LICOS
Centre for Transition Economics

LICOS Discussion Papers

Discussion Paper 138/2003

Creative Destruction and Productivity Growth in an Emerging Economy

Evidence from Slovenian Manufacturing

Jan De Loecker
Jozef Konings

Katholieke Universiteit Leuven

LICOS Centre for Transition Economics
Huis De Dorlodot
Deberiotstraat 34
B-3000 Leuven
BELGIUM
TEL:+32-(0)16 32 65 98
FAX:+32-(0)16 32 65 99
http://www.econ.kuleuven.ac.be/licos

Creative Destruction and Productivity Growth in an Emerging Economy

Evidence from Slovenian Manufacturing

By Jan De Loecker[a,b] and Jozef Konings[a,c]

[a]:Economics Department, Katholieke Universiteit Leuven and LICOS,

Katholieke Universiteit Leuven

[b]: Economics Department, Harvard University

[c]: CEPR, London; IZA, Bonn; WDI, Michigan

December 2003

Acknowledgements:

This paper benefited from presntations at the conference on the Political Economy of Job Creation and Job Desctruction at the ZEI, University of Bonn.We thank John Jackson, Jan Fidrmuc and Mark Schaffer for useful comments.

Abstract

In most transition countries the aggregate level evidence suggests that most industries are just destroying jobs, due to the legacy of communism where over-manning levels of employment were the norm. This paper sheds light on whether the transition process in Slovenian manufacturing has been one of just destruction or in contrast one of creative destruction. To this end we start by documenting gross job flows for the Slovenian manufacturing sector between 1994 and 2000. In contrast to slowly reforming transition economies where the transition process in manufacturing is characterized by little job creation and high job destruction, we find for Slovenian manufacturing a process of both substantial job creation and destruction. This indicates that restructuring in Slovenia involves a substantial reallocation process. We find higher job reallocation in private and small firms where the contribution of entry and exit to the job reallocation process is higher.

We further use the Olley-Pakes methodology to estimate total factor productivity (TFP) and show that TFP has increased in most sectors. We find that this is mainly driven by existing firms becoming more efficient and by the net entry process, i.e. more efficient firms enter the industry.

JEL classification: L60, D21, P20

Key words: creative destruction, total factor productivity, reallocation

1. Introduction

The presence of high labor market turbulence in both market and non-market economies has been documented many times by now[1]. Gross flows of jobs, relative to net flows, are high, persistent, fluctuate over the business cycle and vary between countries (e.g. Goos, 2003). Simultaneous job creation and destruction takes place even within narrowly defined sectors, regions and firm types, which indicates a high degree of firm heterogeneity.

While documenting and comparing job flows for various countries has been fruitful and complementary to the figures provided in aggregate data, we are still left with the question whether high gross flows of jobs are generally a good thing. In most transition countries the aggregate level evidence suggests that most industries are just destroying jobs, due to the legacy of communism where over-manning levels of employment were the norm. A pessimistic interpretation of this aggregate pattern is that most of the manufacturing industries in Central and Eastern Europe cannot compete on world markets, after the collapse of communism and the opening of trade to the rest of the world and hence job destruction reflects declining industries, also in terms of productivity. However, a positive interpretation would be that the aggregate collapse in employment hides a process of creative destruction. Such a process would involve substantial gross job reallocation, where we would observe a decline of unproductive jobs and at the same time an increase of new productive jobs.

The present paper is concerned with tackling these two alternative interpretations. We first document gross job flows for Slovenian manufacturing. In contrast to slowly reforming transition economies where the transition process in manufacturing is characterized by little job creation and high job destruction, we find for Slovenian manufacturing a process of simultaneous job creation and job destruction, which indicates that restructuring in Slovenia involves a substantial reallocation process. Second, we estimate total factor productivity (TFP) using a new method to estimate production functions, due to Olley and Pakes (1996), to document the evolution of productivity and to analyze the importance of reallocation in TFP in Slovenian manufacturing. Thus the question we focus on is whether the restructuring process in Slovenia has been one in which the old manufacturing sector has been just destroyed or whether there has been a process of creative destruction in which the job reallocation process that took place reflects an increase in TFP.

Slovenia is a particularly interesting emerging economy to study as it has been one of the most successful transition countries in the region, reaching a level of GDP per capita which is over 65% of the EU average by the year 2000. Slovenia is a small open economy, most of its trade is with the EU and Croatia. Between 1994 and 2000, the sample period that we study, GDP has been growing at an annual rate of more than 3.5% in real terms. Slovenia is part of the first wave of countries joining the EU in 2004.

The paper is organized as follows. In the next section we introduce the data set and document the basic patterns of gross job flows for the Slovenian manufacturing sector between 1994 and 2000. In section 3 we follow Olley and Pakes (1996) to estimate total factor productivity (TFP), a methodology that allows us to deal with the simultaneity problem and explicitly controlling for selection in estimating TFP. We then decompose TFP to illustrate the importance of net entry and reallocation in explaining TFP growth. In section 4 we conclude.

---

[1] For market economies see Davis, Haltiwanger and Shuh (1996), for emerging markets see e.g.

2. Data and Basic Patterns of Gross Job Flows in Slovenian Manufacturing

2.1.Data

The data that we use are the company accounts of firms operating in manufacturing that we obtained from the Slovenian Central Statistical Office[2]. We have information on 7915 firms between the years 1994 and 2000. However, if we only take into account those firms that report employment, we end up with a sample of 6,391 firms. We have 45% of all firms that are active in export markets, while 54% operate only in the domestic market. Within the sample period we observe entry and exit of firms. In table 1 we show entry and exit patterns over time in Slovenian manufacturing. Over the sample period we have an annual average exit rate of 3.21%, which is comparable to exit rates found in other developing regions. For instance, Clerides, Lach and Tybout (1998) report annual average exit rates for Colombia of 1.7%, for Morocco of 3.7% and for Mexico of 1.5%. The entry rate in our sample is much higher, on average 5.56% per year. This compares to entry rates of 2.7%, 4.9% and 4.8% reported for Colombia, Morocco and Mexico respectively.

The higher entry rates in the Slovenian economy are not that surprising taking into account that the entry of new firms was an important component of the restructuring and the transition process. Under communism entry of new firms was virtually non-existent. With the transition to a market economy also the entry of new enterprises was encouraged and have potentially played an important role in the transition process (e.g. Bilsen and Konings, 1999).

Konings, Lehmann and Schaffer (1996); Brown and Earle (2003); Faggio and Konings (2003).

[2] Representativeness of the dataset is in Appendix A.

In table 2 we present some summary statistics of the main variables used throughout the analysis. We report real sales, real value added, size as measured by employment, capital stock per worker, average wage and real value added per worker (labor productivity). We used a two-digit producer price index to deflate our variables. From table 2 we can see that the size of firms is declining over time and is close to the average size of manufacturing firms in Western economies (see e.g. Hutchinson, 2003). Both real sales, value added and wages went up over the sample period, which suggests that average productivity of Slovenian manufacturing firms increased, a pattern which is consistent with aggregate official statistics and which is one we would expect of an economy that is undergoing successful restructuring.

2.2.Basic Patterns of Gross Flows

We measure gross job flows in the standard way, following Davis and Haltiwanger (1996). We measure job creation (*pos)* as the sum of all employment gains in expanding firms in a given year,t, divided by the average of employment in periods t and t-1. Likewise we define job destruction (*neg*) as the sum of all employment losses in contracting firms in a given year divided by average employment. The sum of these two gives a measure for gross job reallocation (*gross)* and the difference yields the net employment growth rate *(net)*. If we take the difference between the gross job reallocation rate and the absolute value of the net employment growth rate (*gross* -|*net*|), we get a measure for excess job reallocation (*excess*). Such a measure tells us how much job churning is taking place after having accounted for the job reallocation that is needed to accommodate a given aggregate employment growth rate. This measure can be considered as a better measure of the real churning that is going on in a labor market.

Tables 3-10 document some basic facts about gross flows of jobs in Slovenian manufacturing between 1994 and 2000. In table 3 we show the evolution of gross job flows over time, while table 4 reports the corresponding annual averages. From table 4 we can note that on average job destruction slightly dominates job creation over the sample period. A job reallocation rate of 13% on average is comparable to other European market economies such as Belgium, but it is lower than the job flow rates reported for the US and Canada. Also the excess job reallocation is substantial (11% on average), which indicates that the transition process is not just one in which only job destruction takes place, but rather one in which simultaneous high job creation and destruction occurs[3]. From the last two columns in table 4 we can see that the job flow rates that are accounted for by entry and exit of firms are quite substantial: on average 23% of all job creation is accounted for by entry of firms, while 12% of all job destruction is accounted for by exit of firms. Compared to market economies the contribution of entry and exit to these job flows is relatively low. In market economies, typically around 30% of all job creation and job destruction can be accounted for by entry and exit of firms. This lower proportion of the contribution of entry and exit of firms may reflect the fact that we are dealing with underdeveloped and emerging markets, in which state ownership is still important.

Tables 5-10 slice the data in different sub-sets to highlight the heterogeneity of firms in terms of gross job flows in Slovenian manufacturing. We focus on those aspects that seem to be relevant for transition economies, in particular, we look at the difference between private versus non-private firms, exporters versus non-exporters and the difference between various size classes of firms. In table 5 we show the evolution of job flows in private versus state firms, while table 6 reports these flows in terms of annual averages. We can note that job creation is concentrated in the private firms, with a job creation rate of 16% on average, while only 4% for state firms. In contrast, the job destruction rates in the private and state firms are almost the same (6% versus 7%), which results in private firms being net job creators, while state firms being net job destroyers. This is a pattern we would expect in an emerging economy, downsizing the state sector. We can also note that the role of entry and exit is far more important in the private sector than the state sector, which suggests that market forces seem to work better in the private sector than in the state sector. This could also suggest that creative destruction is more important in the private sector than in the state sector. In the private sector the contribution to job destruction accounted for by firm exit is 23%, while this is only 10% in the state sector. The contribution of entry to job creation in the private sector is almost 30%, a figure very comparable to the figures found in market economies. In the state sector this is only 23%. Thus if a process of creative destruction exists where new and more efficient firms push out old and inefficient firms we could expect a more important role of entry and exit in the private sector where restructuring is more likely to take place.

While the privatization of state owned enterprises was an important component of the transition process, a much less studied aspect of the transition process was the very drastic trade reorientation that experienced most of the Central and East European Countries. While before the transition only about 30-40% of all exports went to the EU shortly after the transition this figure jumped to 70% or more and especially so in Slovenia. One reason is the collapse of the CMEA trading system, but

---

[3] This is consistent with the findings of Haltiwanger and Vodopivec (2003) who documented job and

another reason was the potential growth for export markets in the EU. In our data we have firm level information on exports, which allows us to make a distinction between exporting firms and non-exporting firms. A number of authors have pointed out the importance of exports in explaining firm performance. Bernard and Jensen (1999), Clerides et al (1998) show that the more productive firms become exporters. De Loecker and Konings (2003) show that while controlling for such a self-selection process exporting firms in Slovenia become more productive after starting to export. The latter is the so-called learning by exporting hypothesis. We do not intend to address this issue here in detail, rather we want to analyze whether there exists a difference in terms of gross job flows between exporting firms and non-exporting firms. This is done in tables 7 and 8. We can note that on average the gross job flow rates for exporting firms are much lower than those for non-exporting firms. However, the job destruction rate in non-exporting firms is much larger than the job creation rate. In contrast, for exporting firms we find that the job creation rate is about the same to the job destruction rate on average. This suggests that exporting firms provide more stable jobs than non-exporting firms. Non-exporters are downsizing substantially, with a net job destruction rate of -7%. Part of this is likely to be explained by the fact that the average firm size of non-exporting firms is smaller than the average firm size of exporting firms. When we look at the average gross job flow rates according to firm size in table 9 we can note that there exists an inverse relationship between gross job flows and firm size, a pattern also reported for market economies.

Finally, in table 10 we document how job flows vary between different two digit sectors and again we can note one of the stylized facts of job flows, namely that

---

worker flows for Slovenia.

even within narrowly defined sectors we can observe high job creation and destruction rates.

The basic patterns of gross job flows suggest that the transition process is a heterogeneous one, where simultaneous expansion and contraction of firms takes place, even within narrowly defined sectors. Based on evidence from aggregate statistics we would be inclined to believe that manufacturing is just declining in Slovenia. However, the aggregate evidence hides the high turbulence of jobs in Slovenian manufacturing, which may suggest a process of creative destruction, especially so if we observe that the small and private firms seem to have the highest reallocation rates. In the next section we want to go a step further and try to assess whether over this period firms have become more efficient. If a process of creative destruction is taking place we would expect that although many jobs are disappearing, new and better (more productive) jobs are created, replacing these old ones. In terms of firms it means that even as exit takes place, there is simultaneous entry of new and more efficient firms. Some of these patterns seem to be suggested by the data on job creation and destruction. If the transition process is indeed characterized by creative destruction we would expect to find increased total factor productivity in most manufacturing sectors characterized by high job reallocation.

3. **The Evolution of Total Factor Productivity**

3.1.Measuring total factor productivity

Unlike job creation and destruction or firm entry and exit, productivity is not directly observable. However, to assess whether the transition process is one of creative destruction it seems to be imperative to have a reliable measure of total factor productivity (TFP). The traditional method is to compute value added per worker. While this has a number of advantages, most of all its simplicity, it has a number of major disadvantages. In the presence of other input factors, labor productivity may be a misleading measure. It strongly biases one towards finding a trade-off between productivity changes and employment changes. Holding output constant the only way to increase productivity is to lay off workers. With more precise measures of productivity it may be possible to have both increases in productivity and jobs. This suggests that we should compute TFP from estimating a production function. However, the problem with estimating a production function using OLS is that firms that have a large productivity shock may respond by using more inputs, which would yield biased estimates of the input coefficients and hence biased measures of TFP.

Recently a new method to estimate TFP has been proposed by Olley and Pakes (1996), which is the one that we will pursue here. This method is embedded in the theory of firm dynamics and allows us to estimate TFP in a consistent way, without having to rely on instrumental variables. In particular, the maintained assumption is that firms belong to a given industry all face the same input prices and market structure.[4] The only thing in which firms differ is in their levels of productivity. All firms are subject to uncertain future market conditions. The firm is to maximize its expected value of both current and future profits. Current profits are assumed to be a function of the firm's state variables: capital (k) and productivity (ω). Factor prices are assumed to be common across firms and they evolve according to a first order Markov process. At every period the firm faces three decisions: It has to decide

[4] We can relax this assumption easily and allow for e.g. private firms to face different market structures than state owned firms. However, there are reasons to believe that even state firms have started to behave as profit maximizing firms as soft budget constraints especially in Slovenia have disappeared

whether it continues its operations or not whereby it receives a one-time sell-off value Φ and never reappears again. Conditional on staying in the market the firm has to decide about its inputs labor (l) and investment (i).

The latter determines the capital stock at the beginning of each period. The law of motion for capital is given by $k_{t+1}=(1-\delta)k_t+i_t$ where t denotes the time index and we dropped the firm index. Productivity is assumed to be determined by a family of distributions conditional on the information set at time t J_t. This set includes the past productivity shocks. Given this distribution, both the exit and investment decision will crucially hinge upon the firm's perception of the distribution of future market structure given their current information (past productivity). The decision that the firm takes will in turn generate a distribution for the future market structure. The Bellman equation for the dynamic problem then looks as follows

$$V_t(\omega_t, k_t) = \max\left[\Phi, \sup_{i_t \geq 0} \pi_t(\omega_t, k_t) - c(i_t) + \beta E\left(V_{t+1}(\omega_{t+1}, k_{t+1}) \middle| J_t\right)\right] \tag{1}$$

Where V represents the value function of the firm depending on the state variables capital and the productivity shock. If the firm decides to continue its activities, it maximizes its profits. We have to take into account the cost of investment $c(i)$ and β is the discount factor. The expectation about the future value is based on the current information gathered in J. Ericson and Pakes (1995) show that this dynamic problem gives rise to a Markov Perfect Equilibrium strategy for the firm's decision on investment and whether or not to exit the market. We end up with two equilibrium relationships: the investment decision and the survival decision, represented in equation (2) and (3) respectively.

$$i_t = i_t(\omega_t, k_t) \tag{2}$$

---

and restructuring of state firms in anticipation of privatization has been documented for other transition countries (e.g. Aghion et al. 1994).

$$\chi_t = 1 \quad \text{if } \omega \geq \underline{\omega_t}(k_t) \tag{3}$$

$$= 0 \text{ otherwise}$$

Note that the above equations are only time-dependent as they depend on the market structure and the relevant factor prices.

As in Olley and Pakes (1996) we assume that the industry produces a homogeneous product with Cobb Douglas technology and it is given by

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \eta_{it} \tag{4}$$

where *y, l* and *k* denote the output, labor and capital in logs, respectively. The error term is decomposed into an *i.i.d* component (η) and a productivity shock (ω). Firms are indexed by *i* and the years are indexed by *t*. If one would estimate this equation by means of OLS, the estimates would be biased. To see why, we have to turn back to the theoretical framework. The decision on the number of inputs is depending on whether the firm decides to stay in the market or not. Labor is assumed to be the only variable factor and thus its choice can be affected by the current value of ω. In other words, labor is likely to be correlated positively with the error term and therefore makes the OLS coefficient on labor biased upwards. The underlying reasoning for this is that more productive firms will demand more inputs in order to produce more. Capital is assumed to be a fixed factor and is only affected by the distribution of ω, conditional on information at time *t-1* and thus past values of ω. The coefficient of the capital tends to be underestimated by OLS since firms with higher capital stocks remain in the market even with a lower productivity shock (see below). It also hinges upon the spill over effects from the estimate on labor.[5]

Olley and Pakes (1996) show that we can invert the investment decision given that investment is monotonic increasing in all its arguments. This holds only when investment is nonnegative, this is also shown in the Bellman equation ($i \geq 0$). In terms of the empirical application this would mean that we can only use the firms that report positive investment. This empirical issue led to a modification to the Olley and Pakes (1996) estimation algorithm by Levinsohn and Petrin (2003). They suggest using intermediate inputs such as electricity and fuels instead of investment. The disadvantage of the Levinsohn and Petrin (2003) approach, however, is that it is not embedded in a full dynamic model where investment affects future productivity.

We invert the investment equation and write the productivity shock as a function of capital and investment.

$$\omega_t = h_t(i_t, k_t)$$

We plug this function into equation (4) and we collect the constant and the terms depending on capital and investment in a function $\phi(i,k)$.[6] This results in a partial linear model where the error term is not correlated with the freely chosen labor input.

$$y_{it} = \beta_l l_{it} + \phi_t(i_{it}, k_{it}) + \eta_{it} \tag{5}$$

The above can be estimated using standard semi-parametric estimation techniques following Robinson (1989). We use a series estimator using a full interaction term polynomial in investment and capital. This first stage provides us with a consistent estimator for the freely chosen input, labor in this case. To identify the coefficient on capital we use the survival equation and the results from the first stage (b_l). The probability of staying in the market is given by

---

[5] For more on the potential sign of the bias see Levinsohn and Petrin (2003).

[6] One can adjust this function to be different for different types of firms. De Loecker (2003) allows for this function to be different for firms that have affiliates abroad in order to capture the different market structures faced by those firms. In the context of this paper, one could think to let the function be different for private firms or exporting firms. The latter is pursued by De Loecker and Konings (2003) for Slovenian manufacturing, however, the estimates of the labor and capital coefficients in the production function are very similar, so we stick to the current presentation for brevity.

$$
\begin{aligned}
\Pr\{\chi_{t+1}=1|\underline{\omega}_{t+1}(k_{t+1}),J_t\} &= \Pr\{\omega_{t+1}\geq \underline{\omega_{t+1}}(k_{t+1})|\underline{\omega}_{t+1}(k_{t+1}),\omega_t\} \\
&= \rho_t(|\underline{\omega}_{t+1}(k_{t+1}),\omega_t) \\
&= \rho_t(i_t,k_t) \\
&\equiv P_t
\end{aligned}
$$

The probability that a firm survives at time t+1 given its information set J_t and the future market conditions ω_{t+1} is equal to the probability that the firm's productivity is bigger than some threshold, which in turn depends on the capital stock. This clearly shows that – conditional on past productivity – the probability is decreasing in capital and leads to negative capital coefficient bias when not correcting for the selection process.

The information set at time t+1 consists of the productivity shock at time t. We can thus write the survival probability as a function of investment and the capital stock at time t. Just like the first stage estimation, we estimate a probit equation on a polynomial in investment and capital, controlling for year specific market structures by adding year dummies. Now we consider the expectation of $y_{t+1}-\beta_l l_{t+1}$ conditional on the information at time t and survival at t+1.

$$
\begin{aligned}
E[y_{t+1}-\beta_l l_{t+1}|k_{t+1},\chi_{t+1}=1] &= \beta_0+\beta_k k_{t+1}+E[\omega_{t+1}|\omega_t,\chi_{t+1}=1] \\
&= \beta_0+\beta_k k_{t+1}+g(\underline{\omega_{t+1},\omega_t)}
\end{aligned}
$$

As mentioned above, we assume that productivity follows a first order Markov process, i.e. $\omega_{t+1}=E(\omega_{t+1}|\omega_t)+\xi_{t+1}$ where ξ_{t+1} represents the news in the process and is assumed to be uncorrelated with the productivity shock. We substitute for the productivity shock in the above equation using the results from the first stage. Using the law of motion for the productivity shocks we get the following expression

$$
\begin{aligned}
y_{t+1}-\beta_l l_{t+1} &= \beta_0+\beta_k k_{t+1}+E(\omega_{t+1}|\omega_t,\chi_{t+1}=1)+\xi_{t+1}+\eta_{t+1} \\
&= \beta_k k_{t+1}+g(\underline{\omega}_{t+1},\omega_t)+\xi_{t+1}+\eta_{t+1} \\
&= \beta_k k_{t+1}+g(P_t,\phi_t-\beta_k k_t)+\xi_{t+1}+\eta_{t+1}
\end{aligned}
$$

where we used the result from the survival equation and the constant term disappears. The above clearly explains the need for the first stage of the estimation algorithm. Since the capital used in any given period, is assumed to be known at the beginning of that period and knowing that the news at time t+1 is independent of all variables at time t, it means that the news is uncorrelated with capital ($E\xi k = 0$). However, the news is not uncorrelated with the freely chosen input (labor) and this is exactly why it is subtracted from the production equation.

The third step takes the estimates from β_l, ϕ_t and P_t and substitutes them for the true values. We get the coefficient on capital by minimizing the sum of squares of the residuals in that equation. The final step of the estimation consists of running nonlinear least squares on the equation

$$y_{t+1} - b_l l_{t+1} = c + \beta_k k_{t+1} + \sum_{j=0}^{s-m} \sum_{m=0}^{s} \beta_{mj} (\widehat{\phi}_t - \beta_k k_t)^m \widehat{P}_t^{\,j} + e_t \qquad (6)$$

where *s* denotes the order of the polynomial used to estimate the coefficient on capital.

3.2. Results

To compute aggregate TFP we use the estimates for firm level productivity and we look at the evolution of productivity across the sample period (1994-2000).[7] We estimate firm-level productivity estimating a Cobb-Douglas production function for

[7] For a more detailed discussion on the Olley and Pakes (1996) estimator and how it relates to other estimators, we refer to De Loecker and Konings (2003).

every 2-digit NACE sector separately controlling for industry and time effects. We report in appendix B the results of estimating the production function is the various 2-digit sectors using OLS, Fixed Effects (FE) and Olley-Pakes (OP), where we perform the OP estimation algorithm both without and with a survival equation, OP1 and OP2 respectively.

We note that the coefficients on labor and capital using the different estimation methods are different depending on the estimation method used. As expected the coefficient on labor using OLS is biased upward, compared to the OP estimates of the labor coefficient. The coefficient on capital is generally higher when using OP compared to OLS. The fact that the coefficient estimates are different compared to OLS implies that the estimate of aggregate TFP will also be different. The correction for the selection bias has the expected effect, i.e. firms with a higher capital stock can stay in the market with a lower productivity draw. This leads to a negative bias on the capital coefficient when not correcting for it. We also show the estimate for the capital coefficient using the Olley and Pakes (1996) procedure, however, without taking the selection problem into account. It is clear that the OP1 estimate is in general lower than the OP2 estimate, confirming our priors. We will use the OP2 estimates to compute aggregate TFP.

We compute aggregate TFP as the market share weighted sum of the firm level TFP computed on the entire sample of firms, using the estimates of the input coefficients obtained from the OP approach or

$$TFP = y_{it} - b_l l_{it} - b_k k_{it}$$

In table 11 we show the evolution of the productivity index (*Index*) for the various sectors that we study. We can note that TFP has increased in all sectors over the sample period. Considering the high simultaneous job creation and destruction rates documented in the previous section, the increase in TFP suggests a process of creative destruction. In table 11 we also show the relative importance of firm level average productivity (Share mean) and reallocation in aggregate TFP. This allows us to assess whether the increase in aggregate TFP is due to the fact that the average firm is becoming more productive or whether there is a reallocation of market share away from the least productive to the most productive firms.

These two effects can be disentangled by decomposing the productivity index P_t. The productivity index is given by

$$P_t = \sum_{i=1}^{N_t} s_{it} \omega_{it}$$

where s stands for the market share of firm i at time t. We can decompose P into an average unweighted productivity ($\overline{p}_t$) and the sample covariance between productivity and the share. After some manipulations we get the following decomposition following Olley and Pakes (1996),

$$P_t = \overline{p}_t + \sum_{i=1}^{N_t} \Delta s_{it} \Delta \omega_{it}$$

where Δ stands for the deviation from the average ($\Delta x_{it} = x_{it} - \overline{x}_t$). The productivity index is split up in two terms: an unweighted average productivity and a sample covariance term. If the latter is positive, it means that reallocation goes from the less productive towards the more productive. We decompose the productivity index for every different industry at the 2-digit NACE level. The latter implies that the market shares used to weigh the productivity estimates refer to that specific sector.

From table 11 it is clear that there is a large variation in the importance of reallocation across the various industries. For instance in the “chemical sector” we can note that the reallocation component is accounts for more than 20% on average of aggregate productivity, while in the “Food Products” this only amounts to less than 5% on average. A general finding, though, is that it is mainly due to the increase in average productivity that we see an increase in the productivity index and to a lesser extent a shift in market share away from the least productive to the more productive firms. There may, however, be also other reasons for finding an increase in the productivity that are independent of the two (i.e. reallocation and average firm level productivity increases) suggested above. It can be that the less productive firms exit the market and are replaced by more productive firms leading to an increase in the productivity index. Net entry effects are not captured by the decomposition suggested above. To be able to analyze this, one has to look at the change in the productivity index and proceed with another type of decomposition as in for instance Levinsohn and Petrin (2003). Using the same notation we can decompose the change in the productivity index into 5 components; i.e.

$$\Delta P_t = \sum_{i \in A}^{N_A} s_{it-1} \Delta\omega_{it} + \sum_{i \in A}^{N_A} \omega_{it-1} \Delta s_{it} + \sum_{i \in A}^{N_A} \Delta s_{it} \Delta\omega_{it} + \sum_{i \in B}^{N_B} s_{it} \omega_{it} - \sum_{i \in C}^{N_C} s_{it-1} \omega_{it-1}$$

where the set *A* contains the firms that continue their operation between *t* and *t-1*, set *B* contains the entering firm at time *t* and set *C* contains the firm that exited in *t-1*. The change in the productivity index now has different components: i) a pure *within* firm productivity increase, ii) a *between* firm reallocation component, iii) a covariance term and iv) a *net-entry* component. The latter could be important in the context of a transition country where simultaneous entry and exit are a main feature of industrial restructuring. As shares, *s*, we take the employment market shares instead of the sales market shares. This has as an advantage that we can related our job flows analysis more easily to the patterns in total factor productivity. A negative *between* firm component points to the fact that firms that are experiencing productivity growth are downsizing in terms of employment. We perform the analysis at the global manufacturing level and present the different components for the period 1995-2000. An analysis at the 2-digit sector level yielded qualitatively similar results, so we do not report them here for brevity. First we plot the growth in productivity in Figure 1. We can note that for the manufacturing sector as a whole productivity growth has been impressive and positive, except in 1999, which is consistent with the aggregate evidence that industrial output declined in Slovenia in 1999. All in all this pattern of productivity growth suggests that firms have engaged in cost cutting strategies, which may include more efficient use of labor, innovation, but also the replacement of bad jobs by good ones. This latter interpretation seems plausible given the substantial job creation and destruction rates that we observed in manufacturing.

In Table 12 we show the different components of this change in the productivity index. We can note that most of the productivity growth is explained by the *within* firms productivity growth. In other words firms have become more efficient on average, which is in line with the findings reported in table 11. Thus the restructuring of firms, reflected in the aggregate job creation and job destruction process, seems to have resulted in substantial within firm productivity growth. Furthermore, the negative *between* firm effect suggests that increases in productivity have been associated with a reallocation of jobs from more productive to less productive firms. Are in other words more productive firms are downsizing faster than less productive firms. Finally, the *net firm entry* component explains on average 44% of the observed aggregate productivity growth, which is quite substantial. This suggests that encouraging firm entry and exit is good to enhance aggregate productivity. And hence setting up policies that enhances competitive markets, by removing entry and exit barriers, should be good for productivity growth.

4. Conclusion

This paper sheds light on whether the transition process in Slovenian manufacturing has been one of creative destruction. To this end we start by documenting gross job flows for the Slovenian manufacturing sector between 1994 and 2000. In contrast to slowly reforming transition economies where the transition process in manufacturing is characterized by little job creation and high job destruction, we find for Slovenian manufacturing a process of simultaneous job creation and job destruction, which indicates that restructuring in Slovenia involves a substantial reallocation process. We find higher job reallocation in private and small firms where the contribution of entry and exit to the job reallocation process is higher. The findings on job flows are suggestive of a process of creative destruction, rather than just destruction.

The interpretation that the transition process in Slovenia is characterized by such a Schumpeterian process of creative destruction is confirmed in the second part of the paper where we first estimate TFP using the Olley-Pakes approach. We document substantial productivity growth in the Slovenian manufacturing sector that is mainly explained by firms becoming more efficient. Thus the transition process has led firms to engage in more restructuring, by not just destroying jobs, but also creating jobs, which has contributed to gains in firm level productivity. It is this effect that dominates rather than a shift of market share of the least productive to the more productive firms, although in some sectors this effect is more pronounced. Furthermore we show that the net firm entry process explains on average 44% of the productivity growth in Slovenian manufacturing.

We take these results as evidence in favor of a creative destruction process. While we can observe that job destruction is going on, at the same time we observe substantial job creation and productivity gains. Such productivity gains reflect strategies of firms to engage in more efficient ways of producing, by cost cutting or perhaps using new technology. In this process, the entry and exit of firms plays a non-trivial role. Policies that enhance the entry and exit process and hence enhance competitive forces are likely to have a positive effect on productivity growth. Also policies aimed at encouraging firms to engage in restructuring are likely to have a substantial impact on aggregate productivity growth.

References

Aghion, Philippe, Blanchard, Olivier and Burgess, Robin, "The Behavior of State Firms in Eastern Europe, Pre-privatisation", *European Economic Review* 38 (1994), 1179-1361.

Andrews, D.W.K. (1991). Asymptotic Normality of Series Estimators for Nonparametric and Semiparametric Regression Models, *Econometrica*, 59, 307-345

Bernard, A.B. and Jensen, J.B. (1999). Exceptional Exporter Performance: Cause, Effect, or Both, *Journal of International Economics*, 47(1), 1-25.

Bilsen, V. and Konings, J. (1999). Job Creation, Job Destruction and Employment Growth in Newly Established Firms in Transition Countries: Survey Evidence from Romania, Bulgaria and Hungary, *Journal of Comparative Economics*, vol 26, September 1998, pp. 429-445.

Brown and Earle (2003). Interfirm Reallocation, Productivity Growth and the Effects of Privatization and Liberalization, paper presented at annual CEPR/WDI conference in Budapest, July 2003.

Clerides, S.K., Lach, S. and Tybout, J.R. (1998), Is Learning-by-Exporting Important? Micro-Dynamic Evidence from Colombia, Morocco, and Mexico, *Quarterly Journal of Economics* 113(3), 903-947

Davis and Haltiwanger (1996).Gross Job Creation, Gross Job Destruction and Employment Reallocation, *Quarterly Journal of Economics*, Vol 107, pp. 819-63.

Davis, Haltiwanger and Shuh (1996). *Job Creation and Job Destruction*,Cambridge MIT press.

De Loecker, J. (2003). The Belgian Textile Industry: Just Another Declining Industry?, Harvard University mimeo.

De Loecker, J. and Konings, J. (2003). Do Exports Generate Higher Productivity Growth? Evidence from Slovenia., K.U. Leuven and Harvard University mimeo.

Ericson, R. and Pakes, A. (1995). Markov Perfect Industry Dynamics: A Framework for Empirical Work, *Review of Economic Studies*, Vol 62 (1), 53-82.

Faggio, G. and Konings, J. (2003). Job Creation, Job Destruction and Employment Growth in Transition Countries in the 90's, *Economic Systems*, Vol. 27, 129 – 154.

Goos, M. (2003). Gross Job Flows in Europe, mimeo London School of Economics

Haltiwanger, J. and Vodopivec, M. (2003). "Worker Flows, Job Flows and Firm Wage Policies: An analysis of Slovenia", *Economics of Transition*, Vol. 11.

Hutchinson, J. (2003). Is there a Lower Bound to the Firm Size Distribution Comparing Transition Economies with an Established Market Economy, LICOS DP 135.

Keller, W. and Yeaple, S.R. (2003). Multinational Enterprises, International Trade, and Productivity Growth: Firm-level Evidence form the United States, NBER WP 9504.

Konings J., Lehmann, H. and Schaffer, M. (1996). Job Creation and Job Destruction in a Transition Economy: Ownership, Firm Size and Gross Job Flows in Polish Manufacturing, *Labour Economics*, Vol.3, 1996, 299-317.

Levinsohn, J. and Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables., *Review of Economic Studies*, Vol. 70, pp. 317-342.

Olley, S. and Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment Industry, *Econometrica*, Vol 64 (6), 1263-98.

Pakes, A. and Olley, S. (1995). A Limit Theorem for a Smooth Class of Semiparametric Estimators, *Journal of Econometrics*, Vol 65 (1), 1-8.

Robinson, P. (1988). Root N-Consistent Semiparametric Regression, *Econometrica*, 55 (4), 931-954.

Table 1: Entry and Exit between 1995-2000

Year	Exit	Entry	# firms	Exit rate	Entry rate
1995	127	502	3820	3.32	13.14
1996	108	226	4152	2.60	5.44
1997	149	194	4339	3.43	4.47
1998	175	184	4447	3.94	4.14
1999	153	155	4695	3.26	3.30
2000	132	166	4906	2.69	3.38
average	141	238	.	3.21	5.65

Table 2: Summary Statistics

Year	Size	Value Added	Wage	Capital per worker	Sales	Value Added per worker
1994	40.93	580.2	7.93	30.36	1978	14.03
1995	41.31	591.5	8.99	32.18	2105	14.71
1996	37.75	621.5	10.49	37.13	2132	16.45
1997	35.17	676.2	10.63	42.85	2282	18.22
1998	34.15	669.3	11.33	38.62	2363	18.81
1999	33.43	727.2	12.56	41.03	2397	21.02
2000	33.60	778.5	13.26	41.99	2730	21.26
Mean	36.39	668.4	10.93	38.19	2300	18.07

Note: All monetary variables are expressed in real terms, using a two digit PPI to deflate. Since we construct investment from the capital series, we have no information on investment in the first year of our panel. All monetary variables are expressed in thousands of Slovenian Tollars

Table 3: Aggregate Job Flows

	1994-95	**1995-96**	**1996-97**	**1997-98**	**1998-99**	**1999-00**
Pos	.0695	.0413	.0603	.0762	.0445	.0687
Neg	.0604	.0795	.0905	.0654	.0739	.057
Net	.0091	-.0294	-.0302	.0109	-.0294	.0113
Gross	.1299	.1207	.1509	.1416	.1185	.1262
Excess	.1208	.0825	.1206	.1308	.0891	.1149
Entry	.0302	.0038	.0087	.0253	.0070	.0115
Exit	.0026	.0046	.0282	.0087	.0051	.0038

Table 4: Average Job Flows

	Pos	Neg	Gross	Net	Excess	Entry	Exit
Mean	.0601	.0712	.1313	-.0111	.1098	.0144	.0088
Std Dev	.0143	.0126	.0126	.0238	.0194	.0107	.0097

Table 5: Aggregate Job Flows by Owner

	1994-95	1995-96	1996-97	1997-98	1998-99	1999-00
Private Owned						
Pos	.2793	.1342	.1453	.1633	.1051	.1424
Neg	.0514	.0676	.0657	.0820	.0698	.0494
Net	.2279	.0667	.0796	.0813	.0354	.0931
Gross	.3308	.2018	.2111	.2453	.1749	.1919
Excess	.1029	.1352	.1314	.1640	.1395	.0987
Entry	.1328	.0245	.0431	.0308	.0092	.0216
Exit	.0071	.0108	.0103	.0402	.0156	.0075
State owned						
Pos	.0422	.0266	.0432	.0562	.0300	.0479
Neg	.0616	.0813	.0955	.0615	.0749	.0597
Net	-.0193	-.0548	-.0523	-.0054	-.0449	-.0118
Gross	.1038	.1079	.1387	.1177	.1049	.1076
Excess	.0845	.0532	.0865	.1124	.0601	.0957
Entry	.0168	.0005	.0017	.0240	.0065	.0086
Exit	.0020	.0036	.0317	.0015	.0027	.0028

Table 6: Average Job Flows by Owner

	Pos	Neg	Gross	Net	Excess	Entry	Exit
Private Owned							
Mean	.1616	.0643	.2259	.0973	.1286	.0436	.0152
Std Dev	.0607	.0122	.0565	.0669	.0244	.0450	.0126
State Owned							
	Pos	**Neg**	**Gross**	**Net**	**Excess**	**Entry**	**Exit**
Mean	.0410	.0724	.1135	-.0314	.0820	.0097	.0074
Std Dev	.0111	.0143	.0133	.0217	.0221	.0091	.0119

Table 7: Aggregate Job Flows by Exports

	1994-95	1995-96	1996-97	1997-98	1998-99	1999-00
			Exporting			
Pos	.0645	.0347	.0512	.0729	.0398	.0603
Neg	.0485	.0753	.0609	.0535	.0651	.0521
Net	.0159	-.0406	-.0091	.0193	-.0253	.0082
Gross	.1129	.1099	.1129	.1264	.1049	.1123
Excess	.0969	.0693	.1037	.1070	.0796	.1042
Entry	.0280	.0018	.0013	.0261	.0053	.0057
Exit	.0004	.0004	.0012	.0002	.0018	.0002
			Non-Exporting			
Pos	.1184	.1371	.1454	.1136	.0993	.1712
Neg	.1744	.1405	.3878	.1964	.1769	.1219
Net	-.0559	-.0033	-.2424	-.0827	-.0776	.0492
Gross	.2928	.2776	.5332	.3100	.2762	.2931
Excess	.2369	.2743	.2908	.2273	.1986	.2439
Entry	.0506	.0323	.0829	.0163	.0273	.0809
Exit	.0232	.0649	.2995	.1036	.0436	.0472

Table 8: Average Job Flows by Exports

	Pos	Neg	Gross	Net	Excess	Entry	Exit
				Exporting			
Mean	.0539	.0592	.1132	-.0053	.0935	.0114	.0007
Std Dev	.0147	.0099	.0071	.0241	.0154	.0123	.0007
				Non-Exporting			
Mean	.1309	.1996	.3305	-.0688	.2453	.0484	.0970
Std Dev	.0258	.0960	.1001	.0988	.0331	.0283	.1028

Table 9 Average Job Flows By Size Class

	Pos	Neg	Gross	Net	Excess	Entry	Exit
Class 1: 1-5							
Mean	.1499	.4219	.5718	-.2719	.2999	.0527	.2638
Std Dev	.0606	.2096	.1972	.2372	.1212	.0376	.2247
Class 2:5-25							
Mean	.1564	.1261	.2826	.0303	.2393	.0269	0
Std Dev	.0532	.0452	.0887	.0434	.0836	.0309	0
Class3:25-100							
Mean	.0827	.0767	.1594	.0060	.1337	.0191	0
Std Dev	.0293	.0252	.0420	.0350	.0328	.0294	0
Class 4:100+							
Mean	.0484	.0530	.1014	-.0046	.0848	.0122	0
Std Dev	.0156	.0094	.0113	.0232	.0197	.0097	0

Table 10: Average Job Flows by 2-digit Nace2 Sector

	Pos	Neg	Gross	Net	Excess	Entry	Exit
Manufacture of Food Products and Beverages							
Mean	.0399	.0405	.0805	-.0005	.0589	.0039	.0010
Std Dev	.0243	.0110	.0259	.0275	.0181	.0044	.0009
Manufacture of Tobacco							
Mean	0	.1519	.1519	-.1519	0	0	0
Std Dev	0	.1129	.1129	.1129	0	0	0
Manufacture of Textiles							
Mean	.0705	.1075	.1781	-.0370	.1114	.0226	.0118
Std Dev	.0525	.0556	.0851	.0668	.0673	.0244	.0119
Manufacture of Wearing Apparel							
Mean	.0341	.0764	.1105	-.0422	.0628	.0166	.0019
Std Dev	.0151	.0302	.0239	.0413	.0222	.0172	.0015
Tanning and Dressing of Leather							
Mean	.0814	.1408	.2222	-.0594	.1023	.0370	.0245
Std Dev	.0989	.0693	.0949	.1420	.0985	.0787	.0555
Manufacture of Products of Wood and Cork							
Mean	.0571	.0785	.1356	-.0214	.1105	.0081	.0133
Std Dev	.0245	.0221	.0426	.0191	.0437	.0091	.0166
Manufacture of Pulp and Paper							
Mean	.0433	.1044	.1477	-.0610	.0739	.0309	.0274
Std Dev	.0569	.0615	.0919	.0748	.0835	.0570	.0619
Publishing and Printing							
Mean	.0682	.0534	.1217	.0148	.0815	.0126	.0043
Std Dev	.0226	.0349	.0308	.0501	.0160	.0059	.0013
Manufacture of Coke, Refined Petroleum Products							
Mean	.0129	.0404	.0534	-.0274	.0022	.0004	0
Std Dev	.0287	.0317	.0263	.0544	.0025	.0009	0
Manufacture of Chemical Products							
Mean	.0245	.0284	.0529	-.0039	.0331	.0008	.0011
Std Dev	.0161	.0095	.0104	.0243	.0144	.0007	.0012
Manufacture of Rubber and Plastics							
Mean	.0925	.0804	.1729	.0121	.1097	.0431	.0015
Std Dev	.0888	.0453	.1176	.0776	.0840	.0805	.0009
Manufacture of Non-metallic Mineral Products							
Mean	.0409	.0635	.1045	-.0225	.07710	.0082	.0021
Std Dev	.0169	.0167	.0232	.0244	.0247	.0097	.0028
Manufacture of Basic Metals							
Mean	.0396	.0575	.0972	-.0179	.0620	.0039	.0002
Std Dev	.0233	.0269	.0327	.0383	.0403	.0054	.0003
Manufacture of Fabricated Metal Products							
Mean	.0729	.0579	.1309	.0149	.1062	.0136	.0078
Std Dev	.0189	.0231	.0338	.0253	.0416	.0150	.0037
Manufacture of Machinery and Equipment							
Mean	.0894	.0900	.1794	-.0005	.1554	.0075	.0348
Std Dev	.0758	.0841	.1573	.0297	.1603	.0088	.0809
Manufacture of Office Machinery and Computers							
Mean	.1338	.0509	.1848	.0828	.1019	.0076	.0035
Std Dev	.0514	.0192	.0492	.0600	.0385	.0061	.0018

Manufacture of Electrical Machinery and Apparatus							
Mean	.0374	.0419	.0793	-.0045	.0474	.0015	.0012
Std Dev	.0230	.0182	.0143	.0390	.0134	.0007	.0009
Manufacture of Radio, T.V. and Communication Equipment							
Mean	.0849	.0628	.1478	.0221	.1097	.0195	.0038
Std Dev	.0381	.0298	.0539	.0422	.0514	.0341	.0069
Manufacture of Medical, Precision and Optical Instruments							
Mean	.0660	.0568	.1228	.0093	.1001	.0018	.0016
Std Dev	.0382	.0241	.0577	.0275	.0524	.0018	.0016
Manufacture of Vehicles and Trailers							
Mean	.0655	.1016	.1672	-.0361	.1056	.0071	.0041
Std Dev	.0391	.0437	.0529	.0639	.0558	.0135	.0052
Manufacture of Other Transport Equipment							
Mean	.1683	.1101	.2784	.0582	.0827	.1549	.0003
Std Dev	.2322	.0656	.2003	.2762	.1245	.2289	.0005
Manufacture of Furniture							
Mean	.0730	.0707	.1438	.0022	.1285	.0164	.0075
Std Dev	.0308	.0254	.0527	.0202	.0545	.0131	.0119
Recycling							
Mean	.0523	.0324	.0847	.0198	.0591	.0027	.0052
Std Dev	.0247	.0237	.0363	.0321	.0362	.0047	.0071

Table 11: Decomposition of Productivity Index

	Index	Share Mean	Share SCov		Index	Share Mean	Share S Cov
	Food Products				Textiles		
1994	2.82	0.95	0.05	1994	2.97	0.93	0.07
1995	2.79	0.98	0.02	1995	3.02	0.93	0.07
1996	2.86	0.97	0.03	1996	3.25	0.92	0.08
1997	2.87	0.96	0.04	1997	3.36	0.93	0.07
1998	2.94	0.95	0.05	1998	3.37	0.94	0.06
1999	2.89	1.01	-0.01	1999	3.42	0.94	0.06
2000	2.89	0.97	0.03	2000	3.70	0.85	0.15
	Wearing Apparel				Leather and Leather Products		
1994	2.50	0.90	0.10	1994	3.45	0.92	0.08
1995	2.51	0.92	0.08	1995	3.36	0.93	0.07
1996	2.62	0.91	0.09	1996	3.49	0.99	0.01
1997	2.64	0.98	0.02	1997	3.60	0.95	0.05
1998	2.66	0.98	0.02	1998	3.44	1.05	-0.05
1999	2.64	0.99	0.01	1999	3.72	1.01	-0.01
2000	2.65	0.99	0.01	2000	3.74	0.99	0.01
	Wood and Wood Products				Pulp, Paper and Paper Products		
1994	2.85	0.95	0.05	1994	3.46	0.97	0.03
1995	2.93	0.96	0.04	1995	3.51	0.95	0.05
1996	2.96	0.98	0.02	1996	4.05	0.87	0.13
1997	3.06	1.01	-0.01	1997	3.98	0.93	0.07
1998	3.12	0.97	0.03	1998	3.88	0.95	0.05
1999	3.20	0.96	0.04	1999	4.06	0.92	0.08
2000	3.25	0.97	0.03	2000	4.14	0.92	0.08
	Publishing and Printing				Chemicals and Chemical Products		
1994	3.67	0.86	0.14	1994	4.28	0.75	0.25
1995	3.69	0.88	0.12	1995	4.27	0.80	0.20
1996	3.74	0.90	0.10	1996	4.38	0.81	0.19
1997	3.84	0.91	0.09	1997	4.56	0.81	0.19
1998	3.90	0.90	0.10	1998	4.52	0.81	0.19
1999	4.10	0.88	0.12	1999	4.59	0.78	0.22
2000	4.04	0.91	0.09	2000	4.62	0.77	0.23
	Rubber and Plastic Products				Non-Metallic Mineral Products		
1994	3.88	0.79	0.21	1994	3.26	0.90	0.10
1995	3.80	0.83	0.17	1995	3.27	0.95	0.05
1996	4.04	0.85	0.15	1996	3.41	0.92	0.08
1997	4.21	0.83	0.17	1997	3.57	0.92	0.08
1998	4.01	0.89	0.11	1998	3.58	0.92	0.08
1999	4.15	0.87	0.13	1999	3.76	0.90	0.10
2000	4.29	0.86	0.14	2000	3.77	0.89	0.11

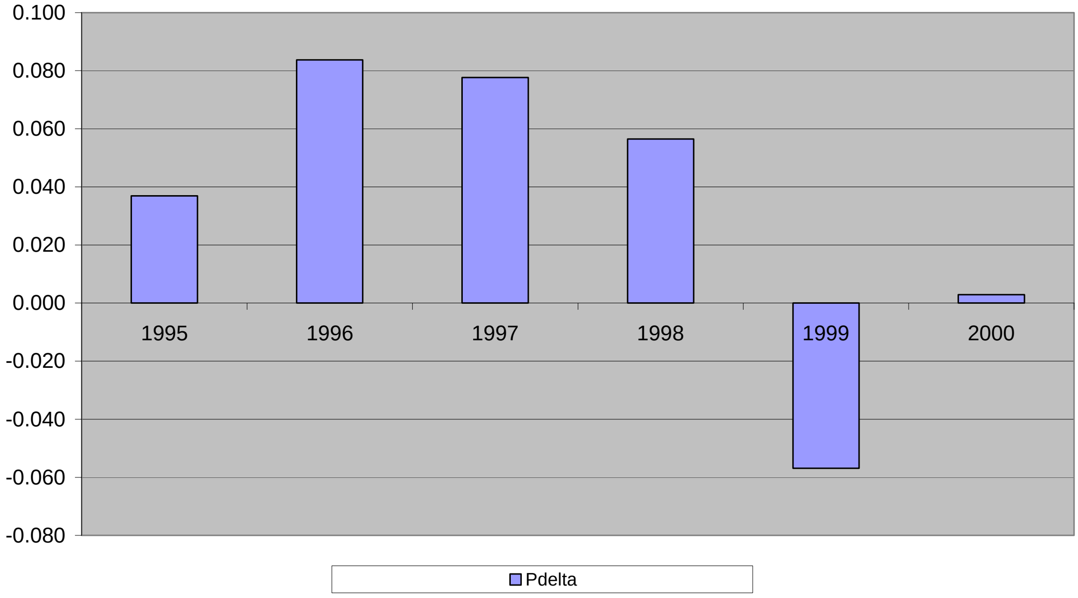
Basic Metals				Fabricated Metal Products			
1994	2.92	1.11	-0.11	1994	3.22	0.87	0.13
1995	3.38	0.97	0.03	1995	3.29	0.89	0.11
1996	3.23	1.07	-0.07	1996	3.43	0.88	0.12
1997	3.66	0.96	0.04	1997	3.54	0.90	0.10
1998	3.65	1.03	-0.03	1998	3.60	0.90	0.10
1999	3.89	0.98	0.02	1999	3.66	0.90	0.10
2000	4.15	0.92	0.08	2000	3.76	0.89	0.11
Machinery and Equipment				Electrical Machinery and Apparatus			
1994	2.91	1.01	-0.01	1994	2.60	1.17	-0.17
1995	2.89	1.02	-0.02	1995	2.69	1.18	-0.18
1996	3.16	0.99	0.01	1996	2.90	1.14	-0.14
1997	3.30	0.98	0.02	1997	3.02	1.14	-0.14
1998	3.32	0.99	0.01	1998	3.00	1.16	-0.16
1999	3.43	0.99	0.01	1999	3.16	1.14	-0.14
2000	3.52	0.99	0.01	2000	3.20	1.14	-0.14
Medical Precision and Optical Instr;				Motor Vehicles, Trailers & Semi-			
1994	3.41	0.91	0.09	1994	3.38	0.86	0.14
1995	3.42	0.95	0.05	1995	3.62	0.85	0.15
1996	3.46	0.97	0.03	1996	3.58	0.85	0.15
1997	3.71	0.95	0.05	1997	3.67	0.91	0.09
1998	3.75	0.97	0.03	1998	3.81	0.85	0.15
1999	3.81	0.96	0.04	1999	4.06	0.86	0.14
2000	3.97	0.94	0.06	2000	4.01	0.87	0.13
Other Transport Equipment				Furniture and N.EC.			
1994	2.70	0.93	0.07	1994	2.56	1.04	-0.04
1995	2.89	1.01	-0.01	1995	2.73	1.02	-0.02
1996	3.04	0.96	0.04	1996	2.81	1.03	-0.03
1997	3.06	0.95	0.05	1997	3.01	1.01	-0.01
1998	3.17	0.88	0.12	1998	2.99	1.03	-0.03
1999	3.40	0.92	0.08	1999	2.98	1.02	-0.02
2000	3.43	0.92	0.08	2000	2.98	1.02	-0.02

Table 12 Different Components of Productivity Index Change

	ΔP	*within*	*between*	*covariance*	*Entry*	*Exit*	*net entry*
1995	3.7%	69%	-125%	-19%	189%	13%	176%
1996	8.4%	138%	-28%	-13%	11%	9%	2%
1997	7.8%	140%	55%	-9%	18%	106%	-87%
1998	5.6%	52%	-6%	-22%	122%	46%	76%
1999	-5.7%	-143%	244%	6%	-31%	-24%	-7%
2000	0.3%	1794%	-1925%	-518%	1059%	310%	749%
Average	**3.8%**	**179%**	**-98%**	**-24%**	**110%**	**66%**	**44%**

Note: The growth in aggregate productivity is computed using employment shares as weights and for the entire pooled manufacturing sector as a whole. The analysis on a sector by sector basis gave qualitatively similar results.

Figure 1: Productivity Index Change



APPENDIX A: Data Appendix

In this appendix we describe the variables in some more detail. All monetary variables are deflated by the appropriate two digit NACE industry deflators and investment is deflated using a one digit NACE investment deflator. We observe all variables every year in nominal values, however, gross investment is not reported but we can calculate it from the information on the book value in capital and the depreciations.

- Value added: sales – material costs in thousands of Tolars

  We only have to assume that output and materials are used in the same proportion and using value added gets rid off of the simultaneity problem of material inputs in the production function, i.e. they respond the fastest to a productivity shock.

- Employment: Number of full-time equivalent employees
- Capital: Total fixed assets in book value
- Investment: calculated from the yearly observed capital stock in the following way with the appropriate depreciation rate varying across industries, i.e. $I_t = K_t - (1-\delta)K_{t-1}$. We experimented using different depreciation rates, ranging between 5% and 20% and we also experimented with the actual reported depreciation rate.

In terms of coverage of the data, we compare the number of employees in our dataset with the total number of paid employees in the Slovenian manufacturing sector. The table below presents the coverage rates for the various years of the sample. We can note that we cover most of manufacturing employment.

	ILO	Sample	Coverage
1994	279000	209865	75.22%
1995	297000	211785	71.31%
1996	283000	206656	73.02%
1997	275000	202151	73.51%
1998	273000	202411	74.14%
1999	260000	205169	78.91%
2000	253000	210007	83.01%

Appendix B: Results of estimating the production function

Sector	***Coefficient on Labor***			***Coefficient on Capital***			
	OLS	FE	OP	OLS	FE	OP1	OP2
Food Products and Beverages	0.9105	0.8228	0.8590	0.1928	0.1911	0.2155	0.2245
	(0.0200)	(0.0423)	(0.0280)	(0.0150)	(0.0298)	(0.0369)	(0.0749)
Textiles	0.8077	0.6336	0.7805	0.1728	0.1015	0.1610	0.1790
	(0.0179)	(0.0383)	(0.0238)	(0.0131)	(0.0203)	(0.0515)	(0.0600)
Wearing Apparel	0.8723	0.8224	0.8615	0.1734	0.1392	0.1021	0.1609
	(0.0165)	(0.0442)	(0.0234)	(0.0134)	(0.0249)	(0.0645)	(0.0595)
Leather and Leather Products	0.7945	0.4215	0.6077	0.2059	0.1163	0.2676	0.3475
	(0.0395)	(0.1146)	(0.0551)	(0.0302)	(0.0516)	(0.1712)	(0.0912)
Wood and Wood Products	0.7946	0.6805	0.7974	0.1914	0.2459	0.1781	0.2014
	(0.0165)	(0.0375)	(0.0220)	(0.0124)	(0.0212)	(0.0820)	(0.0717)
Pulp, Paper and Paper Products	0.7952	0.5788	0.6601	0.2236	0.1814	0.2941	0.2797
	(0.0290)	(0.0696)	(0.0366)	(0.0222)	(0.0375)	(0.1137)	(0.1680)
Publishing and Printing	0.7986	0.6717	0.7035	0.2711	0.1849	0.3268	0.2519
	(0.0169)	(0.0303)	(0.0229)	(0.0114)	(0.0162)	(0.1372)	(0.1377)
Chemicals and Chemical Prod.	0.8089	0.6963	0.6849	0.2694	0.1380	0.3496	0.1950
	(0.0387)	(0.0725)	(0.0472)	(0.0275)	(0.0382)	(0.1209)	(0.1221)
Rubber and Plastic Prod.	0.7276	0.7757	0.7172	0.2791	0.2403	0.2512	0.1673
	(0.0186)	(0.0375)	(0.0243)	(0.0133)	(0.0202)	(0.0762)	(0.1235)
Non-Metallic Mineral Prod.	0.8027	0.7800	0.7705	0.2192	0.1193	X	0.1995
	(0.0218)	(0.0472)	(0.0304)	(0.0154)	(0.0232)	X	(0.1040)
Basic Metals	0.6525	0.7433	0.6427	0.2715	0.2502	0.2890	0.2820
	(0.0376)	(0.0832)	(0.0480)	(0.0307)	(0.0501)	(0.0601)	(0.0758)
Fabricated Metal Prod.	0.7925	0.7917	0.7851	0.2331	0.2100	0.2118	0.1500
	(0.0100)	(0.0224)	(0.0131)	(0.0073)	(0.0118)	(0.0571)	(0.0993)
Machinery and Equipment	0.7495	0.7793	0.8195	0.2328	0.2336	0.1299	0.1971
	(0.0153)	(0.0323)	(0.0176)	(0.0119)	(0.0189)	(0.0664)	(0.0731)
Electrical Machinery & App.	0.7629	0.8593	0.7759	0.2737	0.3035	0.2581	0.3571
	(0.0204)	(0.0527)	(0.0268)	(0.0153)	(0.0249)	(0.1225)	(0.1275)
Medical, Precision & Optical *	0.7723	0.6616	0.7467	0.2349	0.2802	X	0.2279
	(0.0229)	(0.0537)	(0.0295)	(0.0175)	(0.0323)	X	(0.1028)
Motor Vehicles, Trailers	0.7584	0.8517	0.7643	0.2077	0.2365	X	0.1970
	(0.0298)	(0.0654)	(0.0297)	(0.0229)	(0.0311)	X	(0.0982)
Other Transport Equipment	0.7932	0.8425	0.7816	0.1701	0.1620	0.1738	0.0893
	(0.0641)	(0.0851)	(0.0703)	(0.0509)	(0.0635)	(0.0581)	(0.0493)
Furniture and N.E.C. Manuf.	0.8105	0.7675	0.8250	0.2131	0.2226	0.2208	0.2478
	(0.0167)	(0.0346)	(0.0213)	(0.0124)	(0.0187)	(0.0766)	(0.1058)

Note: The use of a series estimator in the first stage yields an estimator for the labor coefficient with known limiting properties (Andrews, 1991). The standard errors on the OP estimator for capital are obtained through block-bootstrapping using 1,00 replications. The standard errors on the capital coefficient tend to be overestimated due to limiting distribution, see Pakes and Olley (1995). The number of observations drop when using the OP methodology due to the dynamic underlying theoretical framework, where the first year of observation is dropped. We estimate the production function at the two digit NACE and include three digit NACE dummies and a time trend in order to allow the non parametric function to be different for the different subsectors within the 2 digit NACE industry and to vary over time. We include the time trend throughout the entire estimation algorithm, i.e. in all three stages of the estimation because we tested and found it to be significant. This is also what Olley and Pakes (1996) find in their dataset.*: Here we used a depreciation rate of 25% for investment, whereas in other industries we take between 10% and 15%.