y}) (\theta_{it} - \theta_{it-\tau}) + \sum_{i \in E} \theta_{it} (y_{it} - \bar{y}) - \sum_{i \in X} \theta_{it-\tau} (y_{it-\tau} - \bar{y}), \quad (6)$$

where

$$\begin{aligned} \bar{\theta}_i &= \frac{\theta_{it} + \theta_{it-\tau}}{2}, \\ \bar{y}_i &= \frac{y_{it} + y_{it-\tau}}{2}, \\ \bar{y} &= \frac{y_t + y_{t-\tau}}{2}. \end{aligned}$$

This decomposition omits the cross or covariance term and thus contains only four terms. Although the first and the second terms are still named within and between effects, they partly reflect what in FHK

<sup>13</sup>Baily, Hulten and Campbell (1992) consider a decomposition, where second and third terms are summed together, while the last two terms do not subtract initial aggregate productivity from initial individual productivity.

<sup>14</sup>Note that this decomposition can and will be used for decomposition of change in total factor productivity.

decomposition is the cross term. The "within" effect in (6) is calculated as a weighted sum of changes of labor productivity with the weights equal to the average labor (or output) shares. The "between" effect is calculated as a sum of labor share shifts weighted by differences between (time) averages of individual and aggregate productivity. In line with the FHK decomposition, entry and exit have a positive contribution only if productivity is higher than the time average of aggregate productivity. The fact that both within and between effects partly reflect the cross effect is the main disadvantage of this method. On the other hand, the results according to this decomposition are far less prone to measurement errors in relation to the choice of either labor or output weights.

Table 16 provides the results of FHK and GR decompositions for aggregate labor productivity growth using both labor and output weights for three subperiods. The key results can be summarized as follows. First, the average annual aggregate labor productivity growth is declining over time, a fact consistent also with declining growth rates for Slovenian GDP per capita. Second, the contribution of within effect varies across time, decompositions and weights, although its contribution is never lower than 48 percent. The large within component indicates that restructuring through within firm growth is just as important mode of labor productivity growth as reallocation (if not more), which refutes the early description of transition primarily as a process of reallocation. Third, the within and between components obtained with FHK decomposition are much larger when labor shares are used as weights as opposed to output weights. FHK themselves have found a similar pattern and partly ascribed it to mismeasurement of labor. However, this difference in within and between components is related to differences in measured cross component, which contains important information. Namely, a negative cross component with labor weights points at negative correlation between growth in labor productivity and employment growth, while a positive cross component with output weights suggests that growth in labor productivity coincided with growth in sales. The transition period can thus be characterized by downsizing in terms of employment and growth of sales (although not in the early transition). Fourth, the contribution of net entry process ranges between 5 and 25 percent, with some indicative time patterns. The contribution of entrants is declining over time, especially when output weights are used. This implies that relative productivity of entrants when compared to initial aggregate productivity has been declining and/or that their size has been decreasing, which can be interpreted as decreasing opportunity for entrants over time or markets saturation. The patterns for exiting firms are less consistent over time. Fifth, the results obtained by GR decomposition are qualitatively similar as the share of within component exceeded 50 percent of aggregate productivity growth. We also confirm FHK conjecture that GR decomposition is more robust to the choice of weights due to lower sensitivity to measurement errors. For the sake of brevity and qualitatively consistent estimates across the methods, in what follows we only show the results obtained by FHK decomposition.

**Table 16: FHK and GR decompositions of aggregate productivity growth, 1994-2003**

FHK, Labor weights						
	Growth rate <sup>1</sup>	Within	Between	Cross	Exit	Entry
1994-1997	10.4	0.93 <sup>2</sup>	0.29	-0.35	0.11	0.03
1997-2000	7.05	0.72	0.45	-0.38	0.16	0.05
2000-2003	5.81	0.97	0.23	-0.26	0.14	-0.09
FHK, Output weights						
	Growth rate	Within	Between	Cross	Exit	Entry
1994-1997	11.1	0.64	0.12	0.02	0.07	0.15
1997-2000	7.04	0.48	-0.04	0.31	0.13	0.12
2000-2003	6.99	0.53	0.06	0.35	0.04	0.02
GR, Labor weights						
	Growth rate	Within	Between	Exit	Entry	
1994-1997	10.4	0.75	0.12	0.17	-0.04	
1997-2000	7.05	0.54	0.24	0.21	0.01	
2000-2003	5.81	0.85	0.12	0.20	-0.16	
GR, Output weights						
	Growth rate	Within	Between	Exit	Entry	
1994-1997	11.1	0.66	0.13	0.12	0.09	
1997-2000	7.04	0.62	0.13	0.18	0.08	
2000-2003	6.99	0.73	0.22	0.09	-0.04	

Source: Author's own calculations.

Notes: <sup>1</sup> The average (annual) aggregate labor productivity growth rate.

<sup>2</sup> The share in the average aggregate labor productivity growth rate.

Next question that we address is on the relative contribution to the aggregate labor productivity growth of firms in different size classes. We tackle this issue by decomposing the aggregate labor productivity for the period 1994-2003 and using the FHK decomposition with both labor and output weights. These results are summarized in Table 17. The contribution of within firm growth to the growth of aggregate labor productivity is either 56 or 70 percent with output and labor weights, respectively. Surprisingly, these values are remarkably similar to those obtained by FHK for U.S. manufacturing for 1977-87, who report 48 and 70 percent.<sup>15</sup> That is, as pointed out in introduction, reallocation was expected to be much more important in the early transition literature. The rankings of contributions of firms in different size classes (the last columns in panels) are in line with size, although contributions of micro and small firms are more than proportional to their employment shares. Note that within firm growth of medium and large firms are the largest individual contributions to aggregate growth, which now also explains that restructuring of larger firms played the key role in productivity growth of large firms. While the remaining results follow these lines, note that cross component is again negative when labor weights are used both for medium and large firms, which implies that growth of productivity was partly generated by downsizing. On the other hand, with output weights, cross component is positive for these firms, which again suggests that growth in productivity was also achieved by increases in sales. Note relatively large between components for micro and small firms, which hints at growth of employment and sales in initially more productive firms. The contributions of entry and exit of firms reveal that firms that medium and large firms that exit contribute positively to aggregate productivity as their initial productivity was below average. The contribution of entering firms is larger in larger firms. In conclusion, the process of aggregate labor productivity growth can be described as a process dominated by larger firms as suggested in Table 15. Nevertheless, small and micro firms have been growing, particularly more productive ones.

**Table 17: FHK decomposition of aggregate productivity growth, size classes**

	Labor weights					
	Within	Between	Cross	Exit	Entry	Total
Micro	0.01 <sup>1</sup>	0.03	0.00	0.00	0.03	0.08
Small	0.02	0.06	-0.01	0.00	0.05	0.11
Medium	0.21	0.01	-0.06	0.03	0.06	0.24
Large	0.47	0.05	-0.06	0.02	0.10	0.57
Total	0.70	0.15	-0.14	0.06	0.23	1.00
	Output weights					
	Within	Between	Cross	Exit	Entry	Total
Micro	0.00	0.01	0.02	-0.02	0.08	0.10
Small	0.01	0.04	-0.01	-0.01	0.06	0.10
Medium	0.13	-0.02	0.02	0.00	0.05	0.18
Large	0.42	-0.01	0.10	-0.01	0.11	0.62
Total	0.56	0.03	0.14	-0.04	0.30	1.00

Source: Author's calculations.

Notes: <sup>1</sup> A share in change of aggregate value added per employee.

From a perspective of building a theory of transition it is important to provide some additional stylized facts on labor productivity distributions of different types of firms. First, Figure 7 compares labor productivity distributions of exiting and surviving firms that were active in 1994 and of entering and surviving firms active in 2003. The labor productivity of exiting firms is lower than that of surviving firms, while productivity of entering firms is lower than productivity of surviving firms.

<sup>15</sup>Their period of analysis is one year longer, which implies that reallocation should be larger in U.S. just for this reason.



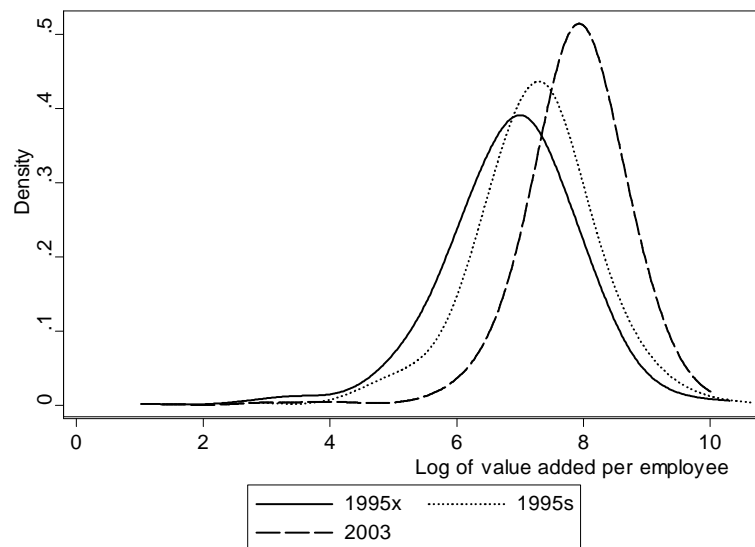
**Figure 7: Labor productivity of entrants, survivors and exitors**



Source: Author's calculations.

Cabral and Mata (2003) have argued that initial size did not matter for subsequent probability of survival of entering firms, which is also shown for our data. They interpreted this evidence against the model of industrial dynamics developed by Jovanovic (1982). In Figure 8, we compare labor productivity of 1995 entrants over time and between surviving and exiting entrants. It is shown that labor productivity shift is primarily due to productivity growth of surviving firms, which can be ascribed to learning process, and only to a lesser extent due to survival of more productive firms. Nevertheless, surviving firms (denoted 1995s) were in 1995 more productive than exiting firms (denoted 1995x). Olley and Pakes (1996), Liu and Tybout (1996) and Aw, Chen and Roberts (1997) have also found that both learning and selection processes are important in explaining dynamics of productivity for new firms.

**Figure 8: Labor productivity of 1995 entrants**



Source: Author's calculations.

Since at least half of aggregate labor productivity growth is generated with inner growth of firms, large firms in particular, it is important to understand, what is the mechanism underlying this growth. A simple answer to this would be catching up due to convergence in capital intensity and technology. In this section, we show that a large contribution to aggregate growth is related to labor productivity of firms that shift closer to the firms with the highest labor productivity. Whether this is due to convergence in capital intensity or technological convergence will not be tackled until next section.

In order to illustrate the labor productivity convergence conjecture, we construct six equally sized classes for logarithm of labor productivity.<sup>16</sup> Using these classes, we perform FHK decomposition for surviving firms over the period 1994-2003 disaggregated by initial and end of period productivity classes. Although by doing so, we may encounter the survival bias, we show in the subsequent analysis that correcting for this bias does not change the main result. Table 18 provides the results of FHK decomposition using labor and output weights (in parentheses). The main message is that firms that were initially in the productivity class 6-8 and end up being in class 8-10 are the main contributors to aggregate labor productivity growth (37 percent). Thus we can conclude that large firms, where majority of aggregate growth is generated, with lower than frontier labor productivity are the key contributors to growth. However, growth of firms that did not shift between productivity classes should not be overlooked as almost 25 percent is generated in these firms. Furthermore, a large between component (9 percent) for firms that were stayed in 8-10 productivity class shows that initially more productive firms were indeed growing by expansion of labor.

**Table 18: FHK decomposition of aggregate productivity growth, productivity classes**

$t \setminus t - 9$	Effect	Labor (output) weights			
		4-6	6-8	8-10	10-12
6-8	Within	0.003 <sup>1</sup> (0.001 <sup>2</sup> )	<b>0.08 (0.03)</b>	-0.01 (-0.01)	-
	Between	-	<b>0.03 (0.01)</b>	0.02 (0.001)	-
	Cross	-	<b>-0.01 (-0.002)</b>	-0.01 (0.002)	-
8-10	Within	0.006 (-)	0.37 (0.25)	<b>0.16 (0.23)</b>	-
	Between	-	0.001 (-0.01)	<b>0.09 (0.03)</b>	0.01 (-0.05)
	Cross	-0.005 (-)	-0.002 (0.13)	<b>-0.01 (0.05)</b>	-0.01 (0.008)
10-12	Within	-	0.08 (0.06)	0.001 (0.003)	- (-0.006)
	Between	-	-0.001 (-)	- (0.001)	-
	Cross	-	-0.08 (-0.03)	- (0.005)	-

Source: Author's calculations.

Notes: <sup>1,2</sup> The contribution to aggregate growth calculated labor (output) weights.

The transitions in labor productivity are also analyzed in Tables 19 and 20, where we show unweighted and weighted transition matrices for the entire transition period. The reader should be aware that time span, choice of productivity classes and weights all affect calculated transition probabilities. The lengthier is the time span between initial and end productivity distribution, the smaller is observed persistence of productivity. Further, for more coarse productivity classes, observed persistence is larger. The extent of measured persistence also depends on whether we use weights or not. Thus we use two different approaches to illustrate the dynamics of labor productivity over time.

In line with findings of Baily, Hulten and Campbell (1992), both tables with unweighted and weighted transition matrices exhibit substantial persistence in labor productivity. For example, we can see in Table 19, where unweighted transition matrix using the productivity classes of Table 18 is shown, that 47 percent of firms in productivity class 8-10 remain there even after 9 years. Nevertheless, even for these firms, we find substantial exit rate (30 percent) or decline of productivity to lower classes (21 percent). This suggests substantial turnover in labor productivity. The survival bias is clearly present as initially more productive firms are less likely to exit, a finding that was already illustrated in Figure 7. Surviving less productive firms are also likely to improve their productivity levels as suggested by below diagonal probabilities.

<sup>16</sup>An alternative (and often used) approach that eliminates the drift in growth of labor productivity constructs these classes relative to the average labor productivity in a given year.

**Table 19: Unweighted transition matrix for labor productivity, 1994-2003**

$t \setminus t-9$	0-2	2-4	4-6	6-8	8-10	10-12	Entry
0-2	<b>0</b>	0	0	0	0	0	0
2-4	0	<b>0</b>	0	0	0	0	0
4-6	0	0	<b>0.02</b>	0.01	0	0	0.02
6-8	0	0.15	0.24	<b>0.34</b>	0.21	0.11	0.59
8-10	1.00	0.10	0.10	0.23	<b>0.47</b>	0.32	0.39
10-12	0	0	0	0	0.005	<b>0.26</b>	0
Exit	0	0.75	0.65	0.42	0.30	0.32	-

Source: Author's calculations.

Notes: The productivity classes are the same as in Table 22.

As a robustness check, in Table 20 we provide weighted transition matrix with productivity classes defined relative to average labor productivity in a given year. The weights used in the calculation of transition probabilities are initial labor shares for surviving and exiting firms and end of period share for entering firms. Table 20 conveys the same message as was summarized above. The dynamics of labor productivity can be described as fairly persistent, where the degree of persistence (or value of diagonal transition probabilities) depends on initial labor productivity. Namely, higher initial labor productivity implies higher persistence. To a large extent, this is related to lower exit rates for initially more productive firms. We also observe substantial shifts in terms of productivity. Firms with initially less than average productivity levels are more likely to improve than remain in the same relative productivity interval, while firms with above than average productivity are more likely to lose their advantage.

**Table 20: Weighted transition matrix for labor productivity**

$t \setminus t-9$	1994-2003						Entry
	1	2	3	4	5	6	
1	<b>0.01</b>	0.02	0.01	0.01	0.01	0.01	0.04
2	0.07	<b>0.13</b>	0.16	0.10	0.07	0.02	0.19
3	0.05	0.15	<b>0.26</b>	0.16	0.12	0.07	0.26
4	0.08	0.09	0.14	<b>0.23</b>	0.18	0.09	0.24
5	0.02	0.07	0.08	0.17	<b>0.26</b>	0.15	0.15
6	0.04	0.01	0.05	0.06	0.16	<b>0.52</b>	0.12
Exit	0.73	0.53	0.29	0.28	0.21	0.14	-

Source: Author's calculations.

Notes: i)  $\bar{y}$  denotes the average labor productivity in a given year.

ii) Weights used in calculation of transition probabilities are initial employment shares.

iii) Productivity classes are: (1)  $y < 0.25\bar{y}$ , (2)  $0.25\bar{y} < y < 0.5\bar{y}$ , (3)  $0.5\bar{y} < y < 0.75\bar{y}$ , (4)  $0.75\bar{y} < y < \bar{y}$ , (5)  $\bar{y} < y < 2\bar{y}$ , (6)  $2\bar{y} < y$ .

## 4.2 Decomposition of labor productivity growth by factors

An encompassing set of stylized facts should also provide some insight into underlying factors of labor productivity dynamics. Hence, we continue by investigation of underlying factors of labor productivity dynamics, particularly, capital intensity and total factor productivity (TFP). In what follows, we show that capital intensity is a poor predictor of labor productivity dynamics, which implies that we ascribe (rightly or wrongly) the features described above to the dynamics of TFP. First, we provide some stylized facts on dynamics of capital intensity and proceed with analysis of TFP.

### 4.2.1 Capital intensity

If capital intensity was the key factor in explaining heterogeneity of levels and growth rates, we should observe a strong relation between capital intensity and labor productivity. Table 21 shows average and aggregate capital intensities for the entire transition period. The average and aggregate capital intensities are defined as unweighted and weighted averages, again using respective labor shares as weights. While both of these measures are fairly volatile, average capital intensity exhibits far weaker trending behavior

than aggregate capital intensity. Respective average growth rates are 0.25 and 1.63 percent. Note that these growth rates are much lower than the average growth rates for average and aggregate labor productivity, which are 5.64 and 7.79 percent, respectively. Furthermore, aggregate capital intensities for different size groups did not correspond to their labor productivity counterparts, both in terms of rankings of levels and growth rates. For example, in 1994, labor productivity of large firms was lower than labor productivity of small firms, while the opposite is true for capital intensity. The only consistent feature between capital intensity and labor productivity is for growth rates of large firms as these had the fastest growth of capital intensity and labor productivity. Nevertheless, the growth rate of capital intensity in large firms is 6 percentage points lower than the growth rate of labor productivity. A simple regression of logarithm of labor productivity on logarithm of capital intensity reveals a regression coefficient of 0.22, for which we can explain utmost 15 percent ( $R_{Adjusted}^2$ ) of labor productivity growth by capital intensity.

**Table 21: Evolution of capital intensity  
[in thousand SIT, constant base in 1994]**

Year	Average <sup>1</sup>	Aggregate <sup>2</sup>				
	All	All	Micro	Small	Medium	Large
1994	3583	3586	3559	3630	3187	3749
1995	3338	3453	3110	3121	3032	3693
1996	3307	3485	3191	3317	2969	3760
1997	3565	3754	3564	3444	3140	4102
1998	3519	3772	3351	3459	3257	4094
1999	3509	3897	3627	3312	3286	4337
2000	3449	3984	3345	3444	3233	4534
2001	3420	4037	3356	3482	3472	4494
2002	3514	3941	3524	3049	3296	4487
2003	3665	4148	3753	3249	3473	4742
Average growth	0.25	1.63	0.59	-1.22	0.96	2.64

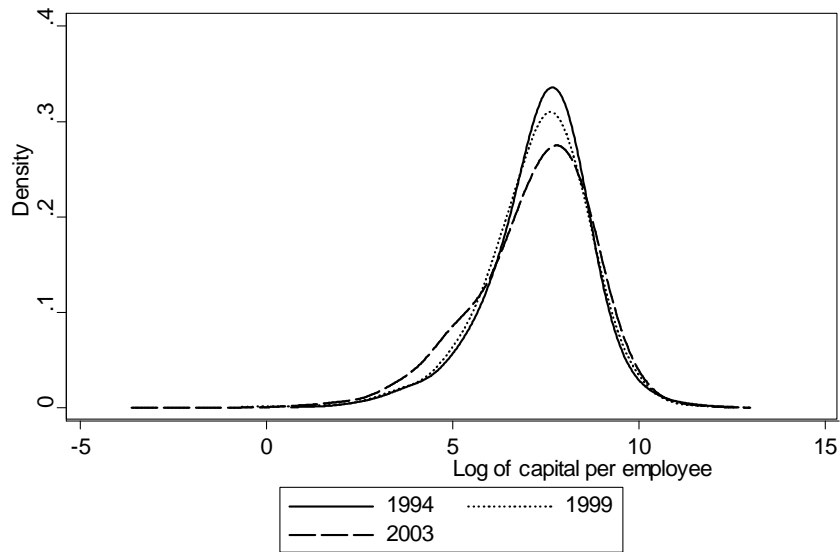
Source: Author's calculations.

Notes: <sup>1</sup> The average value added per employee is calculated as a simple (unweighted) average of individual productivities.

<sup>2</sup> The aggregate value added per employee is calculated as weighted average of individual productivities, where weights used are respective labor shares.

The fact that capital intensity has only modest power to explain labor productivity levels and heterogeneity of growth rates is also illustrated in Figures 9, 10 and 11. In Figure 9, we plot capital intensity distributions for 1994, 1999 and 2003. In contrast with Figure 6, where we track labor productivity distribution shifts over time, there is no clear-cut shift in capital intensity distribution. In addition, capital intensity dispersion has even increased.

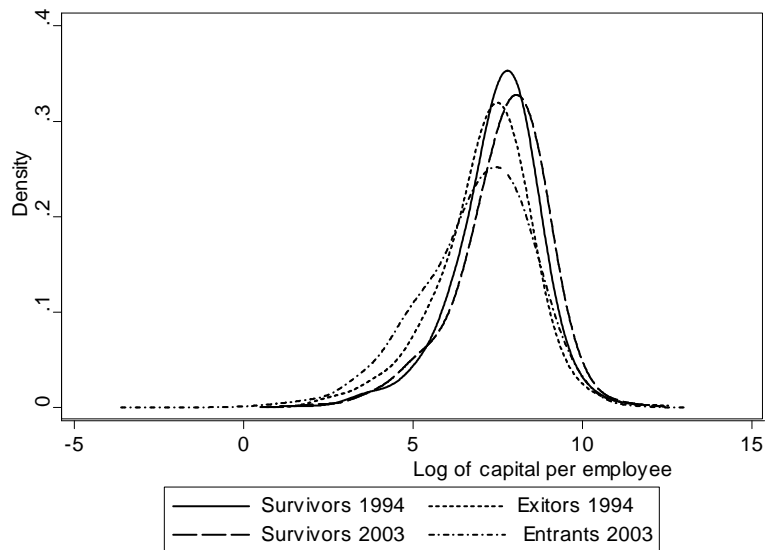
**Figure 9: Capital intensity distributions over time**



Source: Author's calculations.

Figure 10 plots capital intensity of exiting and surviving firms in 1994 and entering and surviving firms in 2003. Again, these distributions exhibit only modest differences, far smaller than those observed for labor productivity. Nevertheless, we find that exitors are less capital intensive than survivors, entrants are less capital intensive than surviving firms. Furthermore, surviving firms exhibit increasing capital intensity.

**Figure 10: Capital intensity distributions for different types of firms**

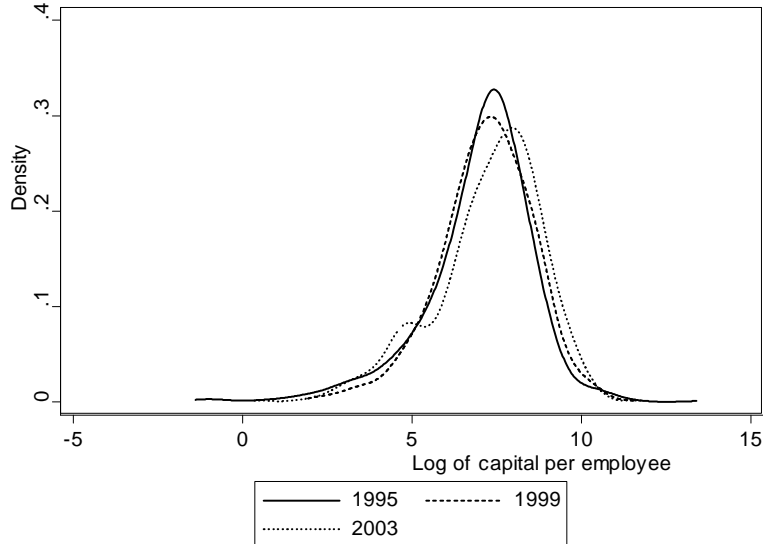


Source: Author's calculations.

Notes: Surviving firms are those that are active both in 1994 and 2003.

In Figure 11, we show capital intensity distributions over time for a cohort of entering firms in 1995. In Figure 8, we see that labor productivity of surviving firms is increasing, while capital intensity shown in Figure 11 exhibits far smaller shift in distribution.

**Figure 11: Evolution of capital intensity for 1995 cohort of entrants**



Source: Author's calculations.

The evidence gathered so far shows that labor productivity differences cannot be explained by differences in capital intensity. Hence TFP must be the underlying force behind the shifts in labor productivity and the remainder to this section investigates its dynamics.

#### 4.2.2 Total factor productivity

The standard approach to estimation of total factor productivity is indirect. It requires estimation of production function and its residuals with added regression constant are estimates of total factor productivity. The estimates of total factor productivity are heavily dependent on consistency of estimates of production function coefficients. Griliches and Mairesse (1995) emphasize that consistency of estimates hinges on: (i) selection of functional form and adequate data, (ii) measurement of inputs and outputs, (iii) quality adjustments for different factors (labor, etc.), (iv) the methodology of sample selection and (v) the choice of estimation procedure. While we have done our best in correctly measuring inputs and outputs (although we have deflators only at 2 digit NACE level), lack of data on labor structure does not allow us to distinguish between workers with different amounts of human capital. Hence, here we only discuss the choice of adequate data, sample selection and estimation procedure.<sup>17</sup>

In the relevant literature, a choice of adequate data is primarily related to the choice between the following two forms of production functions

$$GY_{it} = A_t K_{it}^\alpha L_{it}^\beta M_{it}^\gamma e^{\varepsilon_{it}}, \quad (7)$$

and

$$Y_{it} = A_t K_{it}^\alpha L_{it}^\beta e^{\varepsilon_{it}}, \quad (8)$$

where  $GY_{it}$  and  $Y_{it}$  denote sales and value added for firm  $i$  in period  $t$ ,  $A_{it}$  is an aggregate index of technology,  $K_{it}$  is a measure of capital,  $L_{it}$  is employment and  $M_{it}$  is a measure of material costs.  $\alpha, \beta$

<sup>17</sup>Some authors use translog production function, which includes also higher order terms and interaction terms. For recent examples, see Orazem and Vodopivec (2003) and Sabrianova et al. (2004).

and  $\gamma$  are elasticities to capital, labor and materials, respectively, and  $\varepsilon_{it}$  is an error term. Baily et al. (1992) and FHK estimate (7) in a logarithmic form

$$\ln GY_{it} = \ln A_t + \alpha \ln K_{it} + \beta \ln L_{it} + \gamma \ln M_{it} + \varepsilon_{it}, \varepsilon_{it} \sim i.i.d(0, \sigma^2) \quad (9)$$

and retrieve TFP from it

$$\ln TFP_{it} = \ln GY_{it} - \hat{\alpha} \ln K_{it} + \hat{\beta} \ln L_{it} + \gamma \ln M_{it} = \ln A_t + \varepsilon_{it}, \quad (10)$$

where hats denote estimates. The advantage of using sales as the dependent variable is to avoid the restriction imposed on the way material costs enter production function,  $Y_{it} = GY_{it} - M_{it}$ , while value added as the dependent variable allows more natural interpretation of TFP and allows variation in material input shares. An alternative estimator of TFP with value added as the dependent variable that can be obtained from (8) is

$$\ln TFP_{it} = \ln Y_{it} - \hat{\alpha} \ln K_{it} + \hat{\beta} \ln L_{it} = \ln A_t + \varepsilon_{it}. \quad (11)$$

Recent literature deals also with problems of selection and endogeneity bias in the ordinary least squares (OLS) estimates of production function coefficients. The selection bias is a consequence of entry and exit of firms. For example, more productive firms are less likely to exit. Also, larger firms may afford to exit at lower productivity levels. Hence, average productivity levels may be decreasing with size of firms, which may generate a negative bias in coefficients. Importance of this bias can be observed from comparison of production function estimates based on balanced and full samples of firms.

Tables 22 and 23 provide the estimates of production functions (10) and (11) using both OLS and fixed effects (to allow for persistent firm specific differences in TFP, henceforth FE) for full (unbalanced) sample, which includes firms that enter and exit, and for balanced sample. Olley and Pakes (1996) found for their sample that regression coefficient for capital (labor) was much larger (lower) in full sample than in balanced sample. For example, authors estimated an OLS capital coefficient with value added as a dependent variable 0.308 in full sample and 0.163 in a balanced sample. Respective estimates in our case are 0.230 and 0.218, which leads to conclusion that selection bias is not such a great problem for our data.

The second problem dealt with in the literature is simultaneity or endogeneity of production inputs. If exogeneity of the right hand side variables is not a valid assumption, the OLS estimates may not be consistent. The key problem of simultaneity is of course unobserved heterogeneity in total factor productivity. Persistent (or better fixed) differences of productivity over time could easily be eliminated by first differencing or within transformation. The log of production function given in (8), amended for this unobserved and time invariant heterogeneity has the following form

$$\ln Y_{it} = \alpha \ln K_{it} + \beta \ln L_{it} + \eta_i + \varepsilon_{it} \quad (12)$$

where  $\eta_i$  stands for fixed firm-specific effects that can be eliminated by subtracting individual means or within transformation. That is

$$\ln Y_{it} - \ln Y_{i.} = \alpha(\ln K_{it} - \ln K_{i.}) + \beta(\ln L_{it} - \ln L_{i.}) + \varepsilon_{it} - \varepsilon_{i.}$$

where, for example,  $\ln Y_{i.} = \frac{\sum_{t=1}^T \ln Y_{it}}{T}$ . To the extent that  $\varepsilon_{it}$  are not transmitted to other right-hand side variables, the problem of simultaneity is thus solved. From empirical point of view, this is unlikely to be the case. Furthermore, within transformation is not satisfactory, because capital coefficients are found low and returns to scale are decreasing, a consequence found also for our data. Reader should only compare estimates given in the first and third columns of Table 22. Griliches and Mairesse (1995) point out that this may be a consequence of reduced ratio between information and measurement errors in the data. Downward biased coefficients are also found for estimates using more sophisticated methods that rely on within (or first difference) transformations, such as those proposed by Arellano and Bond (1991) and Bond and Blundell (1998) which are based on generalized method of moments.<sup>18</sup>

A different solution to the problem of endogeneity has been proposed by Olley and Pakes (1996, henceforth OP), who develop estimation equations from a structural model of a dynamically optimizing firm. The advantage over the traditional within approach or GMM type of estimators is that more information is preserved in the original data as it is not transformed. Their innovation is in introduction of an investment equation, which serves as a proxy for the transmitted (but unobserved) technology shocks. The additional benefit of this approach is that unobserved productivity may not be fixed over time.

<sup>18</sup>For example, the estimates of production function coefficients following Arellano and Bond (1991) are  $\hat{\alpha} = 0.12$  and  $\hat{\beta} = 0.50$ , even lower than estimates found for within transformation.

However, Griliches and Mairesse (1995) note that the solution to the problem of simultaneity proposed by OP does not come very far. They note that the estimated marginal productivity coefficients do not differ between (unbalanced) OLS and OP method, which is an indication that the problem of simultaneity is not particularly large. While capital coefficient should be downward biased and labor coefficient upward biased, this was not found on alternative sample of firms used by Griliches and Mairesse. de Loecker and Konings (2003) also find relatively modest differences between OLS and Olley and Pakes estimates for Slovenian manufacturing firms at disaggregated level. Furthermore, the correction was not always in the correct direction. In Table 27, we provide estimates based on a method proposed by Levinsohn and Petrin (2001, henceforth LP) that follows the same ideas as that of OP. Instead of using investment expenditure as a proxy for unobservable technological shocks, they propose to use measures of material inputs, such as energy consumption or costs of materials. They emphasize three main advantages: (i) material costs, unlike investments, respond to the entire productivity shock and not just to unanticipated part of technological shocks; that is, if we split productivity shocks into two components: a serially correlated one and unforecastable part, than investment responds only to a serially correlated shock; as a consequence, some correlation between unobserved technological shock and capital and therefore some bias would remain in the estimated production function coefficients (ii) intermediate inputs provide a simpler link between estimation strategy and economic theory, primarily because intermediates are not state variables; (iii) data advantage; some firms have no investment, which truncates the usable part of the sample, which is not a problem with material costs. For our data, we report the estimates obtained by LP method and find that the correction is not made in the correct direction. Namely, capital coefficient is lower than with OLS, while labor coefficient declines substantially. Such an effect is characteristic when we estimate production function (8) amended by material costs. Inclusion of material costs was suggested by Basu and Fernald (1995), who argue that material inputs may control for temporary productivity shocks that may reflect capacity utilization shifts. Thus, material inputs largely pick up the effect of shocks that are also reflected in labor.

**Table 22: Production function estimations, 1994-2003**

Variable Method Sample	Sales				Value Added
	OLS		FE		Basu-Fernald
	Full	Balanced	Full	Balanced	Full
Capital	0.042 (44.0)	0.049 (36.5)	0.039 (29.3)	0.038 (21.8)	0.137 (58.2)
Labor	0.220 (146.5)	0.200 (102.1)	0.191 (71.2)	0.181 (55.0)	0.581 (156.2)
Mat. Cost	0.736 (603.7)	0.742 (435.4)	0.710 (381.2)	0.719 (273.2)	0.316 (104.4)
Sect. Dum.	Yes	Yes	-	-	Yes
Time Dum.	Yes	Yes	Yes	Yes	Yes
N	42872	17590	42872	17590	42844
$R^2_{Adj}$	0.983	0.991	0.982	0.990	0.900
Variable Method Sample	Value Added				
	OLS		FE		LP
	Full	Balanced	Full	Balanced	Full
Capital	0.218 (87.8)	0.230 (62.4)	0.167 (45.3)	0.161 (31.7)	0.201 (22.2)
Labor	0.796 (228.9)	0.752 (159.9)	0.722 (103.5)	0.682 (76.8)	0.569 (120.3)
Mat. Cost	-	-	-	-	-
Sect. Dum.	Yes	Yes	-	-	-
Time Dum.	Yes	Yes	Yes	Yes	-
N	42852	17590	42852	17590	42844
$R^2_{Adj}$	0.873	0.927	0.860	0.913	-

Source: Author's calculations.

Notes: Sectoral dummies are based on 5 digit NACE classification.

From the discussion above it follows that despite potential biases caused by selection and simultaneity, these may not be that important. In fact, all methods that attempt to correct for these biases fail to correct in expected direction and mostly exhibit decreasing returns to scale. Therefore, we trust the OLS estimates most and provide these for sales and value added for full sample of active firms. However, in order to provide a robustness check, we also present statistics for TFP obtained from LP procedure. The cumulative TFP growth rates calculated either as unweighted or weighted averages when the dependent



variable is sales is around 15 percent, provided in Table 23. Weighted growth rate with employment shares of firms (denoted aggregate) is slightly higher, which again reflects the faster growth rates of larger firms. However, there is inconsistency in results related to small firms, which are found to grow at lowest growth rates, while the rankings of labor productivity growth rates are related to size. This is peculiar also because these firms had also the lowest growth rates for capital intensity. When value added is the dependent variable, the growth rates of TFP are much higher due to different measurement scale. These values, irrespective of the estimation method used are around 60 percent, which is clearly the majority of labor productivity growth. The rankings of TFP growth rates obtained from OLS are related to size, while this is not the case for LP procedure. Nevertheless, it is indisputable that large firms grow with highest growth rates and since these have larger labor share, the cumulative growth rate using labor weights is higher than the cumulative growth rate using simple weights.

**Table 23: Evolution of total factor productivity, 1994-2003**

Average growth 1994-2003	Average <sup>1</sup>	Aggregate <sup>2</sup>				
	All	All	Micro	Small	Medium	Large
Sales, OLS, full sample	0.146	0.153	0.143	0.125	0.155	0.156
Value added, OLS, full sample	0.620	0.644	0.595	0.595	0.598	0.667
LP, full sample	0.617	0.647	0.63	0.60	0.584	0.663

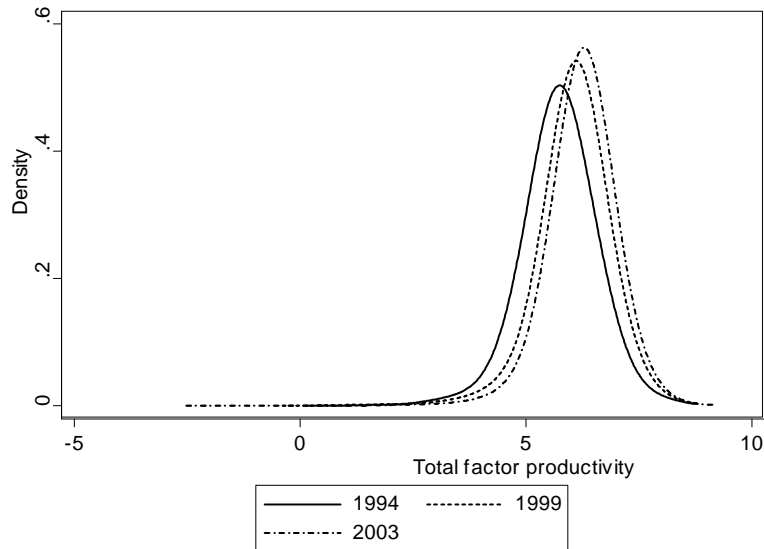
Source: Author's calculations.

Notes: <sup>1</sup> Average TFP is calculated using simple weights (each firm has 1 over number of firms share).

<sup>2</sup> Aggregate TFP is calculated using labor shares as weights.

Figure 12 plots TFP distributions based on OLS estimator and value added as a dependent variable. TFP distribution shifts over time, very much like the shifts observed for labor productivity. Such shifts in aggregate TFP are also found for TFP estimates obtained by alternative methods.

**Figure 12: Evolution of total factor productivity, 1994-2003**



Source: Author's calculations.

Notes: These TFP distributions are based on estimates of TFP by OLS with value added as a dependent variable and full sample of active firms.

We turn, now, to the decomposition of aggregate TFP growth. When we discussed labor productivity, we saw that actual results of decompositions may depend on the method of decomposition, the choice of weights, the length of time span and the period under consideration. The results of TFP decomposition depend, in addition to these, also on the choice of TFP estimator. From discussion so far, it is clear which is our preferred choice of TFP estimator. However, we need to be sure that the main qualitative features are robust to this choice. Therefore, we show in Table 24 the results of FHK decomposition using 3 and 9 year time periods, labor weights and three different TFP estimators. This table allows us to draw several conclusions that complement the evidence on labor productivity dynamics.

First of all, note that the growth rates of TFP growth are declining over time, which explains the declining rates in labor productivity shown in Table 16 and is also consistent with findings of de Loecker and Konings (2003) for Slovenian manufacturing data between 1994-2001 and using OP estimator of TFP. Further, we find that the contribution of within firm growth is again relatively large both for three and nine year time span. Over the period 1994-2003, at least 45 percent of aggregate growth is generated within firms. Since we use labor weights, the results for reallocation terms in Table 24 should also be quite similar to those in top panel of Table 16. This is, however, not the case, which suggests that capital intensity also plays some role in determination of relative importance of different components of aggregate labor productivity growth. The main differences are in the shares of different reallocation components, net entry and covariance effects. The net entry suggests that entering firms are relatively more productive than initial aggregate productivity, while exiting firms have less than average TFP. Further, cross term is much smaller, which implies that shifts in labor share are less negatively correlated to shifts in TFP than with labor productivity. A sensible interpretation of this is that large firms that were downsizing in terms of labor (but not capital) were also increasing labor productivity largely through capital deepening and not through TFP. The contribution of net entry over the entire period (1994-2003) is at least 30 percent, depending on the choice of TFP estimator, which is much higher than that obtained by FHK for U.S. (26 percent).

The results of FHK decompositions of TFP growth provided by de Locker and Konings (2003) for Slovenian manufacturing firms active in the period 1994-2001 are not directly comparable to our results as they use OP estimator for TFP estimation and provide only one year decompositions. However, we can nevertheless compare the qualitative features of results. Their results ascribe unrealistically large contribution to entering and exiting firms, while between component is negative, the opposite of what we find. Why this is the case is not clear as there are several differences in our estimations. They use PPI as deflator for nominal capital, make OP decomposition and use much shorter time span. But, the fact that our results are not very different from those obtained in studies for other countries makes us quite confident.

**Table 24: FHK decompositions for TFP growth, 1994-2003**

Dependent variable: Sales; TFP estimator: OLS						
	Cumulative change	Within	Between	Cross	Exit	Entry
1994-1997	0.06	0.72	0.33	-0.29	0.11	0.13
1997-2000	0.05	0.55	0.24	-0.04	0.15	0.08
2000-2003	0.04	0.50	0.34	-0.20	0.07	0.26
1994-2003	0.15	0.45	0.14	-0.05	0.08	0.36
Dependent variable: Value added; TFP estimator: OLS						
	Cumulative change	Within	Between	Cross	Exit	Entry
1994-1997	0.31	0.69	0.22	-0.13	0.10	0.11
1997-2000	0.18	0.58	0.19	0.004	0.19	0.04
2000-2003	0.14	0.48	0.26	-0.02	0.14	0.13
1994-2003	0.63	0.49	0.14	-0.03	0.07	0.33
Dependent variable: Value added; TFP estimator: LP						
	Cumulative change	Within	Between	Cross	Exit	Entry
1994-1997	0.26	0.70	0.07	0.09	0.14	-0.01
1997-2000	0.15	0.56	-0.06	0.21	0.35	-0.06
2000-2003	0.13	0.38	0.15	0.18	0.35	-0.13
1994-2003	0.55	0.47	-0.004	0.16	0.13	0.20

Source: Author's own calculations.

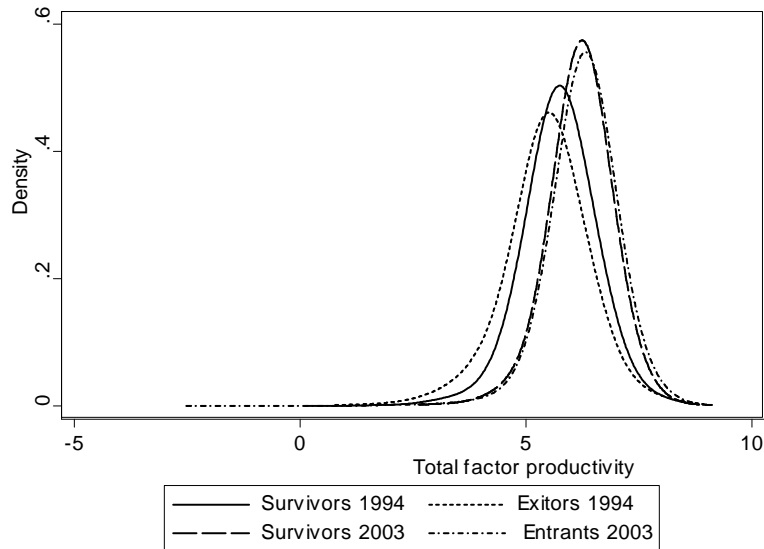
Notes: <sup>1</sup> Absolute change in TFP.

<sup>2</sup> Share in change of TFP in parentheses.

<sup>3</sup> The weights used in decompositions are labor shares.

In order to complement the evidence given in Figures 7 and 8, we show in Figures 13 and 14 TFP distributions for different types of firms. In particular, Figure 13 contains TFP distributions for surviving, entering and exiting firms. Again, we can see that exiting firms were less productive in terms of TFP in 1994, while entering firms were just as productive (if not more) as surviving firms. This evidence confirms the fact that entering firms are mainly less intensive in capital, while just as productive in terms of TFP.

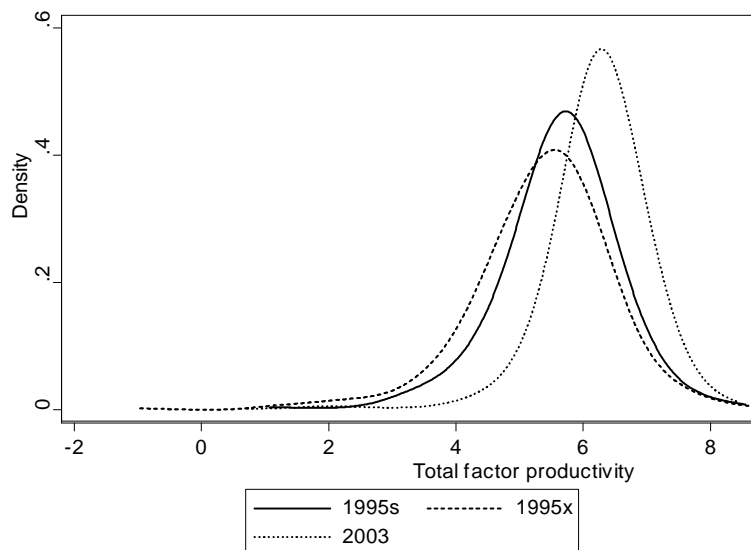
**Figure 13: TFP distributions for different types of firms**



Source: Author's calculations.

Figure 14 shows compares TFP distributions for cohort of 1995 entrants over time and between surviving and exiting entrants. Clearly, surviving entrants (denoted 1995s) were in 1995 more productive than exiting entrants (denoted 1995x). This is again an indication that initial productivity matters for subsequent growth, although the main change came from subsequent TFP improvements and not selection. This finding is consistent with both Jovanovic (1982) and Ericson and Pakes (1995) models, although note that size distributions show no advantage for initially more productive (and thus more likely to be surviving) firms, which contrasts Jovanovic's idea of passive learning.

Figure 14: TFP distributions for cohort of 1995 entrants



Source: Author's calculations.

So far, we have shown that the dynamics of firms with different size exhibit quite different dynamics during transition and have different relative contributions to aggregate labor productivity growth. Therefore, we should expect that FHK decompositions of TFP growth disaggregated with respect to size of firms should provide better understanding of aggregate productivity growth. In Table 25, we show these decompositions for three different subperiods and the entire period of available data. The results confirm our conjecture that within effect in large firms is the largest component in these decompositions, irrespective of the time period under consideration. In fact, the relative contributions to aggregate growth are again ranked with size of firms. The data reveal little systematic time variation. We can see that within component has a decreasing importance over time, mainly related to decreasing shares of medium and large firms. This is partly related to disappearance of a negative cross effect over time. While in the early transition process, simultaneous labor decline (downsizing) and an increase in TFP generated a large negative covariance term, this has changed already in the second subperiod. The between effect for small firms has also declined over time, which can be interpreted as increasing employment share in these more productive firms. The contribution of net entry is increasing over time, although consistent patterns cannot be traced in the data.

**Table 25: Size and FHK decomposition for TFP growth**

1994-1997						
	Total	Within	Between	Cross	Exit	Entry
Micro	0.07	0.02	0.02	0.00	0.00	0.02
Small	0.11	0.02	0.09	-0.04	0.01	0.03
Medium	0.28	0.16	0.03	-0.02	0.04	0.07
Large	0.54	0.50	0.08	-0.08	0.05	-0.01
Total	1.00	0.70	0.22	-0.13	0.10	0.11
1997-2000						
	Total	Within	Between	Cross	Exit	Entry
Micro	0.07	0.02	0.06	-0.03	0.01	0.01
Small	0.09	0.03	0.03	0.02	0.01	0.01
Medium	0.20	0.11	0.04	0.00	0.06	0.00
Large	0.64	0.42	0.06	0.01	0.12	0.02
Total	1.00	0.58	0.19	0.00	0.19	0.04
2000-2003						
	Total	Within	Between	Cross	Exit	Entry
Micro	0.07	0.01	0.02	-0.01	0.01	0.03
Small	0.10	0.03	0.04	-0.02	0.01	0.05
Medium	0.30	0.11	0.08	0.01	0.11	0.01
Large	0.52	0.33	0.13	0.00	0.01	0.04
Total	1.00	0.48	0.26	-0.02	0.14	0.13
1994-2003						
	Total	Within	Between	Cross	Exit	Entry
Micro	0.08	0.01	0.02	0.01	0.00	0.04
Small	0.14	0.01	0.07	-0.02	0.00	0.07
Medium	0.28	0.12	0.01	0.01	0.04	0.10
Large	0.50	0.35	0.04	-0.04	0.04	0.12
Total	1.00	0.49	0.14	-0.03	0.07	0.33

Source: Author's calculations.

Notes: The TFP is estimated by OLS and value added as a dependent variable. Labor weights are used in decompositions.

As argued above, the pattern of productivity convergence may be partly responsible for aggregate labor productivity growth. Here we show that TFP growth in firms that were initially lagging behind caught up and thus made the largest contribution to aggregate labor productivity growth. Table 26 contains the results of FHK decomposition for TFP using both labor and output weights. In order to be able to give an indication of convergence, we again classify firms in several TFP classes. Note that 37 percent of aggregate TFP growth is generated in firms that moved from a productivity class 4-6 to 6-8, which are firms that were lagging behind. This finding is also robust to choice of weights. However, since results in Table 26 are only indicative of the relative importance of growth of productivity of firms that are initially lagging behind in TFP, the real test of this is provided in Table 27, where we also control for survival or self-selection bias.

**Table 26: FHK decomposition for TFP growth and shifts in productivity classes, 1994-2003**

		Labor (output) weights			
2003 \ 1994	Effect	<2	2-4	4-6	6-8
2-4	Within	-	-	-0.01 (-0.01)	-
	Between	-	-	-	-
	Cross	-	-	0.01 (0.01)	-
4-6	Within	-	0.01 (0.00)	<b>0.05 (0.02)</b>	-0.01 (-0.02)
	Between	-	0.00 (0.00)	<b>0.01 (0.00)</b>	0.01 (-0.01)
	Cross	-	0.00 (0.00)	-	-0.01 (0.01)
6-8	Within	0.01 (0.00)	0.01 (0.00)	0.37 (0.37)	<b>0.06 (0.10)</b>
	Between	0.00 (0.00)	0.00 (0.00)	0.00 (-0.02)	<b>0.10 (0.08)</b>
	Cross	0.00 (0.00)	0.00 (0.00)	0.00 (0.12)	<b>-0.02 (0.01)</b>

Source: Author's calculations.

- Notes: i) The contribution to aggregate growth calculated labor (output) weights.  
ii) The TFP is estimated by OLS and value added as a dependent variable. Labor weights are used in decompositions.

The system of equations that is estimated and shown in Table 27 is very similar to that in equations (2) and (3). The only difference is that instead of size equation, we have TFP equation

$$\begin{aligned} \ln TFP_{it} &= \delta_0 + \delta_1 \ln TFP_{it-\tau} + \delta_2 \ln S_{it} + \delta_3 TimeD + \delta_4 SecD + \varepsilon_{it}, \\ \Pr(Survival_{it} = 1) &= \theta_0 + \theta_1 \ln TFP_{it-\tau} + \theta_2 \ln S_{it} + \theta_3 TimeD + \theta_4 SecD + \xi_{it}, \end{aligned} \quad (13)$$

where  $\delta$ 's are regression coefficient for TFP equation and  $\theta$  are coefficients in survival equation. The estimation procedure is again Heckman's maximum likelihood estimation. The most important finding is that while initial TFP is positively related to end of period TFP, an indication of persistence of TFP differences, these differences are smaller. In particular, a coefficient for initial TFP with value 0.22 as found in columns (1) and (2), implies that growth of TFP is negatively related to initial TFP levels. Given that we correct for survival bias, this can be interpreted as catch up of firms that were technologically lagging behind. The respective coefficients in columns (3)-(6), where we show estimates for subsequent periods, we find that the speed of convergence has been declining. In conclusion, firms that were initially less productive were indeed more likely to exit. However, even after correcting for this survival bias, we still find that more productive firms grow at lower growth rates.

**Table 27: Relationship between growth of TFP, size and initial TFP**

Equation	Period					
	1994-1997		1997-2000		2000-2003	
$TFP_{it}$	(1)	(2)	(3)	(4)	(5)	(6)
$\ln S_{it}$	-0.029 (-5.01)	0.059 (1.52)	-0.016 (-3.04)	0.15 (4.87)	0.002 (0.47)	0.13 (4.0)
$(\ln S_{it})^2$	-	-0.034 (-2.41)	-	-0.05 (-4.96)	-	-0.04 (-3.9)
$(\ln S_{it})^3$	-	.0032 (2.39)	-	0.004 (4.59)	-	0.003 (3.5)
$TFP_{it-3}$	0.22 (9.93)	0.22 (10.2)	0.35 (15.7)	0.44 (20.7)	0.473 (20.3)	0.47 (20.1)
Time Dum	Yes	Yes	Yes	Yes	Yes	Yes
Sec. Dum	Yes	Yes	Yes	Yes	Yes	Yes
<i>Cons</i>	4.70 (35.5)	4.62 (35.6)	3.90 (27.9)	3.14 (23.7)	2.98 (20.7)	2.95 (20.5)
Survival						
$\ln S_{it}$	-0.026 (-1.73)	0.13 (1.31)	0.02 (1.37)	0.54 (6.8)	0.169 (11.7)	0.62 (8.3)
$(\ln S_{it})^2$	-	-0.084 (-1.95)	-	-0.20 (-5.7)	-	-0.18 (-5.3)
$(\ln S_{it})^3$	-	0.010 (2.06)	-	0.02 (5.1)	-	0.02 (4.4)
$TFP$	0.215 (5.93)	0.205 (5.60)	0.258 (7.69)	0.36 (10.1)	0.35 (10.3)	0.33 (9.8)
Time Dum.	Yes	Yes	Yes	Yes	Yes	Yes
Sec. Dum.	Yes	Yes	Yes	Yes	Yes	Yes
<i>Cons</i>	-0.0001 (-0.00)	0.06 (0.24)	-0.58 (-2.73)	-1.38 (-6.3)	-1.78 (-8.61)	-1.87 (-8.9)
$\rho(s.e.)$	-0.756	-0.755	-0.789	0.09	0.07	0.07
$\chi^2(1)$	57.5 (0.00)	55.5 (0.00)	174.7 (0.00)	33.9 (0.00)	18.2 (0.00)	18.3 (0.00)
Log $L$	-3607.9	-3598.7	-4622.8	-4626.5	-4541.6	-4512.9
N	3166	3166	4200	4200	4332	4332

Source: Author's calculations.

Notes: i) Dummies for 2 digit NACE sectors included in both equations.

Asterisk denotes 5 percent significance level.

The standard errors of estimates are heteroskedasticity robust, based on Huber-White estimator of variance.

## 5 Concluding remarks

The motivation for this paper was to compile a set of stylized facts that would provide guidance in building theoretical models of industrial dynamics during transition. Understanding of what was happening in manufacturing sector of one of the transition countries allows us to summarize the basic elements that

any model should have. First, the model should feature heterogeneity of firms, both in terms of size, labor and total factor productivity. Initially, FSD and FPD should be negatively related, while by the end of transition positive relationship should be restored. Second, the model should contain constraints on growth of small firms in order to generate observed persistence in size. A realistic approach to this is introduction of two production factors, labor and capital. While labor can be free of adjustment costs, we should have firm specific capital. This firm specific capital prevents also labor to flow from less to more productive firms. The speed of reallocation can be further reduced by assumption of financing constraints, which is consistent with empirical evidence for Slovenia (Konings and Xavier, 2003). Third, the model should feature entry and exit process, where entering firms are on average smaller and less productive. Surviving entrants should be more productive than those that exit. Furthermore, exiting firms should also be on average smaller and less productive. Fourth, dynamics of TFP should exhibit productivity convergence, which in the simplest form can be specified as stochastic autoregressive process with less than perfect persistence in productivity. This mechanism would generate faster growth rates in TFP in large initially less productive firms. In conclusion, any dynamic general equilibrium model that contains these four elements should be able to replicate the qualitative features of industrial dynamics during the process of transition.

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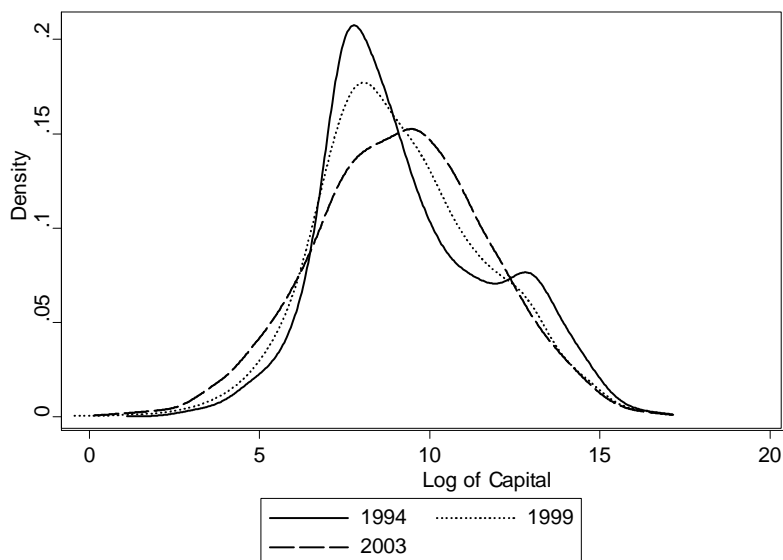


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# Appendix

## Appendix A

**Figure A1: Evolution of capital distribution**



**Table A1: Evolution of firm size distribution**

Class\Year	1994	1997	2000	2003
1	26.5 (0.39)	24.2 (0.49)	21.8 (0.48)	17.0 (0.40)
2	13.5 (0.40)	14.4 (0.58)	13.4 (0.59)	13.2 (0.60)
3	6.78 (0.30)	8.79 (0.53)	9.13 (0.61)	9.56 (0.65)
4	4.93 (0.29)	5.60 (0.45)	6.63 (0.58)	6.69 (0.61)
5	3.59 (0.27)	4.22 (0.43)	4.59 (0.51)	3.54 (0.40)
7	5.20 (0.50)	5.53 (0.72)	5.58 (0.82)	6.90 (0.98)
9	3.04 (0.38)	3.54 (0.61)	4.00 (0.74)	4.67 (0.88)
12	2.89 (0.46)	4.18 (0.93)	4.45 (1.07)	5.90 (1.42)
15	1.89 (0.40)	2.16 (0.61)	2.81 (0.87)	3.05 (0.94)
20	2.65 (0.72)	3.31 (1.21)	3.49 (1.38)	3.34 (1.35)
24	1.37 (0.45)	1.52 (0.69)	1.62 (0.81)	2.36 (1.18)
29	1.50 (0.60)	1.89 (1.03)	2.02 (1.20)	2.31 (1.39)
35	1.43 (0.69)	1.72 (1.12)	1.85 (1.37)	2.17 (1.58)
49	3.01 (1.89)	2.30 (1.97)	2.43 (2.70)	3.88 (3.76)
99	6.36 (6.89)	5.65 (8.37)	5.62 (8.99)	6.15 (9.92)
249	8.67 (20.2)	6.45 (20.5)	6.07 (21.4)	5.53 (19.7)
499	3.95 (20.7)	2.78 (20.1)	2.43 (18.8)	2.38 (18.8)
999	1.82 (17.8)	1.10 (15.3)	1.06 (16.3)	0.96 (16.4)
1000+	1.0 (26.6)	0.65 (24.2)	0.52 (20.8)	0.43 (19.0)

Source: Author's own calculations.

Notes: i) The numbers given are shares of firms in total number of firms and shares of employees in aggregate manufacturing employment for active firms (in parentheses).

ii) The size classes are defined by upper size class.

## Appendix B: Transition matrices

The process of shifts in size distribution is regarded as a stochastic Markov process, which implies only dependence of probability of shift to a given class on size class one period earlier. Note that this approach is only consistent with some models of industrial dynamics, such as that of Ericson and Pakes (1995) where technology that determines the size of firms is assumed to follow a first order Markov process. In a model developed by Jovanovic (1982) size in a given year depends on productivity levels (and thus size) observed in the entire history of a firm. Thus, first order Markov process is not a realistic description if their model is the most adequate description of the data. However, Ericson and Pakes (1998) show that size in manufacturing is not dependent on size in the entry period, which is a proof that Ericson and Pakes (1995) model may be more adequate.

The size distribution (or productivity) in a given period, say  $t$ , is denoted with  $S^t$ , where the elements of  $S^t$  are the shares of firms in different size classes. That is,  $S^t = \{s_1^t, s_2^t, \dots, s_{n+1}^t\}$ , where  $s_j^t$  denotes a share of number of firms in the size class  $j$ . In order to allow for entry and exit, the "reservoir" state  $s_{n+1}^t$  denotes the share of firms that either exit or enter. Unless the share of firms that enter and exit are the same, which usually is not the case, we can write two different vectors  $S^t$ , one containing the share of new firms and one containing the share of firms that exit. Naturally, the shares in different classes form a unit simplex, which is implied by  $\sum_j s_j^t = 1$ .

The evolution of FSD (or productivity distribution) over time can be described by the following process

$$S_x^{t+1} = P S_e^t, \quad (14)$$

where  $P$  denotes the square stochastic transition matrix, elements of which are transition probabilities or relative frequencies,  $p_{ij}$ , which denote the share of firms that are in size class  $i$  and move to size class  $j$  between periods  $t$  and  $t + 1$ . This transition probability is calculated as a ratio between number of firms that moved from class  $i$  to class  $j$  and total number of firms in class  $i$  in period  $t$ . Note that these ratio can be interpreted as transition probabilities estimated by unrestricted maximum likelihood estimators<sup>19</sup>. Also, given our definition, the column sum of transition probabilities is always equal to 1, that is  $\sum_i p_{ij}$ ,

thereby satisfying the condition for a Markov or stochastic matrix. The structure of (14) can be written as follows

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1e} \\ p_{21} & p_{22} & \cdots & p_{2e} \\ \vdots & \vdots & \ddots & \vdots \\ p_{x1} & p_{x2} & \cdots & 0 \end{bmatrix}, S_x^{t+1} = \begin{bmatrix} s_1^{t+1} \\ s_2^{t+1} \\ \vdots \\ s_x^{t+1} \end{bmatrix}, S_e^t = \begin{bmatrix} s_1^t \\ s_2^t \\ \vdots \\ s_e^t \end{bmatrix}$$

where  $p_{ij}$ , where  $i$  and  $j$  are less or equal to  $n$  (in our case equal to 4 or 20), are transition probabilities for surviving firms.  $p_{ie}$  are shares or probabilities that firms entering between periods  $t$  and  $t + 1$  fall in size class  $i$ , while  $p_{xj}$  are shares or probabilities that firms in size class  $j$  exit between periods  $t$  and  $t + 1$ . The matrix  $S_e^t$  denotes the shares of firms in period  $t$ , where the last element denoted with  $s_e^t$  corresponds to share of entering firms in firms active in period  $t$  and entering firms between  $t$  and  $t + 1$ . Similarly,  $S_x^{t+1}$  denotes share of firms in different size classes in period  $t + 1$  and  $s_x^{t+1}$  denotes the share of firms that exit between  $t$  and  $t + 1$  in total number of firms active at the end of the period and number of firms that

<sup>19</sup>Following Amemiya (1986), we can write the likelihood function of the first-order time invariant Markov model conditional on the initial distribution as

$$L = \prod_i \prod_j p_{ij}^{m_{ij}},$$

where  $m_{ij}$  is total number of firms moving between classes  $i$  and  $j$ . Maximizing the log of this likelihood function given a set of constraints  $\sum_i p_{ij} = 1, j = 1, 2, \dots, n + 1$ , we can write Lagrangian for this maximization problem

$$S = \sum_i \sum_j m_{ij} \log p_{ij} - \sum_j \lambda_j (\sum_i p_{ij} - 1).$$

The first order conditions are

$$m_{ij} = \lambda_j p_{ij}.$$

Summing both sides over  $i$  and using constraints, we obtain

$$\hat{p}_{ij} = \frac{n_{ij}}{\sum_i n_{ij}}.$$

exit. Note that shares of active firms in different classes in Table 3 were presented without distinction between surviving and exiting and entering firms. However, in order to fully characterize the transition probabilities, this is the only way to represent the data. If entry rates were equal to exit rates, we could simplify notation, so that  $S_x = S_e = S$ . However, the data in Table 1 show that entry rates exceeded exit rates for most of the transition period, while the differences were declining until 2001.

The likelihood ratio test for time homogeneity or stationarity of transition matrices follows the exposition of Anderson and Goodman (1957):

$$LR = -2 \log \prod_i \prod_j \left( \frac{p_{ij}}{p_{ij}^*} \right)^{m_{ij}} \sim \chi_{(n+1)n}^2,$$

where  $m_{ij}$  denotes the number of firms that transit between size classes  $i$  and  $j$  and  $p_{ij}^*$  denotes the benchmark transition probabilities. The benchmark transition probabilities may be theoretical or some sort of average of empirical transition matrices. The number of degrees of freedom for this  $\chi^2$  distribution is  $(n+1)n$ , where  $n+1$  is the number of size classes, in our case equal to 5 with respective degrees of freedom equal to 20.