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Job reallocation and productivity growth in a post-socialist economy: Evidence from Slovenian manufacturing

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Abstract

This paper studies whether job reallocation in Slovenia, a post-socialist economy, has been associated with gains in total factor productivity (TFP). We document the importance of entry and exit in job reallocation and show that TFP has increased mainly due to existing firms' increasing efficiency and through net entry of firms. Underlying aggregate TFP growth is job destruction by state firms and reallocation of employment to private firms.

JEL classification: L60; D21; P20
Keywords: Creative destruction; Total factor productivity; Reallocation

1. Introduction

High labor market turbulence in market and non-market economies has been documented many times.[1] Gross flows of jobs relative to net flows are high, persistent, fluctuate over the business cycle, and vary between countries (e.g. Messina et al., 2004; Goos, 2003), and simultaneous job

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[1] For market economies see Davis et al. (1996), for emerging markets see e.g. Konings et al. (1996); Brown and Earle (2004) and Faggio and Konings (2003).

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creation and destruction take place even within narrowly defined sectors, regions and firm types, indicating a high degree of firm heterogeneity. While documenting and comparing job flows has been fruitful and complementary to aggregate data, the question remains to be answered whether high gross flows of jobs are desirable. In most post-socialist countries the aggregate evidence suggests destruction of jobs due to the legacy of communism, where over-manning was the norm. A pessimistic interpretation of this aggregate pattern is that manufacturing industries in central and eastern Europe have been unable to compete on world markets after the collapse of communism and the opening of trade, and so job destruction reflects declining industries. An optimistic interpretation is that the aggregate collapse in employment hides a process of creative destruction. This would involve substantial gross job reallocation, with a decline of unproductive jobs accompanied by increases in new productive jobs.

This paper investigates these two interpretations for the case of Slovenia. We first document gross job flows for the Slovenian manufacturing sector. In contrast to slowly reforming post-socialist economies where the transition process in manufacturing is characterized by little job creation and high job destruction, we find simultaneous job creation and job destruction, indicating that restructuring in Slovenia has involved 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 growth.

Slovenia is of particular interest to study, as it has been a successful transition economy reaching a level of GDP per capita over 65% of the EU average in the year 2000. Given that aggregate data suggest substantial productivity growth, it is interesting to identify micro-economic determinants through answers to the questions: can a process of creative destruction explain Slovenia's aggregate success story; how important has job creation and destruction been in private firms compared to state firms; and is aggregate productivity growth driven by firm-specific productivity improvements or by reallocation of resources from less efficient to more efficient firms?

In the next section we introduce the data set and document the basic patterns of gross job flows between 1994 and 2000. In Section 3 we estimate TFP. We then decompose TFP to illustrate the importance of net entry and reallocation in explaining TFP growth. Section 4 concludes.

2. Data and basic patterns of gross job flows

2.1. Data

The data, which are from the company accounts of manufacturing firms available at the Slovenian Central Statistical Office, have been used for various applications and are representative for the manufacturing sector (e.g. Damijan et al., 2004a,b). Information is available on 7915 firms between the years 1994 and 2000. However, if we only take into account those firms that report employment, we have a sample of 6391 firms. We cover each year, on average, more than 75% of total manufacturing employment. Self-employed individuals are excluded. 45% of all firms are active in export markets, while 55% are only in the domestic market. Within the sample period we observe entry and exit of firms.[2] Appendix A describes the

[2] The data on exit and entry are from the Slovenian statistical office and there is no re-entry possible. Exit is defined as no longer being active in the market.

data in some more detail and shows summary statistics (Table A2). Table A3 shows entry and exit patterns over time: over the sample period there was an annual average exit rate of 3.21% and an annual average entry rate of 5.56%. Table A4 compares these with entry and exit rates for market economies including Estonia, the only post-socialist economy for which comparable entry and exit rates seem to have been reported. Except for Portugal, in Western market economies the average exit and entry rates are higher, the average exit rate varying between 6.5% and 14% and the average entry rate between 5.4% and 15.6%. Compared to Estonia, the Slovenian exit and entry rates are lower. However, the average entry rate in Slovenia is about twice as high as the average exit rate, as in Estonia, while the average entry and exit rates in market economies are about equal. This is not surprising, taking into account that the entry of new firms was an important component of the restructuring and transition process. Under communism, entry of new firms was virtually non-existent. With the transition to a market economy, entry of new enterprises was encouraged and has played an important role in the transition (e.g. Bilsen and Konings, 1998).

Perhaps more surprising are the relative low entry and exit rates in Slovenia. One explanation could be related to the persisting presence of soft budget constraints, which allows firms to survive and in equilibrium fewer firms to enter.

In Fig. A1 in Appendix A we see that – although making one of the most successful transitions – Slovenia still has a relatively high index of soft budget constraints (as constructed by the EBRD, 1999), while in Estonia soft budget constrains seem to be far less frequent. Slovenia has a less competitive market environment than Estonia. The EBRD has computed an index of market selection, which captures the degree to which firms can enter and expand. While for Slovenia an index of market selection of .38 is reported (the best is 1), Estonia has an index of .78 (EBRD, 1999).

2.2. Basic patterns of gross flows

We measure gross job flows in the standard way, following Davis and Haltiwanger (1992). Job creation (pos) is 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 obtain 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.

Table 1 shows that on average the job reallocation rate in Slovenian manufacturing (13.1%) is in line with those of other post-socialist countries, which varies between 7.7% in Hungary and 15% in Estonia. As is the case in other post-socialist countries, the job destruction rate dominates the job creation rates, which could reflect downsizing as a consequence of past labor hoarding in communist countries.

Tables 2–6 document and confirm some basic stylized facts about gross flows of jobs between 1994 and 2000. Table 2 shows the evolution of gross job flows over time, and the annual averages. On average job destruction slightly dominates job creation over the sample

Table 1
Job flows in selected countries

Country	Pos	Neg	Gross
Slovenia	.060	.071	.131
Bulgaria (1)	.015	.103	.118
Estonia (1)	.050	.096	.147
Romania (1)	.035	.076	.111
Hungary (2)	.011	.066	.077
Poland (3)	.048	.095	.143
Russia (4)	.026	.100	.126
Ukraine (5)	.023	.104	.127
EU (6)	.041	.038	.079
USA (7)	.092	.113	.205

Note: The figures in the table are all for the manufacturing sector in the various countries as reported in various studies: (1) for the period 1993–1996 as reported in Faggio and Konings (2003), (2) for the period 1995–1996 as reported in Bilsen and Konings (1998), (3) for the period 1995–1999 as reported in Warzynski (2003). We report averages over the sample period, (4) for the period 1997 as reported in Acquisti and Lehman (2000), (5) for the period 1999 as reported in Konings et al. (2003), (6) for the period (1992–2001) averages over various EU countries as found in Messina et al. (2004) and (7) As reported by Davis and Haltiwanger (1992) for the period 1972–1986.

period. Also excess job reallocation is substantial (10.9% on average), which indicates simultaneous high job creation and destruction.[3]

From the last two rows in Table 2 we see that the job flow rates that are accounted for by entry and exit of firms are substantial: on average 22.1% of all job creation is accounted for by entry of firms, while 11.4% of all job destruction is accounted for by exit of firms. The combined contribution of entry and exit of firms in Slovenian manufacturing in job reallocation is 17.2%.[4]

Tables 3–6 slice the data in different sub-sets to highlight the heterogeneity of firms in terms of gross job flows. We focus on those aspects that seem to be relevant for post-socialist economies, in particular, the difference between private versus non-private firms, exporters versus non-exporters, and the difference between various size classes of firms. Table 3 shows the evolution of job flows in private versus state firms as well as the annual averages. Job creation is concentrated in the private firms, with a job creation rate of 16% on average, with 4% for state firms. In contrast, job destruction rates in the private and state firms are almost the same (6% versus 7%). Private firms are therefore net job creators, while state firms are net job destroyers. Since the role of entry and exit is far more important in the private sector than the state sector, 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 22%, while this is only 8.6% in the state sector, suggesting the still existing soft budget constraints for state owned enterprises and their larger mean size. The contribution of entry to job creation

[3] This is consistent with the findings of Haltiwanger and Vodopivec (2003) who documented job and worker flows for Slovenia.

[4] The average share of entry in the job creation and exit in the job destruction are obtained by averaging (Entry/Pos) and (Exit/Neg) over the years, respectively. The share of entry and exit – combined – in job reallocation is obtained by looking at the following fraction: ((Entry+Exit)/Gross).

Table 2
Aggregate job flows

	1994–95	1995–96	1996–97	1997–98	1998–99	1999–00	Mean (SD)
Pos	.0695	.0413	.0603	.0762	.0445	.0687	.0601 (.0143)
Neg	.0604	.0795	.0905	.0654	.0739	.057	.0712 (.0126)
Net	.0091	−.0294	−.0302	.0109	−.0294	.0113	−.0111 (.0238)
Gross	.1299	.1207	.1509	.1416	.1185	.1262	.1313 (.0126)
Excess	.1208	.0825	.1206	.1308	.0891	.1149	.1098 (.0194)
Entry	.0302	.0038	.0087	.0253	.0070	.0115	.0144 (.0107)
Exit	.0026	.0046	.0282	.0087	.0051	.0038	.0088 (.0097)

in the private sector is 23%, a figure comparable to the figures found in market economies (e.g. 20% for the U.S. as documented by Davis and Haltiwanger, 1992). In the state owned sector this contribution is only slightly lower, 21% resulting in a more pronounced role of entry and exit in job reallocation in the private sector (23.9%) as opposed to the state sector (14.5%). 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, and in the replacement of state by private firms.

While the privatization of state owned enterprises was an important component of the transition from socialism, a less studied aspect has been trade reorientation.[5] In our data we have firm-level information on exports, which allows us to distinguish between exporting firms and non-exporting firms. De Loecker (2004) shows that firms in Slovenia became more productive after starting to export.[6] This reflects the so-called learning-by-exporting hypothesis. We do not intend to address this issue here in detail. Rather we analyze whether there exists a difference in terms of gross job flows between exporting firms and non-exporting firms. This is done in Table 4.

On average the gross job flow rates for exporting firms are lower than those for non-exporting firms. However, the job destruction rate in non-exporting firms is 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, suggesting that exporting firms provide more stable jobs than non-exporting firms. Non-exporters have been downsizing substantially, with a net job destruction rate of −7%. Part of this is due to 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 5, we note an inverse relationship between gross job flows and firm size, which is a pattern also reported for market economies.

Finally, in Table 6 we document how job flows vary between different NACE 2-digit sectors. Again we can note one of the stylized facts of job flows, namely that even within narrowly defined sectors we observe high job creation and destruction rates.

The basic patterns of gross job flows suggest that the transition process is heterogeneous, with simultaneous expansion and contraction of firms even within narrowly defined sectors. The

[5] Under the CMEA 30–40% of all exports went to the EU, and with the end of the CMEA this increased to 70% or more.

[6] A number of authors have pointed out the importance of exports in explaining firm performance. Bernard and Jensen (1999) and Clerides et al. (1998) show that more productive firms become exporters.

Table 3
Aggregate job flows by ownership

	1994–95	1995–96	1996–97	1997–98	1998–99	1999–00	Mean
Private owned							
Pos	.2793	.1342	.1453	.1633	.1051	.1424	.1616
Neg	.0514	.0676	.0657	.0820	.0698	.0494	.0643
Net	.2279	.0667	.0796	.0813	.0354	.0931	.0973
Gross	.3308	.2018	.2111	.2453	.1749	.1919	.2259
Excess	.1029	.1352	.1314	.1640	.1395	.0987	.1286
Entry	.1328	.0245	.0431	.0308	.0092	.0216	.0436
Exit	.0071	.0108	.0103	.0402	.0156	.0075	.0152
State owned							
Pos	.0422	.0266	.0432	.0562	.0300	.0479	.0410
Neg	.0616	.0813	.0955	.0615	.0749	.0597	.0724
Net	−.0193	−.0548	−.0523	−.0054	−.0449	−.0118	−.0314
Gross	.1038	.1079	.1387	.1177	.1049	.1076	.1135
Excess	.0845	.0532	.0865	.1124	.0601	.0957	.0820
Entry	.0168	.0005	.0017	.0240	.0065	.0086	.0097
Exit	.0020	.0036	.0317	.0015	.0027	.0028	.0074

evidence from aggregate statistics would suggest that manufacturing has been declining. However, the aggregate evidence hides the high turbulence of jobs in Slovenian manufacturing, which suggests a process of ‘creative destruction’, especially if small and private firms have the highest reallocation rates.

In the next section we go a step further and assess whether firms have become more efficient. If a process of creative destruction has been taking place, we expect that, although many jobs are disappearing, new and better (more productive) jobs are being created. As exit takes place, there is entry of new and more efficient firms. If the transition is indeed characterized by ‘creative

Table 4
Aggregate job flows by export status

	1994–95	1995–96	1996–97	1997–98	1998–99	1999–00	Mean
Exporting							
Pos	.0645	.0347	.0512	.0729	.0398	.0603	.0539
Neg	.0485	.0753	.0609	.0535	.0651	.0521	.0592
Net	.0159	−.0406	−.0091	.0193	−.0253	.0082	−.0053
Gross	.1129	.1099	.1129	.1264	.1049	.1123	.1132
Excess	.0969	.0693	.1037	.1070	.0796	.1042	.0935
Entry	.0280	.0018	.0013	.0261	.0053	.0057	.0114
Exit	.0004	.0004	.0012	.0002	.0018	.0002	.0007
Non- exporting							
Pos	.1184	.1371	.1454	.1136	.0993	.1712	.1309
Neg	.1744	.1405	.3878	.1964	.1769	.1219	.1996
Net	−.0559	−.0033	−.2424	−.0827	−.0776	.0492	−.0688
Gross	.2928	.2776	.5332	.3100	.2762	.2931	.3305
Excess	.2369	.2743	.2908	.2273	.1986	.2439	.2453
Entry	.0506	.0323	.0829	.0163	.0273	.0809	.0484
Exit	.0232	.0649	.2995	.1036	.0436	.0472	.0970

Table 5
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
SD	.0606	.2096	.1972	.2372	.1212	.0376	.2247
Class 2: 5−25							
Mean	.1564	.1261	.2826	.0303	.2393	.0269	0
SD	.0532	.0452	.0887	.0434	.0836	.0309	0
Class 3: 25–100							
Mean	.0827	.0767	.1594	.0060	.1337	.0191	0
SD	.0293	.0252	.0420	.0350	.0328	.0294	0
Class 4: 100+							
Mean	.0484	.0530	.1014	−.0046	.0848	.0122	0
SD	.0156	.0094	.0113	.0232	.0197	.0097	0

destruction', we expect to find increased total factor productivity in 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, we require a reliable measure of total factor productivity. The traditional method is to compute value added per worker. While this has a number of advantages, most of all simplicity, there are a number of major disadvantages. In the presence of other input factors, labor productivity may be a misleading measure, since it is strongly biased 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 consider both increases in productivity and jobs. This suggests that we should compute TFP by 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. Furthermore, not taking into account the exit of firms with negative productivity shocks may further bias TFP measures obtained from estimating a production function using simple OLS. We therefore use the Olley–Pakes (1996) method for estimating production functions, which controls for the above problems and has been applied in recent applications (e.g. Pavcnik, 2002; Keller and Yeaple, 2003).

Assuming a Cobb–Douglas production technology, we can obtain an estimate for TFP by estimating

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \eta_{it} \tag{1}$$

where y_{it} indicates log real output in firm i at time t, l is the log of labor, k is the log of capital, proxied by tangible fixed assets, ω is a firm-specific productivity shock and η is a

Table 6
Average job flows by 2-digit Nace2 sector

	Pos	Neg	Gross	Net	Excess	Entry	Exit
Food products and beverages							
Mean	.0399	.0405	.0805	−.0005	.0589	.0039	.0010
SD	.0243	.0110	.0259	.0275	.0181	.0044	.0009
Tobacco							
Mean	0	.1519	.1519	−.1519	0	0	0
SD	0	.1129	.1129	.1129	0	0	0
Textiles							
Mean	.0705	.1075	.1781	−.0370	.1114	.0226	.0118
SD	.0525	.0556	.0851	.0668	.0673	.0244	.0119
Wearing apparel							
Mean	.0341	.0764	.1105	−.0422	.0628	.0166	.0019
SD	.0151	.0302	.0239	.0413	.0222	.0172	.0015
Leather and leather products							
Mean	.0814	.1408	.2222	−.0594	.1023	.0370	.0245
SD	.0989	.0693	.0949	.1420	.0985	.0787	.0555
Wood and wood products							
Mean	.0571	.0785	.1356	−.0214	.1105	.0081	.0133
SD	.0245	.0221	.0426	.0191	.0437	.0091	.0166
Pulp, paper and paper products							
Mean	.0433	.1044	.1477	−.0610	.0739	.0309	.0274
SD	.0569	.0615	.0919	.0748	.0835	.0570	.0619
Publishing and printing							
Mean	.0682	.0534	.1217	.0148	.0815	.0126	.0043
SD	.0226	.0349	.0308	.0501	.0160	.0059	.0013
Coke, refined petroleum products							
Mean	.0129	.0404	.0534	−.0274	.0022	.0004	0
SD	.0287	.0317	.0263	.0544	.0025	.0009	0
Chemicals and chemical products							
Mean	.0245	.0284	.0529	−.0039	.0331	.0008	.0011
SD	.0161	.0095	.0104	.0243	.0144	.0007	.0012
Rubber and plastic products							
Mean	.0925	.0804	.1729	.0121	.1097	.0431	.0015
SD	.0888	.0453	.1176	.0776	.0840	.0805	.0009
Non-metallic mineral products							
Mean	.0409	.0635	.1045	−.0225	.07710	.0082	.0021
SD	.0169	.0167	.0232	.0244	.0247	.0097	.0028
Basic metals							
Mean	.0396	.0575	.0972	−.0179	.0620	.0039	.0002
SD	.0233	.0269	.0327	.0383	.0403	.0054	.0003

(*continued on next page*)

Table 6 (*continued*)

	Pos	Neg	Gross	Net	Excess	Entry	Exit
Fabricated metal products							
Mean	.0729	.0579	.1309	.0149	.1062	.0136	.0078
SD	.0189	.0231	.0338	.0253	.0416	.0150	.0037
Machinery and equipment							
Mean	.0894	.0900	.1794	−.0005	.1554	.0075	.0348
SD	.0758	.0841	.1573	.0297	.1603	.0088	.0809
Office machinery and computers							
Mean	.1338	.0509	.1848	.0828	.1019	.0076	.0035
SD	.0514	.0192	.0492	.0600	.0385	.0061	.0018
Electrical machinery and apparatus							
Mean	.0374	.0419	.0793	−.0045	.0474	.0015	.0012
SD	.0230	.0182	.0143	.0390	.0134	.0007	.0009
Radio, TV and communication equipment							
Mean	.0849	.0628	.1478	.0221	.1097	.0195	.0038
SD	.0381	.0298	.0539	.0422	.0514	.0341	.0069
Medical, precision and optical							
Mean	.0660	.0568	.1228	.0093	.1001	.0018	.0016
SD	.0382	.0241	.0577	.0275	.0524	.0018	.0016
Motor vehicles and trailers							
Mean	.0655	.1016	.1672	−.0361	.1056	.0071	.0041
SD	.0391	.0437	.0529	.0639	.0558	.0135	.0052
Other transport equipment							
Mean	.1683	.1101	.2784	.0582	.0827	.1549	.0003
SD	.2322	.0656	.2003	.2762	.1245	.2289	.0005
Furniture and NEC manufacturing							
Mean	.0730	.0707	.1438	.0022	.1285	.0164	.0075
SD	.0308	.0254	.0527	.0202	.0545	.0131	.0119
Recycling							
Mean	.0523	.0324	.0847	.0198	.0591	.0027	.0052
SD	.0247	.0237	.0363	.0321	.0362	.0047	.0071

white noise error term. It is ω that potentially causes a simultaneity problem. The essence of the Olley–Pakes approach relies on the theory of firm dynamics, which shows that investment can be modeled as a positive and monotonic increasing function of the productivity shock, ω, and capital (Ericson and Pakes, 1995). The investment function is used to identify the productivity shock. Inverting the investment function allows the productivity shock to be substituted out, which allows consistent estimation of the labor coefficient. In each period the firm decides whether to continue operations or to exit, depending on the productivity shock it experiences. This allows in a second step to identify the capital coefficient (for details see Appendix B).

3.2. The evolution and decomposition of total factor productivity

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). We estimate firm-level productivity using (1) for every 2-digit NACE sector separately controlling for 3-digit NACE industry and time effects.[7] In Appendix B we report the results of estimating the production function for the various 2-digit sectors using OLS, Fixed Effects (FE) and Olley and Pakes (OP).

The coefficients on labor and capital using the different estimation methods differ depending on the estimation method used. Given that productivity shocks and labor usage are positively correlated, we expect the labor coefficient to be upward biased under OLS, which is confirmed in Table B1. The FE estimator controls for this. However, it assumes a time invariant productivity shock resulting in biased estimates (Olley and Pakes, 1996). This result in itself is interesting and adds to the literature on labor-managed firms.[8] Under the assumption of profit maximization, a higher productivity shock leads to greater demand for labor and higher production. However, labor-managed firms maximize income per worker and reduce employment and output when they draw a high productivity shock. Prasnikar et al. (1994) test the competing prediction on a sample of Yugoslav (including Slovenian) firms and find that the firms are somewhere between the two paradigms. We find the OLS coefficient on labor is biased upwards, suggesting that during the period 1994–2000 firms behaved as profit maximizers. 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. Without correcting, this leads to a negative bias on the capital coefficient.[9] We shall use the OP estimates to compute aggregate TFP. Our estimate for TFP follows from the production function and is given by

$$\tilde{\omega}_{ijt} = \exp\left(y_{ijt} - b_{jl}l_{ijt} - b_{jk}k_{ijt}\right).$$

With this measure in hand, we can compute an aggregate productivity index, which is a share weighted sum of the firm-level TFP ($\tilde{\omega}$) computed on the entire sample of firms, using the industry-specific estimates of the input coefficients (b_{jl} and b_{jk}) obtained from the OP approach. $\tilde{\omega}_{ijt}$ refers to the estimated total factor productivity of firm i active in industry j at time t and has a clear economic interpretation, since we express it in monetary units, i.e. thousand of Slovenian Tolars. The productivity index of industry j at time t is given by

$$P_{jt} = \sum_{i=1}^{N_t} s_{ijt}\tilde{\omega}_{ijt} \tag{2}$$

where s_{ijt} stands for a firm-specific weight of firm i active in industry j at time t. Given our interest in the process of *job* reallocation and how productivity (growth) has evolved in

[7] We excluded a small number of sectors from the TFP analysis that were present in the job flows analysis, mainly due to the limited number of available data that we had. For instance, the tobacco industry is not included as this is a monopoly in Slovenia.

[8] We would like to thank Jan Svejnar for pointing this out to us.

[9] We also estimated the capital coefficient using the Olley and Pakes (1996) procedure, however, without taking the selection problem into account. It is clear that this estimate is in general lower than the OP with the survival correction, confirming our priors.

manufacturing, we compute an aggregate productivity index using employment based shares, rather than output based market shares, or $s_{ijt}=L_{ijt}/\sum_i L_{ijt}$.

To assess how the evolution of aggregate TFP depends on firm-level improvements in TFP versus reallocation of employment between firms various decompositions can be used. No clear consensus exists on which is the most appropriate to use, just as there is no clear consensus on the appropriate weights (shares) that should be used (for a discussion see Van Biesebroeck, 2003). We use two different decompositions that are frequently used in the literature. The first, due to Olley and Pakes (1996), splits the aggregate productivity index into an unweighted mean and a (cross-sectional) sample covariance term. The extent to which the share of the sample covariance changes over time tells us something about the importance of reallocation of employment between *existing* firms in TFP growth. Formally, the index P is decomposed as

$$P_{jt} = \tilde{\bar{\omega}}_{jt} + \sum_{i=1}^{N_t} \left(s_{ijt} - \bar{s}_{jt}\right)\left(\bar{\omega}_{ijt} - \overline{\tilde{\omega}}_{jt}\right)$$

where $\overline{\tilde{\omega}}_{jt}$ and $\bar{s}_{jt}$ represent unweighted mean productivity and mean share of industry j, respectively. In Table 7 we show the productivity index and the relative importance of firm-level average productivity and reallocation in aggregate TFP. This allows us to assess whether the increase in aggregate TFP is due to the average firm becoming more productive or whether there is a reallocation of market share away from the least productive to the most productive firms. The first year of the sample period – 1994 – is normalized to one and other years are expressed with respect to this base year. We note that (on average) the output growth in Slovenian manufacturing sector has been impressive and positive: on average the productivity index went up by more than 63% by the end of the sample period (2000). It is also clear that there is quite some heterogeneity among the different sectors within the manufacturing sector, ranging from a small increase of 7% in the

Table 7
The evolution of the productivity index

Industry	1994	1995	1996	1997	1998	1999	2000
Food products and beverages	1.00	.96	1.05	1.09	1.11	1.10	1.07
Textiles	1.00	1.06	1.30	1.37	1.37	1.46	1.37
Wearing apparel	1.00	.99	1.09	1.12	1.16	1.13	1.07
Leather and leather products	1.00	.89	.98	1.12	.94	1.21	1.33
Wood and wood products	1.00	1.06	1.08	1.19	1.25	1.36	1.45
Pulp, paper and paper products	1.00	1.05	1.77	1.42	1.46	1.69	1.85
Publishing and printing	1.00	.99	1.05	1.19	1.21	1.43	1.44
Chemicals and chemical products	1.00	.99	1.09	1.35	1.28	1.38	1.44
Rubber and plastic products.	1.00	.93	1.16	1.37	1.16	1.41	1.44
Non-metallic mineral products	1.00	.97	1.11	1.25	1.26	1.50	1.50
Basic metal products	1.00	1.49	1.43	1.87	2.01	2.35	2.77
Fabricated metal products	1.00	1.08	1.19	1.33	1.34	1.49	1.59
Machinery and equipment	1.00	1.06	1.58	1.88	1.92	2.15	2.32
Electrical machinery and apparatus	1.00	1.11	1.34	1.55	1.53	1.77	1.89
Medical, precision and optical	1.00	1.08	1.11	1.37	1.41	1.53	1.72
Motor vehicles and trailers	1.00	1.16	1.09	1.26	1.43	1.46	1.61
Other transport equipment	1.00	1.16	1.44	1.39	1.68	1.89	2.03
Furniture and NEC manufacturing	1.00	1.11	1.21	1.45	1.47	1.42	1.47
Average	1.00	1.06	1.23	1.37	1.39	1.54	1.63
Share mean productivity	1.17	1.24	1.38	1.53	1.60	1.73	1.77
Share sample covariance	−.17	−.17	−.16	−.17	−.21	−.19	−.14

'Wearing Apparel' sector to a steep increase of 277% in the 'Basic Metals' industry. We further decompose the productivity index for every different industry at the 2-digit NACE level. The latter implies that the employment shares used to weigh the productivity estimates refer to that specific sector. The sample covariance term is negative, suggesting that more productive firms are downsizing. For brevity we do not report the decomposition for every industry, but there is a large variation in the importance of reallocation across the various industries.

The within-firm productivity growth has been the main reason for the steady growth in TFP rather than reallocation. Firms become more productive by downsizing, which suggests that the process of aggregate productivity growth is driven mainly by the job destruction process. It is clear from Table 7 that there is great heterogeneity among the different industries, which makes it necessary to look at the micro-economic causes and foundations of productivity growth rather than some general trend. Both the roles of entry and exit vary considerably across the different sectors of the manufacturing.

However, there may be other reasons for an increase in aggregate productivity that are independent of reallocation as measured by the cross-sectional sample covariance and average firm-level productivity increases, in particular, the simultaneous entry and exit of firms (employment) where unproductive firms (jobs) exit (are destroyed) and replaced by more productive firms (jobs). This is the Schumpeterian *creative destruction process*. The decomposition above cannot disentangle these net entry effects. We therefore use another type of decomposition as developed by Foster et al. (2001), and applied for instance by Levinsohn and Petrin (2003b). Using the same notation we can decompose the *change* (where Δ stands for the year-to-year change ($\Delta x_{it}=x_{it}-x_{it-1}$)) in the productivity index into 4 components; i.e.

$$\Delta P_{jt} = \sum_{i \in A}^{N_A} s_{ijt-1}\Delta\tilde{\omega}_{ijt} + \sum_{i \in A}^{N_A} \tilde{\omega}_{ijt-1}\Delta s_{ijt} + \sum_{i \in A}^{N_A} \Delta s_{ijt}\Delta\tilde{\omega}_{ijt} + \left(\sum_{i \in B}^{N_B} s_{ijt}\tilde{\omega}_{ijt} - \sum_{i \in C}^{N_C} s_{ijt-1}\tilde{\omega}_{ijt-1} \right) \tag{3}$$

Here set A contains the firms that continue their operation between t and $t-1$, set B contains the entering firms at time t and set C contains the firms that exited in $t-1$. The change in the productivity index now has the different components reported in Table 8: (i) a pure *within*-firm productivity increase (*Within Prod*), (ii) a *between*-firm reallocation component (*Reallocation*), (iii) an interaction term (*Covariance*) and (iv) a *net-entry* component (*Net Entry*), the term in brackets in (3). The latter could be important in the context of a post-socialist country where simultaneous entry and exit is a feature of industrial restructuring. A negative *between*-firm

Table 8
Decomposition of productivity index: share of components

Year	Within prod (%)	Reallocation (%)	Covariance (%)	Net entry (%)
1995	57.8	9.3	−30.2	63.1
1996	165.7	−48.2	−26.6	9.1
1997	92.6	12.2	−6.0	1.2
1998	139.9	25.3	−89.6	24.4
1999	173.9	−68.8	−6.7	1.7
2000	110.3	.4	−12.7	2.0
Average	123.4	−11.7	−28.6	16.9

Note: This is the decomposition as expressed in Eq. (3) and reports the median over industries.

component points to the fact that firms that are experiencing productivity growth are downsizing in terms of employment. In Table 8 we show the share of the different components of this change in the productivity index summarized over the different industries. Given the high degree of heterogeneity across the different industries, we look at the median of the different components across the manufacturing industries. Furthermore we report averages of these shares over the years, filtering out the cyclicality in the share of the various components in TFP growth over the sample period.

We can note that most of the productivity growth is explained by the *within*-firm productivity growth. In other words firms have become more efficient on average, which is in line with the findings reported in Table 7. 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 (on average −11.7%) suggests that increases in productivity have been associated with a process where more productive firms are downsizing faster than less productive firms. The covariance term tells us how much of the change in productivity is correlated with the change in employment. It has no specific economic interpretation except for the fact that this term is crucial in order to measure the other two (reallocation and real productivity) in a correct way (also see Levinsohn and Petrin, 2003b). It is negative in almost all years across industries, confirming that firms that grow in productivity become smaller in size. This is what can be expected in a post-socialist economy, suffering from over-manning levels.

More importantly, however, the *net firm entry* component explains – averaged over the sample period – 16.9% of the observed aggregate productivity growth, which is substantial, and in some years even more. In 1995 and 1998 the net entry component accounted for 63.1% and 24.4% of the productivity growth, respectively. The creative destruction process that took place in the Slovenian manufacturing sector is not that much caused by reallocation of employment *between* existing firms, rather by entry of more productive firms replacing unproductive ones. This suggests that encouraging firm entry and exit is important to enhance aggregate productivity. And hence setting up policies that enhance competitive markets, by removing entry and exit barriers, should be important for productivity growth.

Finally, we know from our job flow analysis that private firms are net job creators, the role of entry and exit is far more important in the private sector and that exporting firms provide more stable jobs. Therefore we further split up every component in the decomposition represented in Eq. (3) according to ownership (private and state owned), presented in Table 9. Formally this means that we just split up the sum of the different components into a set of private and state owned enterprises. The same decomposition could be broken down by export status, however, the export status within firms is quite unstable over the sample period and makes the year-to-year change in the productivity index very sensitive to these changes.[10]

Table 9 presents the results of this decomposition broken down by ownership. We can note that the relatively high within component reported in Table 8 is mainly due to state firms becoming more efficient. While in Table 8 we noted a negative reallocation component, suggesting that more efficient firms are downsizing in terms of employment, from Table 9 we can see that this negative reallocation is driven by the state firms that are downsizing. In other words they are getting rid off the over-manning levels. However, for private firms we can note

[10] Firms start to export, quit exporting, switch export status over the sample period. For more on this we refer to De Loecker (2004).

Table 9
Decomposition of productivity index by ownership: share of components

Year	Within Prod		Reallocation		Covariance		Net entry	
	Private (%)	State (%)	Private (%)	State (%)	Private (%)	State (%)	Private (%)	State (%)
1995	58.9	−1.1	96.5	−87.2	−24.0	−6.2	56.3	6.8
1996	29.0	136.7	27.8	−76.0	−18.4	−8.2	9.1	.0
1997	20.3	72.3	18.9	−6.7	−4.7	−1.3	1.2	.0
1998	28.8	111.1	127.7	−102.4	−66.2	−23.3	24.4	.0
1999	56.5	117.4	1.0	−69.9	−3.5	−3.2	1.7	.0
2000	28.6	81.8	21.0	−20.7	−7.0	−5.7	2.0	.0
Average	37.0	86.4	48.8	−60.5	−20.6	−8.0	15.8	1.1

Note: The components for private and state owned are represented by 'private' and 'state', respectively.

on average a positive reallocation component, which is quite substantial and on average more important in explaining TFP growth than the within component (48.8% versus 37% respectively). This means that employment is being reallocated from less efficient to more efficient private firms. Finally, the relatively important net entry component in explaining TFP growth reported in Table 8 is almost entirely driven by the entry of new private or de novo firms as can be seen from the last two columns in Table 9.

These findings are consistent with our results from our job flow analysis. Considering the high simultaneous job creation and destruction rates documented in the previous section, the increase in TFP suggests a process of creative destruction. State firms behave differently than private firms, the former destroy jobs to become more efficient, while the latter are characterized by reallocation of employment to the more productive firms. Furthermore, the net entry of de novo private firms is an important component in explaining overall TFP growth.

4. Conclusions

This paper sheds light on whether the transition process in Slovenian manufacturing has been one of creative destruction. As in other post-socialist economies, the transition process in manufacturing has been characterized by a high job destruction rate that dominates the job creation rate, which is likely a reflection of the communist legacy of labor hoarding and firms attempting to increase efficiency levels by reducing jobs. Furthermore, the typical stylized fact of high heterogeneity between firms in terms of job flows is confirmed.

Firm entry and exit have been important in the creative destruction process. More than 22% of all job creation has been due to firm entry, while more than 11% of all job destruction is accounted for by exit of firms. These figures are even higher for private and small firms, suggesting that state firms still enjoy soft budget constraints.

We document substantial productivity growth mainly explained by firms becoming more efficient and entry of more efficient firms, rather than a shift in employment shares towards the more efficient existing firms. On average, the net entry process (entry minus exit) accounts for about 17% of observed aggregate productivity growth. State firms behave differently than private firms, with the former destroying jobs to become more efficient, while the latter are characterized by reallocation of employment to the more productive firms. Net entry of de novo private firms is an important component in explaining overall TFP growth. Policies that enhance the entry of de novo private firms will therefore increase productivity as are policies that restructure state firms.

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Appendix A. Data appendix

This appendix describes the variables that we use in more detail. All monetary variables are deflated by the appropriate 2-digit NACE industry deflators and investment is deflated using a 1-digit NACE investment deflator. We observe all variables every year in nominal values, however. Gross investment is not reported but can be calculated from the information on the book value of capital and depreciation.

- 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 eliminates 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, $I_t = K_{t+1} - (1-\delta)K_t$. 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 as reported by ILO. The table below presents the coverage rates for the various years of the sample. We cover most (around 75%) of the total manufacturing employment.

Table A1
Sample representation (using 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%

Table A2
Summary statistics

Year	Size	Value added	Wage	Capital pw	Sales	Value added pw
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: pw: per worker; all monetary variables are expressed in real terms, using a 2-digit NACE industry PPI to deflate and are expressed in thousands of Slovenian tolars.

Table A3
Entry and exit between 1995 and 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 A4
Manufacturing entry and exit rates in selected countries (year-averages)

Country	Entry rate	Exit rate	Period
Estonia	13.0	7.0	1996/2000
Canada	10.2	8.7	1985/1997
Germany	5.4	6.6	1979/1996
USA	8.8	8.0	1990/1996
Finland	9.0	6.8	1990/1997
Portugal	3.0	1.9	1984/1978
UK	15.6	14.3	1987/1997
Italy	7.8	8.4	1988/1993
Netherlands	9.0	6.5	1988/1997
France	11.9	10.5	1990/1996
Denmark	9.1	10.7	1982/1994

Source: Own calculations and OECD (2002) and Masso et al. (2004) for the figures on Estonia.

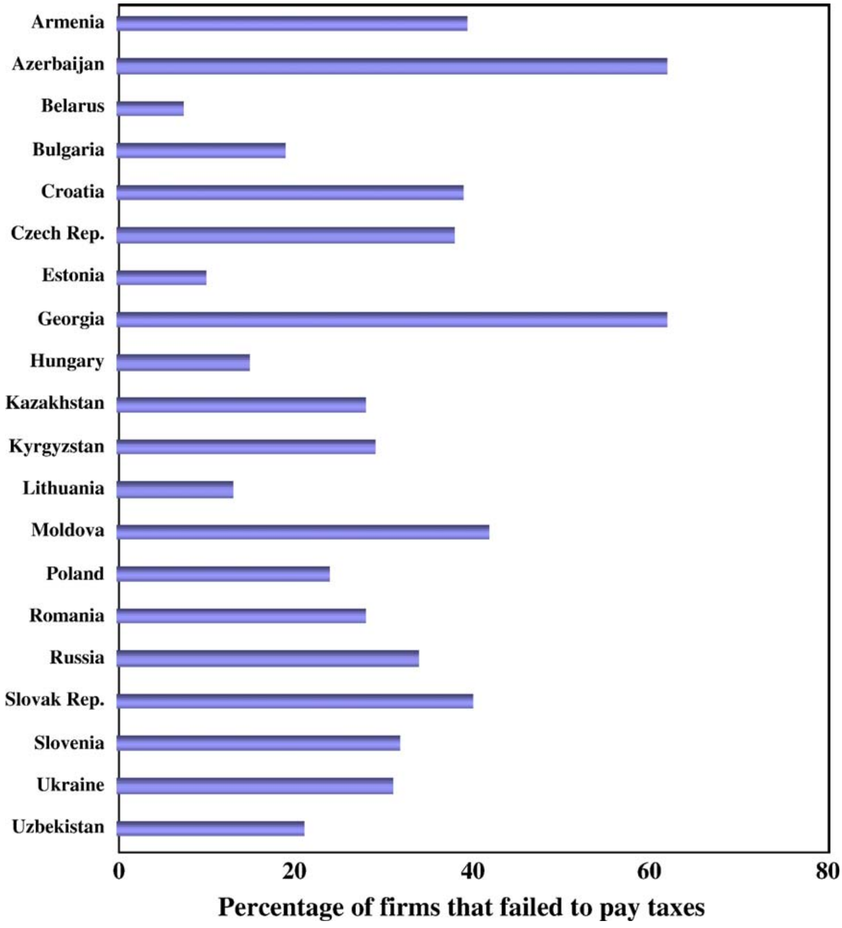

Fig. A1. Soft budget constraints in post-socialist economies (EBRD, 1999).

Appendix B. Estimating total factor productivity

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

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \eta_{it} \tag{A.1}$$

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.

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. 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 (2003a). They suggest using intermediate inputs such as electricity and fuels instead of investment. 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 substitute this function into Eq. (A.1) and we collect the constant and the terms depending on capital and investment in a function $\phi(i, k)$ where for now we drop the firm index i. One can adjust this function to be different for different types of 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 (2004) for the Slovenian manufacturing sector. This results in a partial linear model where the error term is not correlated with the freely chosen labor input.

$$y_{it} = \beta_l l_{it} + \phi_t(i_{it}, k_{it} + \eta_{it}) \tag{A.2}$$

The above can be estimated using standard semi-parametric estimation techniques following Robinson (1988). 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

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

The probability that a firm survives at time $t+1$ given its information set J_t and the future market conditions 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 $t+1$.

$$E\left[y_{t+1} - \beta_l l_{t+1} | k_{t+1}, \chi_{t+1} = 1\right] = \beta_k k_{t+1} + E\left[\omega_{t+1} | \omega_t, \chi_{t+1} = 1\right] = \beta_k k_{t+1} + g\left(\underline{\omega}_{t+1}, \omega_t\right)$$

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

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

where we used the result from the survival equation. 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

Table B1
The estimated coefficients of the production function

Sector	Coefficient on labor			Coefficient on capital		
	OLS	FE	OP	OLS	FE	OP
Food products and beverages	.9105 (.0200)	.8228 (.0423)	.8590 (.0280)	.1928 (.0150)	.1911 (.0298)	.2245 (.0749)
Textiles	.8077 (.0179)	.6336 (.0383)	.7805 (.0238)	.1728 (.0131)	.1015 (.0203)	.1790 (.0600)
Wearing apparel	.8723 (.0165)	.8224 (.0442)	.8615 (.0234)	.1734 (.0134)	.1392 (.0249)	.1609 (.0595)
Leather and leather products	.7945 (.0395)	.4215 (.1146)	.6077 (.0551)	.2059 (.0302)	.1163 (.0516)	.3475 (.0912)
Wood and wood products	.7946 (.0165)	.6805 (.0375)	.7974 (.0220)	.1914 (.0124)	.2459 (.0212)	.2014 (.0717)
Pulp, paper and paper products	.7952 (.0290)	.5788 (.0696)	.6601 (.0366)	.2236 (.0222)	.1814 (.0375)	.2797 (.1680)
Publishing and printing	.7986 (.0169)	.6717 (.0303)	.7035 (.0229)	.2711 (.0114)	.1849 (.0162)	.2519 (.1377)
Chemicals and chemical products	.8089 (.0387)	.6963 (.0725)	.6849 (.0472)	.2694 (.0275)	.1380 (.0382)	.1950 (.1221)
Rubber and plastic products	.7276 (.0186)	.7757 (.0375)	.7172 (.0243)	.2791 (.0133)	.2403 (.0202)	.1673 (.1235)
Non-metallic mineral products	.8027 (.0218)	.7800 (.0472)	.7705 (.0304)	.2192 (.0154)	.1193 (.0232)	.1995 (.1040)
Basic metals	.6525 (.0376)	.7433 (.0832)	.6427 (.0480)	.2715 (.0307)	.2502 (.0501)	.2820 (.0758)
Fabricated metal products	.7925 (.0100)	.7917 (.0224)	.7851 (.0131)	.2331 (.0073)	.2100 (.0118)	.1500 (.0993)
Machinery and equipment	.7495 (.0153)	.7793 (.0323)	.8195 (.0176)	.2328 (.0119)	.2336 (.0189)	.1971 (.0731)
Electrical machinery and apparatus	.7629 (.0204)	.8593 (.0527)	.7759 (.0268)	.2737 (.0153)	.3035 (.0249)	.3571 (.1275)
Medical, precision and optical	.7723 (.0229)	.6616 (.0537)	.7467 (.0295)	.2349 (.0175)	.2802 (.0323)	.2279 (.1028)
Motor vehicles and trailers	.7584 (.0298)	.8517 (.0654)	.7643 (.0297)	.2077 (.0229)	.2365 (.0311)	.1970 (.0982)
Other transport equipment	.7932 (.0641)	.8425 (.0851)	.7816 (.0703)	.1701 (.0509)	.1620 (.0635)	.0893 (.0493)
Furniture and NEC manufacturing	.8105 (.0167)	.7675 (.0346)	.8250 (.0213)	.2131 (.0124)	.2226 (.0187)	.2478 (.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 1000 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 drops 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 2-digit NACE and include 3-digit NACE dummies and a time trend in order to allow the non parametric function to be different for the different sub sectors 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.

$t+1$ is independent of all variables at time t, it means that the news is uncorrelated with capital $(E(\xi_{t+1}k_{t+1})=0)$.

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_1, ϕ_t and P_{t+1} 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

$$y_{t+1} - b_l l_{t+1} = c + \beta_k k_{t+1} + \sum_{j=0}^{s-m} \sum_{m=0}^{s} \beta_{mj} \left(\widehat{\phi} t - \beta_k k_t\right)^m \widehat{P}_{t+1}^{j} + e_{t+1} \tag{A.3}$$

where s denotes the order of the polynomial used to estimate the coefficient on capital. In Table B1 we present the estimated coefficients for the various industries.

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