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**Do Exports Generate Higher Productivity? Evidence from Slovenia.**

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# Do Exports Generate Higher Productivity? Evidence from Slovenia.\*

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## Abstract

I use matched sampling techniques to analyze whether firms that start exporting become more productive, controlling for the self selection into export markets. To this end, I use micro data of Slovenian manufacturing firms operating in the period 1994-2000. Simple OLS regressions establish a strong correlation between various productivity measures and export status at the firm-level as documented before by Bernard and Jensen (1999). I estimate total factor productivity correcting for sample selection and for the simultaneity bias using the Olley and Pakes (1996) framework where I allow exporting firms to face different market structures and relax the assumption that productivity follows an exogenous Markov process. Overall I find that export entrants become on average 8.8 percent more productive once they start exporting. The productivity gap between exporters and their domestic counterparts increases further over time, reaching a 12.4 percent higher productivity growth after 4 years of exporting. These results also hold at the industry level and are robust to other controls that may be associated with increased productivity, such as private ownership. Using information on the (firm-level) destination of exports, I find that the productivity gains are higher for firms exporting only towards high income regions.

**JEL Code:** L1, D24

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# 1 Introduction

One of the main empirical regularities that characterizes exporters is that they are more productive than non exporters.<sup>1</sup> It is this empirical finding that is often cited as an argument for active export promotion in many developing countries. The literature suggests that at least two mechanisms can explain a positive correlation between exporting and productivity. The first is related to self-selection: It is only the more productive firms that engage in export activities and are able to compete in international competitive markets. The second explanation is the ‘learning-by-exporting’ hypothesis: Because firms enter into export markets they gain new knowledge and expertise which allows them to improve their efficiency level. Some authors have argued that exporting firms may gain access to technical expertise from their buyers, which non exporters do not have.<sup>2</sup> While the self-selection hypothesis has been confirmed by various authors, the evidence on the learning hypothesis has been less clear-cut. Recently various authors have addressed the question at hand using various techniques applied on different datasets. There has been a substantial evidence in favor of self-selection as documented by Bernard and Jensen (1999) for the US, Clerides, Lach and Tybout (1998) for Colombia, Mexico and Morocco, Aw, Chung and Roberts (2000) for Taiwan. As mentioned before, the evidence in favor of learning by exporting has been less clear cut. Some recent studies including Aw, Chung and Roberts (2000) for Korea, Van Biesebroeck (2005) for Côte-d’Ivoire and Girma *et al.* (2003) for UK have documented that firms experience significant productivity increases after entering the export market.

This paper contributes in various aspects. Firstly, I use an unique firm-level dataset covering virtually the entire manufacturing sector of Slovenia for the period 1994-2000. Slovenia is a particularly interesting emerging economy to study as it has been successfully transformed from a socially planned economy to a market economy in less than a decade, reaching a level of GDP per capita over 65 percent of the EU average by the year 2000. Furthermore, the transition from plan to market implied the opening up of the economy to the West, which resulted in a substantial increase in exports in a very short period of time. Between 1994 and 2000 total real exports in Slovenian manufacturing doubled, while the number of firms entering export markets nearly quadrupled. These drastic changes in trade orientation leaves us with a natural experiment, which provides a rich background to analyze the relationship between export behavior and firm performance. There is

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<sup>1</sup>Empirical contributions include Roberts and Tybout (1997), Clerides, Lach and Tybout (1998), Bernard and Jensen (1999), Van Biesebroeck (2005), Alvarez and Lopez (2004). Theoretical contributions include Melitz (2003) and Bernard *et al* (2003).

<sup>2</sup>See Evenson and Westphal (1995), Westphal (1993), Grossman and Helpman (1991) and World Bank (1993).

some circumstantial evidence pointing to the potential gains from exporting in the case of Slovenia, the Slovenian Times (2005, vol 3, no 32) reported that “... *Slovenia [of all the Yugoslav republics] had the closest links with these developed economies, it also had a comparative advantage in terms of copying and adapting their production techniques and employing them in the production that were subsequently exported to southern markets*”.

Secondly, I suggest a modification to the Olley-Pakes (1996) method to estimate total factor productivity, which allows me to control for the potential endogeneity of input factors. This method also allows me to model sample selection, which may be important in an emerging economy that is characterized by exit of the least efficient firms.<sup>3</sup> I modify the Olley and Pakes (1996) by introducing export into the structural model, allowing market structures faced by exporters to differ from domestic firms. This correction is important in several respects. Firstly, it controls for unobserved productivity shocks that are correlated with the export status of a firm and therefore leads to reliable estimates of the production function coefficients. Secondly, by allowing different market structures - capturing the mode of competition, demand conditions, exit barriers, ... - for exporting firms I filter out all effects common to exporters within an industry. These productivity estimates are then used to verify whether entering the export markets leads to productivity gains, both instantaneously and in future years. Therefore, if I still find evidence for productivity gains after entering the export market, it suggests a more fundamental process taking place at the firm level.

Thirdly, this paper uses matched sampling techniques as developed by Heckman *et al.* (1997) based on an underlying selection model into export markets. I look at the productivity effects of firms *entering the export market*, as opposed to studies that base their analysis on the export status. The latter blurs the analysis by mixing effects of continuing to export and starting to export. My methodology allows to verify the impact of starting to export on the future productivity path. This is in contrast to recent studies (e.g. Van Biesebroeck; 2005 and Blalock and Gertler; 2003) that identify one parameter that captures the effect of exporting on productivity, not allowing the effects after e.g. 3 years of exporting to be different from the instantaneous impact. The latter is crucial since entering the export market might not have an immediate effect on productivity. I also verify to which extent the productivity gains depend on the destination of the exports, i.e. low versus high income regions.

Finally, I estimate productivity using a production function where I allow for endogenous productivity gains over time through past export experience relaxing the assumption that productivity follows an exogenous first order Markov process.

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<sup>3</sup>See De Loecker and Konings (2005). In addition I also consider an additional decision to export, modelling the self selection into export markets.

I organize the paper as follows. In section 2. I discuss the data set and perform some preliminary analysis. In section 3. I discuss the estimation procedure for getting reliable estimates of productivity and spend some time on the underlying structural model since I extend this later on. I report the results on the production function coefficients and the resulting total factor productivity (TFP) estimates. In section 4. I present the sample matching technique and demonstrate how this allows me to test the learning-by-exporting hypothesis, after controlling for self-selection in export markets. In section 5. I perform various robustness checks including the destination of exports and allow productivity to depend on past export experience, i.e. relaxing the assumption that unobserved productivity follows an exogenous Markov process. I then collect the main findings and the last section concludes the paper.

## 2 Data and Preliminary Analysis

### 2.1 Data Description<sup>4</sup>

The data are taken from the Slovenian Central Statistical Office and are the full company accounts of firms operating in the manufacturing sector between 1994-2000.<sup>5</sup> I have information on 7,915 firms and it is an unbalanced panel with information on entry and exit. If I only take into account those (active) firms that report employment, capital stock and sales, I end up with a sample of 20,580 total observations over the sample period. Table 1 shows the number of firms that I observe each year and those that are exporting. While in 1994 about 1,539 firms were exporting, by 2000 2,335 did so or this represents an increase of 52 percent. The entire number of firms increased also over this period by 42 percent resulting in a net increase of 10 percent more exporters over a seven year period. In the last column I show the number of firms that started exporting. On average 16 percent of the exporting firms are new entrants in the export market. It is essentially the variation in productivity between those new export entrants and similar domestic firms that I will use to verify the learning by exporting hypothesis. As mentioned above, it is this unique setting that allows me to verify the impact of *starting to export* on the productivity trajectory. In total I observe 1,872 firms that enter the export market at different points in time. The latter is crucial in order to control for time effects when analyzing the impact on the productivity path. It is important to note that only 7 percent of the export entrants are new firms entering the market. This leaves me with

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<sup>4</sup>For full details and representativeness of the data see Data Appendix

<sup>5</sup>The unit of observation is that of an establishment (plant). In the text I refer to this unit of observation as a firm. Related work using the same data source includes Damijan et al, (2004a, 2004b) and Konings and Xavier (2003).

around 1,700 export entrants that were active on the domestic market before entering the export market. Turning back to the central question what drives the robust high correlation between productivity and firm-level export status: self-selection or learning by exporting? In order to disentangle the causality from export status to productivity I have to control for the self-selection explicitly, essentially conditioning on pre-export levels of productivity.

The increased importance of exports in Slovenian manufacturing becomes also clear from Figure 1 where I plot real domestic and export sales, expressed as an index with base year 1994 set equal to 1. We can note that both domestic and export real sales have increased between 1994 and 2000, however, the increase in exports has been stronger than the one in domestic sales. This paper essentially verifies the extent to which entering foreign markets through exporting has led to significant productivity improvements using firm-level data.

The structural change that has been going on in Slovenian manufacturing is also revealed by the patterns of enterprise turnover. In Table 2 I show the entry and exit patterns in the data. Over the sample period I find an annual average exit rate of 3 percent, 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 percent, for Morocco of 3.7 percent and for Mexico of 1.5 percent. The entry rate in my sample is much higher, on average 5.65 percent per year. This compares to entry rates of 2.7 percent, 4.9 percent and 4.8 percent reported for Colombia, Morocco and Mexico respectively. The high 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 has potentially played an important role in the transition process (e.g. Bilsen and Konings, 1999).

Finally, in Table 3 I present summary statistics for some basic variables that I use later on in the analysis. I 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) where I used a two-digit producer price index to deflate the variables.<sup>6</sup> From Table 3 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. Both real sales, value added and

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<sup>6</sup>This, however, does not fully capture the differences in price indices across countries where firms are exporting to. It could be that exporting firms sell their products at higher prices and therefore deflating their sales by a Slovenian price index might not fully capture price evolutions. I address this issue in more detail in the robustness checks (section 5) by using the information on the destination of the exports.

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 Preliminary Analysis

In this section I perform a rough preliminary analysis to show whether the facts found in the literature - that exporting firms have different characteristics compared to non exporting firms - also holds for a transition economy like Slovenia. Following Bernard and Jensen (1999) and others, I run the following OLS regression

$$X_{ikt} = \alpha + \beta EXP_{ikt} + \gamma l_{ikt} + \sum_j \delta_j Time_j + \sum_k \lambda_k Ind_k + \varepsilon_{ikt} \quad (1)$$

where  $X_{ikt}$  refers to the characteristics of firm  $i$  at period  $t$  active in industry  $k$ ,  $EXP$  is an export dummy equal to one when the firm is an exporter and zero otherwise and  $l$  is the log of the number of employees of firm  $i$ . I control for industry and year effects, where subscripts  $k$  and  $j$  run through the number of industries ( $Ind$ ) and years ( $Time$ ), respectively. The interest lies in the coefficient  $\beta$  that tells us whether the relevant firm characteristic is different for exporting firms relative to non exporting ones. Moreover, it has a clear economic interpretation, i.e. it reveals the percentage differential between exporters and non exporters. Table 4 shows the results of estimating equation (1). It is clear that exporters differ significantly from non exporters. Using labor productivity as a rough measure for productivity, I find that exporting firms are on average 29.59 percent more productive. This paper is exactly about disentangling this stable correlation between export status and productivity. I provide a methodology to analyze the causality from export status to productivity (learning by exporting) controlling for the selection into export markets. In addition my methodology allows to test whether future productivity (and the productivity trajectory) changes after entering the export market.

Furthermore, exporters pay on average higher wages (16.14%), sell more (58.63%), operate on a larger scale, invest more (37.49%) and are more capital intensive (36%). These results are in line with the findings of Bernard and Jensen (1995) for the U.S.A., Bernard and Wagner (1997) for Germany, Isgut (2001) for Columbia and Van Biesebroeck (2005) for sub-Saharan Africa among others.<sup>7</sup>

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<sup>7</sup>Recently Fernandez and Isgut (2005) and Wagner (2005) surveyed various studies analyzing the link between export status and productivity.



### 3 Productivity: Estimation Strategy and The Coefficients of the Production Function

In this section I discuss my estimation strategy for getting reliable estimates of the production function.<sup>8</sup> Secondly, I discuss the resulting estimated coefficients and I compare them to the OLS, Fixed Effect and the standard Olley and Pakes (1996) method. Finally I briefly discuss the trend of aggregate productivity in the Slovenian manufacturing sector.

#### 3.1 Estimating Total Factor Productivity

I now turn to the estimation strategy to estimate productivity which is built on Olley and Pakes (1996). The strength of this approach lies in two innovations: First it allows us to control for the simultaneity bias when estimating production functions, without having to rely on instruments. This is important as it is often hard or impossible to find good instruments. The second innovation of this approach is that it controls for potential selection bias in estimating production functions. This is especially relevant in the context of transition as selection is likely going to be an intrinsic part of the transition process, where unproductive firms leave the industry and are being replaced by more productive ones. Ignoring this selection mechanism may bias estimates of aggregate TFP. This approach has recently been used to analyze the impact of trade liberalization on plant productivity in Chile by Pavcnik (2002) and to analyze the effect of FDI on productivity of domestic firms (Keller and Yeaple, 2003).

I extend the Olley and Pakes (1996) framework by allowing market structure (factor markets, demand conditions, ...) to be different for exporting firms by introducing export into the underlying structural model.

Let firm behavior be described as follows. It maximizes 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 ( $\omega$ ). 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 whether it continues its operations or not whereby it receives a one-time sell-off value 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 I dropped the firm index for ease of notation. Productivity is assumed to be determined by a family

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<sup>8</sup>I rather estimate a value-added generating production function since I do not observe physical output. However, I interpret productivity in a broad sense, i.e. condition on the level of inputs how much more value added does a firm generate (is more productive) than another.

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.

I modify the standard Olley and Pakes (1996) framework by introducing export as a state variable, i.e. the decisions to invest and to exit the market depend on whether a firm exports or not. From the preliminary analysis we know that exporters invest more per worker and I also find higher exit rates across all industries for non exporting firms (see Table 2), i.e. 2.9 percent versus 0.3 percent on average. The consistent lower exit rates for the sample of exporting firms across industries and over time is striking. However, some of these effects are captured in the Olley and Pakes (1996) approach as well. In their model firms exit whenever they draw a productivity shock that is lower than some threshold value which depends on the capital stock of the firm. The latter is related to the export status since exporters tend to be more capital intensive. By incorporating the export status into the investment and exit rule explicitly, I can control for the entire market structure differences according to export status instead of only controlling through the capital stock. Note that the investment policy function in Olley and Pakes (1996) is a solution to a complicated dynamic programming problem and depends on all the primitives of the model like demand functions, the specification of sunk costs, form of conduct in the industry and others (Akerberg, Benkard, Berry and Pakes; 2005). All these factors are now allowed to be different and evolve different over time for exporting firms.

Furthermore, since I deflate value added with a Slovenian PPI, I do not control for the fact that output and factor prices might be different and/or evolve different over time for exporting firms. Therefore I drop this assumption and incorporate the export dummy in the investment and survival equilibrium equations.<sup>9</sup>

More formally, I explicitly take into account that exporting firms face different market structures and factor prices when decisions are made about investment and exiting the market. Formally this means that the investment equilibrium relation can be represented as follows (2)

$$i_{it} = i_t(\omega_{it}, k_{it}, e_{it}) \quad (2)$$

where  $e$  denotes the export dummy. I assume that investment is still monotonically

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<sup>9</sup>One could also let the sell-off value be higher for exporting firms, however, this would not change the dynamic problem as long as the rate at which sell-off value increases with capital stock is lower than the rate of the continuation value.

increasing in productivity conditioned on export status.<sup>10</sup> Note that here I assume that the investment decision at time  $t$  depends on the capital stock which is predetermined at  $t$  through the investment decision at  $t - 1$ . Productivity evolves over time according to a first order Markov process. Furthermore, the survival decision depends on export status through the productivity shock at  $t$  and through the capital accumulation process, i.e. investment. Exporting firms tend to be more capital intensive and therefore remain active with a lower productivity shock compared to a non exporter.

$$\Pr(\chi_{t+1} = 1|I_t) = \Pr(\chi_{t+1} = 1|\omega_t, \underline{\omega}_{it+1}(k_{it+1})) \quad (3)$$

$$\begin{aligned} &= \tilde{\rho}_t(\omega_t, \underline{\omega}_{it+1}(k_{it+1})) \\ &= \tilde{\rho}_t(i_t, k_t, e_t) \end{aligned} \quad (4)$$

My estimation strategy is similar to Olley and Pakes (1996) except for the fact that the first stage estimation and the survival equation will now include the export dummy and all terms interacted with the export dummy. In this way I have introduced export as a state variable in the dynamic program of the firm. The decision rule on export is similar to the survival decision; only now a firm exports whenever it reaches an upper threshold of productivity (self-selection). However, it is not needed in the estimation since it is observed whether a firm exports or not.

The first stage of the estimation algorithm is in fact almost identical to introducing export as input, however, I allow it to interact with the terms of the polynomial in capital and investment as given in (5)

$$y_{it} = \beta_0 + \beta_l l_{it} + \tilde{\phi}_t(i_{it}, k_{it}, e_{it}) + \eta_{it} \quad (5)$$

where  $\tilde{\phi}_t(i_{it}, k_{it}, e_{it}) = \beta_k k_{it} + h_t(i_{it}, k_{it}, e_{it})$ . The polynomial in the three variables will improve the estimation in the third stage when identifying the capital coefficient. When introducing the export dummy as an input in the production one has to identify the coefficient on export in the third stage as well. This implies that one has to assume that export status only affects the average of the future productivity distribution and hence leaves no scope for learning by exporting to be a heterogenous process across firms. In addition the effect is assumed to be time-invariant, i.e. every year exporting raises output (conditioned on labor and capital) by the coefficient estimated on the export dummy. In section 5.2. I discuss these underlying assumptions and implications in greater detail.

The last stage is now a NLLS estimation on (6)

$$y_{it+1} - b_l l_{it+1} = \beta_0 + \beta_k k_{it+1} + g(\hat{\phi}_{it} - \beta_k k_{it}, \hat{P}_{it+1}) + v_{it+1} \quad (6)$$

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<sup>10</sup>For a similar setup including a proof I refer to Van Biesebroeck (2005)

where  $\tilde{\cdot}$  reflects that export status is also controlled for. The error term ( $v$ ) is decomposed into the *i.i.d.* shock ( $\eta$ ) and the news term in the Markov process ( $\xi$ ). As in Olley and Pakes (1996) I assume that productivity follows a first order Markov process implying that  $\omega_{t+1} = E(\omega_{t+1}|\omega_t) + \xi_{t+1}$ . Note that here the productivity shock is based on the results from the first stage ( $\tilde{\phi}_t(i_{it}, k_{it}, e_{it}) - \beta_k k_{it} = h_t(i_{it}, k_{it}, e_{it}) = \omega_{it}$ ) and thus also controls for the export status of a firm.

It is clear that the different estimation algorithm has an impact on the estimated production function coefficients. Compared to the standard Olley and Pakes (1996) approach I expect the labor coefficient to be lower since export status is strongly positively correlated with the productivity shock. In addition to investment and capital, export proxies for productivity shocks that are unobserved. The identifying assumption to estimate the capital coefficient in the standard OP method is that any shock in productivity between period  $t$  and  $t + 1$  is uncorrelated with the capital stock at  $t + 1$ . If export status is not controlled for, part of the unobserved productivity shock (at time  $t$ ) correlated with the export status ends up in the error term  $v_{t+1}$  in equation (6). By the law of motion of capital -  $k_{it+1} = (1 - \delta)k_{it} + i_{it}$  - capital is no longer orthogonal to the error term  $v_{it+1}$  that still captures some variation in productivity correlated with the export status, violating the identifying assumption. When correcting for the export status  $\tilde{\phi}$  exactly controls for this.

The direction of the bias in the capital coefficient is less clear since it impacts both through the selection equation and the productivity shock. However, the variation in the capital stock that is attributed to the variation in output -purified from the variation in labor - is now conditioned on the export status of the firm. As shown in Table 4, exporters are - on average - more capital intensive. Therefore in order to recover the correct estimates of the production function, it is important to control for the export status that works both through the instantaneous productivity shock impacting labor and over time through the capital accumulation process.

The resulting estimate for the productivity shock is now obtained controlling for the fact that market conditions are different and evolve differently for firms that sell in foreign markets.<sup>11</sup> Again, I stress that these conditions are still assumed to be common to all exporters within a given industry.

In terms of verifying whether entering the export markets makes firms more productive, I now filter out market structure specific shocks that are different for exporters (like demand conditions, factor markets, exit barriers, ...) and do not attribute them to pro-

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<sup>11</sup>Exporters might experience faster technological change. Therefore, I checked whether technological change was different for exporters by interacting the time trend with export status, in addition to the full interacted polynomial.

ductivity gains for exporters. However, these factors are constant across exporters within a given industry. On a more conceptual level, these market conditions might just be one of the driving forces behind the learning process. So if I still find evidence for productivity gains for exporters, it means that additional firm-specific factors play a significant role in making exporters more productive once they start exporting (e.g. contact with foreign buyers, location, destination of exports,... ). and it is purified from differences in price trends of factor prices and market conditions common to all exporters within an industry.

### 3.2 Coefficients of the Production Function

Since the proportion of input factors and input prices may differ across different industries, I estimate the production function for each 2-digit NACE<sup>12</sup> sector separately (which is equivalent to a three digit US SIC classification). Making the assumption that firms within the same sector face the same input prices is less problematic than extending this assumption to the entire manufacturing sector. In addition I include 3-digit NACE industry dummies to control for different subsectoral (unobserved) shocks within a given industry, both in the production process and in the output market.<sup>13</sup> In terms of the underlying structural framework including the export state variable, these subsectoral dummies control for differences in market structures among the various activities within a given industry having an impact on the investment decision.

In Appendix B, I compare my estimates (OP-EXP) with different estimation methods, OLS, Fixed Effects (FE) and the standard Olley-Pakes (OP). We can see that - as expected - the OLS typically over-estimates the labor coefficient and underestimates the capital coefficient, however there is some variation across industries. The assumption of a time-invariant productivity shock - fixed effects estimator - addresses the bias in the labor coefficient but makes the capital coefficient close to zero because a capital stock tends to be quite stable over time. The OP estimator clearly addresses the simultaneity problem as suggested in the theoretical framework: the OP estimator on labor is consistently lower than the OLS coefficient confirming the positive correlation. I also ran OP without correcting for the selection bias and the capital coefficients were considerably lower. It is clear that taking into account the exit rule has an effect on the capital coefficient and

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<sup>12</sup>The NACE classification system is the standard industrial classification system in the EU, comparable to the SIC or NAICS classification system in the US.

<sup>13</sup>For instance, when estimating the coefficients of the production function for the Food Products industry (NACE 15) I include 3-digit NACE dummies to control for unobserved subsectoral shocks, where the subsectors are Production, processing and preserving of meat and meat products(151), Processing and preserving of fish and fish products (152), Processing and preserving of fruit and vegetables (153), Manufacture of vegetable and animal oils and fats (154), Manufacture of dairy products (155), Manufacture of grain mill products, starches and starch products (156), Manufacture of prepared animal feeds (157), Manufacture of other food products (158) and Manufacture of beverages (159).

hence on estimated productivity. I find that the difference between both capital coefficient estimates is bigger when the exit rate is higher in that given industry, confirming my prior. Given the transition process where simultaneous entry and exit takes place as part of the restructuring towards a market economy, it is crucial to control for the non random exit of firms in the industry.

Including the export variable into the OP framework leads to somewhat different estimates of the production function. As expected, the labor coefficient is estimated - if anything - lower. The export status is as established before positively correlated with the unobserved productivity shock and therefore controlling for the export status leads to a lower estimate on the labor coefficient. The sign of the bias of the capital coefficient is less clear since it works both through the productivity shock and the exit decision and it is clear from Table B.1. that it is important to control for export status in order to identify the capital coefficient.

Throughout the estimation algorithm I introduce a time trend and I take into account that market structures change over years. In almost all industries it turns out to be an important control variable for the estimates on the production function coefficients. The fact that OLS overestimates the coefficient of labor and mostly underestimates the coefficient on capital makes it hard to predict a bias in the measure for productivity (*TFP*).

### 3.3 Total Factor Productivity and Aggregate Productivity

With the coefficients of the production function in hand, I recover a productivity measure and I calculate *TFP* in the following way (7)

$$TFP_{ijt} = y_{ijt} - b_{lj}l_{ijt} - b_{kj}k_{ijt} \quad (7)$$

where  $b_{lj}$  and  $b_{kj}$  denote the OP-EXP estimators for labor and capital respectively for industry  $j$ . As also noted by Olley and Pakes (1996) taking the exponential of (7) leads to a productivity measure that lies closer to the natural definition of productivity. However, the scope of this paper is to analyze the productivity gains from entering the export market expressed in percentages that leads to the same answer using both measures of productivity. In order to use the data as efficient as possible I impose coefficient stability on the model. In this way I can use all firms in my sample across the entire sample period 1994-2000.<sup>14</sup>

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<sup>14</sup>However, this measure of productivity is not the true unobserved productivity shock. It also includes the *i.i.d.* component which is assumed to be zero on average but this need not to be true. To get the

Overall mean productivity increases in every industry and there are some productivity differences among the different industries. One explanation for the differences in productivity levels between industries could be the reallocation of market share towards more productive plants and the extent of this could explain why some industries lag behind, i.e. there is no sufficient reallocation towards the more productive firms. (see De Loecker and Konings; 2005 for more on this). To get at the importance of exporters I construct a conventional productivity index where I weigh firms' productivity by its market share as in Olley and Pakes (1996). I split this index up into two groups: exporting and non exporting firms and I normalize the first year (1994) to 1. Table B.2 in Appendix B shows that the productivity index increased by 16 percent for exporters and only by 10 percent for non exporters by 1999. As noted in De Loecker and Konings (2005) the increase in aggregate productivity in the Slovenian manufacturing is largely due to the average firm becoming more productive and the net entry process. The next section provides a framework to evaluate the importance of increased export participation to this increase in productivity.

## 4 Learning By Exporting in Addition to the Self Selection Story?

Before I introduce the econometric model in order to asses the learning by exporting hypothesis I present a graphical framework to show the intuition behind my test. I am interested in whether firms become more productive - or grow faster in productivity - once they have entered the export market. Figures 2 and 3 show the two competing hypotheses. On the horizontal axis I plot a time scale and it is zero for the period where firms enter or exit the export market. For firms that never export or always export throughout the sample period this is just the median of the sample period, i.e. 1997. On the vertical axis I plot average productivity for four different groups: never exporters, always exporters, starters and quitters. The learning by exporting hypothesis deals with the right side of the vertical line (at scale equal zero) and asks whether firms become more productive after exporting. The self-selection hypothesis deals with the left side of the vertical line (at scale equal zero) and asks whether prior to exporting, these firms were just more

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true unobserved productivity component we have to go back to the estimation algorithm. After the third stage we have everything in hands to compute it using the notion of the non parametric function from the first stage ( $\hat{\phi}_{it} - b_k k_{it} = \omega_{it}$ ). This measure for productivity may perform better as it is purified from the *i.i.d.* shocks. However, when I compared both measures I found that the averages are close to each other and that both were highly correlated. I therefore opted for using the usual measure of TFP as it allows me to use all firm observations, in contrast to the 'purified' measure where I can only use the restricted sample, i.e. the one used in the OP estimation algorithm with only positive investment.

productive than the rest. Figure 2 provides some evidence of learning by exporting in the Wearing Apparel industry, whereas from Figure 3 it does not seem to hold in the Furniture industry. In Figure 2, average productivity of the firms that start exporting increases drastically whereas this is not the case in Figure 3. It is also interesting to note that the average productivity of firms that quit the export market goes up after falling the years before the exit.<sup>15</sup> The latter is merely based on graphical inspection and I check whether my econometric results confirm these priors.

My methodology will control for the self-selection process and test for the learning by exporting hypothesis by creating control groups using matching techniques based on average treatment models as suggested by Heckman et al. (1997). However, in the analysis I do not use the always exporting firms since that they do not provide us with the dynamics, i.e. I do not observe their decision to export and consequently makes it impossible to test both hypotheses. I match *starters* with non exporters. The identifying assumption in estimating the treatment effect - export - comes from the introduction of the state variables - productivity and capital stock - in the matching procedure and they have a strong interpretation in my underlying structural framework.

## 4.1 The Econometric Model

I use my estimated *TFP* measures (OP-EXP) to tackle the question whether in addition to self-selection there are learning by exporting effects.<sup>16</sup> To this end I use a method that is mainly used in the field of labor economics, which is based on matched sampling (Heckman et al., 1997, 1998).<sup>17</sup> The method exists in constructing a counterfactual, which allows us to analyze how productivity of a firm would have evolved if it had not started exporting. The main problem in this type of analysis is that we do not observe the counterfactual and therefore we need to match the exporting firm with a control group of similar firms that do not export. The aim of this methodology is to evaluate the causal effect of exporting on productivity or productivity growth. I re-scale the time periods in such a way that a firm starts exporting at  $s = 0$ . Let  $\omega_{is}$  be the outcome at time  $s$  ( $s \geq 0$ ) following entry in export markets at  $s = 0$  and consider the binary variable  $START_i$  taking on the value one if a firm  $i$  starts to export. The causal effect can be verified by looking at the following difference:  $(\omega_{is}^1 - \omega_{is}^0)$ , where the superscript denotes the export behavior. The crucial problem in this analysis is that  $\omega_{is}^0$  is not observable. I

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<sup>15</sup>This is an interesting observation on itself, however, it lies beyond the scope of this paper. In terms of policy implications the impact of quitting the export market on firm performance seems somewhat less interesting.

<sup>16</sup>The self selection hypothesis is pretty well established both theoretically (Melitz, 2003) and empirically (Clerides, Lach and Tybout, 1998; Bernard and Jensen, 1999; Aw, Chung and Roberts, 2000).

<sup>17</sup>Girma et al (2002) apply this method to tackle the same question for UK firms.



follow the micro-econometric evaluation literature (Heckman et al., 1997, 1998) and define the average effect of exporting on export market entrants as

$$E \{ \omega_{is}^1 - \omega_{is}^0 | START_i = 1 \} = E \{ \omega_{is}^1 | START_i = 1 \} - E \{ \omega_{is}^0 | START_i = 1 \} \quad (8)$$

The key difficulty is to identify a counterfactual for the last term in equation (8), which is the productivity effect entrants in export markets would have experienced, on average, had they not participated in export markets. In order to identify this group I assume that all differences between exporters and the appropriate control group can be captured by a vector of observables including the pre-entry level of productivity. The intuition behind selecting the appropriate control group is to find a group that is as close as possible to the exporting firm in terms of its predicted probability to start exporting. More formally, I apply the 'propensity score matching' method as proposed by Rosenbaum and Rubin (1983a, 1983b and 1984). This boils down to estimating a probit model with a dependent variable equal to 1 if a firm starts exporting and zero elsewhere on a matrix of lagged observables  $\mathbf{X}$  including productivity.<sup>18</sup>

I model the probability of starting to export as follows. *START* is a dummy variable that is 1 when a firm's *starts* exporting, whereas *EXP* is a dummy that is 1 when a firm exports. In the latter case the firm could have been exporting the year before and thus we have to include lagged export status as well. It also captures the idea that firms undergo fixed costs to start exporting. The difference in interpretation with using the latter specification is that one is modelling the probability of *continuing to export* rather than *starting to export*. In addition, including the lagged export status introduces another problem: correlation with lagged productivity and this is exactly what the treatment effect is trying to avoid. The point estimates on the right hand side variables are very important for the matching procedure later on.<sup>19</sup>

My specification of the propensity score can be represented as follows

$$\Pr \{ START_{i,0} = 1 \} = \Phi \{ h(\omega_{i,-1}, k_{i,-1}, PRIVATE_{i,-1}, \dots) \} \quad (9)$$

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<sup>18</sup>Note, that I do not attribute the effect of more efficient firms entering the market to learning by exporting effects since the estimation technique requires at least one observation prior to starting to export. De Loecker and Konings (2005) show that the entry of more efficient firms contributed significantly to the sharp increase in total factor productivity in the Slovenian manufacturing.

<sup>19</sup>The other model would look as follows  $\Pr \{ EXP_{it} = 1 \} = f(\omega_{it-1}, k_{it-1}, EXP_{it-1}, PRIVATE_{it-1})$ . Furthermore there is a clear difference in the estimated treatment effects between both models (start vs start/continue). The effect of starting to export on *TFP* is much (at least twice as high) bigger than continuing to export. The fact that I do not find such a high effect in this model is because we ask whether firms that were possibly already exporting become more productive after another year of exporting. The effects of starting to export are thus swamped by continuing exporters. Firms that export throughout the entire sample period are not analyzed as they do not provide us with the necessary dynamics.

where  $\Phi(\cdot)$  is the normal cumulative distribution function.<sup>20</sup> The re-scaling of the time periods implies that the probability of starting to export is regressed on variables prior to this period  $s = 0$  and I use subscript  $-1$  to denote this. I take a full polynomial in the elements of  $h(\cdot)$  as to free up the functional form and improve the resulting matching (Woolridge, J., 2002). I include the firm's state variables - as defined in the dynamic program - productivity and capital stock. The most important variable in estimating the propensity score estimation clearly is the productivity variable. This controls for the entire pre-export productivity path and thus controls for the self-selection process. Given the assumption that productivity follows a Markov process, I condition on - except for the news component - the entire pre-export productivity levels. Differences in productivity will be conditioned on pre export levels of productivity and the rest of the variables captured by  $\mathbf{X}$ . Furthermore I include an ownership variable, *PRIVATE*, which is a dummy variable equal to 1 if the firm is private owned. I also include a full set of year dummies and industry dummies to control for common aggregated demand and supply shocks. Let the predicted export probability be denoted by  $p_i$ , i.e. the propensity score.

Note that my identifying assumption to estimate the learning by exporting effect - as with any treatment estimator - is that any unobservable left in the propensity score is uncorrelated with the decision to start exporting. I have experimented with adding additional firm characteristics (e.g location, size,...) to relax this assumption and results were invariant to this.

To verify the learning by exporting effects I perform the following algorithm (Becker and Ichino, 2003): i) split the sample in  $k$  equally spaced intervals of the propensity score  $p_i$  and test within each interval whether the average propensity score of the treated and the control units do not differ, ii) if the latter test fails, split up interval and test again and continue this until it holds in every interval, iii) within each interval test whether the first moment of the elements in  $\mathbf{X}$  are not different for the treated and the control units (Balancing hypothesis). If the latter test is rejected a less parsimonious functional form of  $h(\omega, k, PRIVATE)$  is considered, i.e. including higher order terms.

The matching is based on the method of the 'nearest neighbor'<sup>21</sup>, which selects a non

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<sup>20</sup>This is essentially what most studies do when testing the self selection hypothesis, i.e. if the coefficient on productivity is positive and significant there is evidence for self selection and it is also the case in the Slovenian manufacturing sector. In all specifications the coefficients on productivity are positive and highly significant. Also private ownership and the capital stock are estimated with a positive sign.

<sup>21</sup>I also experimented with other matching techniques, e.g. the Mahalanobis one-to-one matching and Imbens et al (2001) that implements the specific matching estimators developed in Abadie and Imbens (2002), including their bias-corrected matching estimator. My results do not change, however, the one-to-one matching is more sensitive to the underlying probability to export model.

exporting firm  $j$  on the following criteria

$$|p_i - p_j| = \min_{k \in \{EXP=0\}} (p_i - p_k)$$

This results in a group of matched exporting - non exporting firms needed in order to evaluate the causal impact of exporting on productivity. I match within each 2 digit NACE sector and thus I create a control group within narrow defined sectors as opposed to matching across the entire manufacturing sector (Girma et al, 2002). This is likely to be important as the marginal effects of various variables on the probability to start exporting may differ substantially between different sectors due to different technological and market conditions firms face in different industries. This implies that I estimate the probability to start exporting for each industry separately, allowing the coefficients to differ among the various industries.<sup>22</sup>

An important hypothesis that I test in every specification is whether the Balancing hypothesis holds. The latter states that the mean of every variable in  $\mathbf{X}$  has to be the same for both the treated and the control group within every block. In this way I match on the probability to export controlling for firm characteristics captured by  $\mathbf{X}$ , and in addition I restrict the first moment of the distribution to be the same across both groups.<sup>23</sup>

Once I have this counterfactual in hand, I use the difference-in-differences (*DID*) methodology to assess the impact of exporting on productivity, i.e. the learning by exporting effect. The estimator of the learning by exporting effect -  $\beta_{LBE}$  - is calculated in the following way. Assume  $N$  firms that started exporting and a set  $C$  of control firms and  $\omega^1$  and  $\omega^c$  are the estimated *TFP* of the treated and the controls, respectively. Denote  $C(i)$  as the set of control units matched to firm  $i$  with a propensity score of  $p_i$ . And from the above we know that  $C(i) = \min_j \|p_i - p_j\|$  since I use the nearest neighbor matching technique. The number of control firms that are matched with an observation  $i \in T$  is denoted as  $N_i^c$  and the weight  $w_{ij} = \frac{1}{N_i^c}$  if  $j \in C(i)$  and zero otherwise. In this way every firm  $i$  that started exporting is matched with  $N_i^c$  control firms. I stress that the matching is always performed at the time the firm starts exporting and  $s = \{0, 1, \dots, S\}$  denotes the time periods after the decision to start exporting ( $s = 0$ ). I introduce two estimators getting at the productivity effect at every time  $s$  (10) and a cumulative productivity effect

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<sup>22</sup>Note that this is important as the coefficients are crucial for the matching and the resulting estimated productivity gains. This approach is less restrictive than estimating the probability to export for the entire manufacturing sector and including industry dummies. The latter only controls for average propensity to enter the export market by industry, however, the impact of productivity, capital, ownership and other controls are assumed to be the same across all industries.

<sup>23</sup>Note that I only test for the first moment of the elements in  $X$  to be the same for the treated and the control firms. The underlying assumptions of reducing the multi-dimensional matching to a one-dimensional (propensity score) variable are based on the entire distribution and not just the mean. For more on the balancing hypotheses and testing for higher moments I refer to Imbens (2003).

(11). The estimator  $\beta_{LBE}^s$  at every period  $s$  after the decision to start exporting is then given by

$$\beta_{LBE}^s = \frac{1}{N_s} \sum_i \left( \omega_{is}^1 - \sum_{j \in C(i)} w_{ij} \omega_{js}^c \right) \quad (10)$$

In words, I estimate the productivity premium of firms that started exporting compared with (a weighted average of) productivity of a control group based on nearest neighbor matching at every period  $s$ . It tells us how more productive exporters are at  $s$  periods after initiating into export activities.

However, we are also interested how the effects of starting to export impacts the productivity trajectory. Therefore I estimate the average cumulative treatment effect, i.e. the productivity gain *gathered* over a period  $s$  after the decision to start exporting. The estimator  $\beta_{LBE}^S$  is given by

$$\beta_{LBE}^S = \frac{1}{N_S} \sum_i \left( \sum_{s=0}^S \omega_{is}^1 - \sum_{s=0}^S \sum_{j \in C(i)} w_{ij} \omega_{js}^c \right) \quad (11)$$

This provides me with an average cumulative productivity gain at every time period and plotting these estimated coefficients over time gives us a relation between time ( $t$ ) and the productivity gain.<sup>24</sup> The estimate at a time  $s$  gives the productivity premium starters have gathered over time. Note that in this way I follow the productivity path of a given firm over years following the decision to start exporting compared to the path of the control group, whereas the estimate in (10) is not restricted to firms with  $s$  consecutive observations.

I look at both the effect of starting to export on the level of productivity and on productivity growth. The latter takes into account the unobserved firm specific effects, however, it alters the interpretation of the treatment - export. In the latter I check whether firms that started exporting will grow faster in their productivity than if they had not entered the export market. I consider both the year-to-year productivity growth ( $\omega_s^1 - \omega_{s-1}^1$ ) and productivity growth compared to the pre-export level of productivity ( $\omega_s^1 - \omega_{-1}^1$ ). I show that both effects have somewhat different interpretations, i.e. exporting firms might become more productive and grow faster with respect to their pre-export productivity level, however, they need not to grow faster every year after entering the export market.

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<sup>24</sup>The cumulative estimator  $\beta_{LBE}^S$  is not exactly equal to the sum of the pure time estimator  $\beta_{LBE}^s$  due to the unbalancedness of my data. Formally,  $\sum_s \beta_{LBE}^s \neq \beta_{LBE}^S$  since  $N$  varies with  $s$ . Also see section 5.3 for more on this.

Blundel and Costa Dias (2000) mention that a combination of matching techniques and difference-in-differences is likely to improve the quality of non experimental evaluation studies. Essentially the *DID* removes effects of common shocks and provides us with a clear estimate of the treatment variable (export) on the productivity difference between exporting and not exporting. Table 5 presents the results for the different sectors and for the manufacturing as a whole for productivity level and productivity growth.<sup>25</sup>

## 4.2 Estimating Productivity Gains at The Manufacturing Level

I now turn to main results as shown in Table 5A. This table captures various specifications getting at the various ways that entering the export market might impact productivity. In row (a) I show the simple level difference in productivity at every period  $s$ . This estimate tells us how much more productive an export entrant is compared to *similar domestic firms* at every point in time. Row (b) shows the effect on the year-to-year productivity growth rate, whereas in row (c) I show the estimated productivity growth rates with respect to the pre-export level of productivity ( $\omega_{i-1}$ ) at every period  $s$ . Finally row (d) and (e) present the results of the cumulative productivity effect, reflecting the productivity gains gathered after  $s$  periods of exporting. I note that the sample of firms used to estimate the effects in the last two rows is different from specification (a), (b) and (c). In the first three rows firms with at least 2 observations at the relevant periods (one to perform the matching and one at  $s$ ) are used in estimating the relevant effect. When estimating the cumulative effects of starting to export I need a minimum of  $s + 2$  consecutive observations per firm since I am summing the productivity gains by firm over time, where  $s = \{0, 1, 2, 3, 4\}$ .<sup>26</sup>

In the overall sample export has a positive and significant treatment effect on productivity, i.e. confirming the learning by exporting hypothesis (Table 5A). The magnitude of the coefficients are to be interpreted as percentages, exporting firms become on average 8.8 percent more productive once they start exporting. The productivity gap widens further in later years, after 4 years of exporting ( $s = 3$ ) exporters are around 13 percent more productive. Note that the effect is positive but no longer significantly estimated after 5 years of exporting ( $s = 4$ ) as the sample size decreases, i.e. only firms that entered the export market in 1996 or before are considered here.

Starting to export causes productivity growth to be significantly higher compared to

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<sup>25</sup>My results are robust to excluding firms that switch export status during the sample period. I also dropped quitters out of the control group and find that it does not change the results.

<sup>26</sup>This might introduce a selection bias by only keeping surviving firms over a  $s + 2$  period. If anything I expect my results to be even stronger as I compare export entrants to surviving domestic firms. I refer to section 5.3. for more discussion on the potential selection bias.

the pre-export productivity level, i.e. 7.9 percent. Compared to this pre-export productivity level, exporters grow faster in future periods, e.g. entrants into export markets have grown 12.4 percent faster after 4 years of exporting. The year-to-year growth rates are estimated positively but insignificant, suggesting that exporters grow more with respect to their pre-export level of productivity compared to their domestic counterparts. However, they do not significantly grow faster year to year upon entering the export market. Although the analysis so far is performed at the manufacturing level, I can still conclude that *starting* to export raises productivity instantly and also in the years following to start in export activities. The latter is also reflected in significant higher productivity growth rates.

I check whether cumulative productivity has increased after the start of export activities where I estimate equation (12) that considers the following outcome:  $\sum_{s=0}^j (\omega_{is}^1 - \omega_{is}^0)$  for  $s = \{0, 1, 2, 3, 4\}$ . The cumulative effect tells us how more productive a firm is that started exporting after  $s$  years. I interpret this as the 'productivity gain' over a period after the decision to start exporting. E.g. firms that started to export are 17.7 percent more productive after two years of exporting than those firms that did not. It is different from the estimate at every time  $s$ . The cumulative productivity after e.g. 4 years of exporting is not equal to summing the estimates at time 1, 2 and 3. This is due to the fact that in order to estimate the cumulative effect at period 4, I need firms with at least 5 consecutive observations. I find that cumulative productivity is significantly higher for exporters in all the years following the export activity, resulting in a 46 percent higher productivity after 4 years.

Using the standard Olley and Pakes (1996) technique for estimating productivity, I still find evidence for learning by exporting although somewhat higher, exporters become on average 10.4 percent more productive once they start exporting as opposed to 8.8 percent. The future cumulative productivity effects remain significant and are even estimated slightly higher. As mentioned above, the fact that I find a lower effect from starting to export on productivity (immediately) - controlling for differences in market structures and factor prices - suggests that facing different market structures might just be one of the many reasons why firms become more productive after initiating in export activities. The fact that I still find evidence for learning by exporting when controlling for this, implies that there are other mechanisms at work that are firm-specific. One of those potential factors is the destination market of the exports, high or low income regions. I address this in the next section.

I plot the cumulative productivity trajectory in Figure 4 ( $\beta_{LBE}(b)$ ) next to the baseline result using the standard OP estimator ( $\beta_{LBE}(a)$ ). Introducing the extra control - export status - in the structural framework leads to somewhat higher effects on future

productivity. However, the results do not change a lot and the trajectories over time are very similar. Also note that using my preferred estimate for the productivity path I do not find a decrease in the productivity gap after 5 ( $s = 0$ ) years of exporting. Firms that initiated in export activities will have a significantly higher level of *TFP* than their matched counterpart that did not started exporting in the years following their export decision. From this graph it is clear that the exporters increase the productivity gap with respect to their domestic counterparts, however at a decreasing rate.

Tybout (2003) argues that the decision to export could well have occurred prior to the export sales entering the database. The argument mostly raised in favor of learning by exporting is that of contact with foreign buyers and the foreign market. Therefore one can argue that this occurs before actual export takes place (Grossman and Helpman; 1991, Worldbank; 1993 and Evenson and Westphal; 1995). This might suggest that the estimated productivity gain at  $s = 0$  is picking up productivity improvements both due to 'preparing for exporting' at  $s = -1$  and due to selling on the foreign market at  $s = 0$ . In order to indicate whether the instantaneous productivity gains are only due to 'preparation for export' the estimate on productivity levels should exceed that of the productivity growth at  $s = 0$  since in my model learning by exporting cannot occur before  $s = 0$ . I find that indeed the instantaneous effect at  $s = 0$  is bigger (0.088) than the productivity growth effect at  $s = 0$  (0.079) suggesting that additional productivity gains take place from exporting.<sup>27</sup>

Finally, since a relatively small share of plants start exporting - compared to non exporting firms - and these firms differ in many characteristics from non exporters, it might be that the treatment and control group do not overlap. Therefore I check every specification by restricting it to a common support on the propensity score. The last row in Table 5 shows the results on cumulative productivity restricting it to observations that lie within the common support of the propensity score. The results do hardly change suggesting that the control group is appropriate to evaluate the learning effect.<sup>28</sup>

### 4.3 Digging Deeper: Matching at the Industry Level

So far I have used an underlying structural model which not only adds strength to the interpretation of the results but conditions on the entire pre-export productivity path

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<sup>27</sup>This reasoning has an implication for the robust finding of self selection into export markets. These studies find that lagged productivity is highly significant in explaining the probability to export. However, this could also pick up the fact that firms 'get ready' to export and need to become more efficient, which is more than a pure exogenous market selection effect. In section 5.3 I deal with the immediate level effect and future effects in somewhat more detail.

<sup>28</sup>In the following sections I prefer the results obtained without imposing the common support constraint, since I can use more observations to verify the learning by exporting.

in the matching procedure. I now improve this method by estimating the effect within narrow defined industries (NACE 2 digit) and I find that the picture is somewhat different. When I perform the analysis at more disaggregated level, I find that for most sectors (13 out of 16) the treatment effect is estimated positively, however, the magnitude and timing of the productivity gain varies across industries.<sup>29</sup> The previous analysis is based on a matching procedure that takes into account the industry unobservables that matter for the decision to export. However, the effect on productivity from entering the export is estimated using the entire manufacturing sector. Now I present the separate estimation for the different industries within the manufacturing, however, leading to a lower number of observations for identifying the parameter of interest.

This apparent discrepancy between the overall manufacturing results and the more disaggregated analysis at the 2-digit sector level reflects the fact that the more disaggregated the analysis, the more correct the treatment effect can be tested. Controlling for industry specific characteristics seems to be important to analyze the causal effect of exporting on firm performance. The problem with performing the matching procedure across the entire manufacturing sector as opposed to matching within a more narrow defined industry, is that there can be unobservables that are industry specific that are correlated with the decision to export. The latter breaks down the independence assumption that is crucial for the matching estimator to be consistent (see also Heckman *et al.* (1997) for more on this). And if one does not take into account the differences of productivity trajectories - that are independent of export - one may attribute this to export. A disadvantage to verify whether productivity is affected by exporting at the industry level is the low number of new exporters at every point in time. For instance, the effect of starting to export on productivity has a positive effect for the "Publishing and Printing" industry, however, is estimated insignificantly.

There is a wide range in the effects of starting to export on productivity across the industries. I can also identify sectors where starting to export does not have an initial effect on productivity, however, learning starts in years following the decision to export

I also find a negative effect although insignificant of starting to export for the 'Furniture and NEC' (36) sector on productivity. Note that my econometric results confirm the suggestions from the graphical inspection (Figure 2 and 3) concerning the 'Wearing Apparel' (18) and the 'Furniture' (36) sector.

Furthermore, it may also take some time before the effects of exporting start kicking in. Therefore I look at the difference in cumulative productivity between exporting firms

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<sup>29</sup>Because I perform the analysis at more disaggregated level I have to give up some power in the tests due to the lower number of observations. I also drop switchers out of the analysis to avoid that exporting firms end up in the control group once they stopped exporting.



and their matched counterfactual at  $s$  for  $s > 0$ . The results are presented in Table 5C. Engaging into export activities also significantly increases productivity in the years following the start of export activities, however the effect varies strongly across industries. Table 5D lists the industries where starting to export leads to higher productivity instantly or in later years. It is clear that if one only checks whether exporters become more productive immediately after entering the export market, results might be misleading. In order to test for learning by exporting it is therefore crucial to look at the entire productivity trajectory after entering the export market. The latter is not surprising since learning occurs over time - if there is any - and it might only have an impact on productivity in a later phase.

## 5 Robustness Checks

In this section I provide various robustness checks on the results established in the previous section. Firstly I incorporate the destination of exports and split up the destination country by 'income level'. This also addresses the concern that measured productivity gains from exporting are potentially capturing demand related variables like differences in output prices. Secondly, I allow for endogenous firm-specific productivity improvements over time, relaxing the assumption that productivity follows an exogenous Markov process over time. Finally, I discuss the impact of entering the export market on the immediate level of productivity versus future productivity gains.

### 5.1 Does Destination of Exports Drive Results?

The robust finding of additional productivity gains exporters experience once they start exporting was established in the previous section. However, one could argue that these 'learning effects' depend largely on the destination of the exports. If most of the products shipped abroad are destined to high income and developed countries, the scope for improving production and quality is expected to be higher. Some evidence suggest that exporters learn from their buyers on the international market and that the extent to which this occurs depends on characteristics of the destination country (Westphal; 2002). I now include the destination of exports. Firstly, I present the pattern of destination using firm-level information on the export orientation. Secondly, I include the export destination information in the propensity score estimation capturing the different conditions of the markets firms export to. The latter control also takes into account that export prices (for a given product) can be different depending on the destination market. Since I do not observe firm-level physical output and use value added, unobserved firm-level price

variation away from the industry producer price index can potentially bias the productivity estimates.<sup>30</sup> The extent to which differences in output prices between exporters and domestic firms are present, I control for these by including the export dummy into the Olley and Pakes (1996) framework (section 3.1.) allowing market structures - including output market characteristics (prices, demand, ...) - to be different between exporters and domestic producers within a given industry. However, if output prices in the various foreign markets differ for exporters within an industry, my OP-EXP does not control for this. Therefore I verify whether productivity gains are present for both high and low income regions, getting at differences in export prices within industries correlated with the destination of exports.

### 5.1.1 Pattern of Export Destination

I now present the destination structure of the exporters in my sample. The dataset used until now has no firm-level information on destination of exports. However, I was able to get information for a sub sample of exporters listing the regions they export their products to.<sup>31</sup> I matched this information with the firm-level dataset and this resulted in 1,090 firms having information on the destination of export, covering around 50 percent of exporting firms. I grouped the destination information in 8 groups: Africa, Asia, North-America, South-America, Western Europe, Southern Europe, Central and Eastern Europe including former countries of the Soviet Union (CEE) and Others (Australia, New Zealand, ...). On average firms export to around 3 to 4 different destinations.

In Table 6 I present the destination portfolio and the destination pattern for the entire manufacturing as well as by industry. In panel A I present the fraction of firms that export to a given destination by industry. On average 90 percent of the firms export towards Western and Southern Europe and Central and Eastern Europe. Around a third of exporters sell their products in Asia and North America. The pattern across the different industries is quite stable. Note that this information does not take into account the importance of the various export destinations in firm-level sales. This table clearly shows that a large majority of the exporters ships their products to high income countries

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<sup>30</sup>For more on this I refer to De Loecker (2005) where a methodology is suggested to correct for this omitted price variable bias in a framework of multi-product firms. An alternative view is that if some firms - conditioned on their level of inputs - are able to generate more sales, it means that they perform better and firms can be ranked accordingly. Prices are no real concern in the latter interpretation. However, as mentioned in Katayama et al (2004), the implications for welfare crucially hinge upon the correct productivity estimates, controlled for price setting power.

<sup>31</sup>The data were made available by the Chamber of Commerce and Industry in Slovenia under the label of *SLOEXPORT*. This database has information on the various destinations (by country) by exporting firms. Furthermore it also covers industry classification, export share in income, number of employees, age, company size. An online version of this data is available at [www.gzs.si/sloexport](http://www.gzs.si/sloexport).

(North-America and Europe). This suggests that the scope for learning from foreign buyers is present. However, technology diffusion from exporters to non exporters can boost productivity of domestic firms. The latter is being taken care of in my econometric model since non exporters productivity trajectory are used as a control.

In panel B I present the destination portfolio providing information on which destination markets firms tend to sell. The table has to be interpreted as follows: 8 percent of exporters selling on the African market also sell their products on the Asian market. As expected, given that a firm exports to Western Europe, it is very likely that it also exports to Southern Europe and Central and Eastern Europe, and the other ways around as well. The figures on the diagonal are - up to some rounding both across years and industries - equal to the averages shown in the upper panel (A).

### 5.1.2 Using Destination Information in Matching

Here I verify whether the learning effects found in section 4. are driven by firms exporting to high income regions (North-America and Western and Southern-Europe). In terms of the underlying propensity score matching, I now split the sample according to the income level of the destination market and I estimate the learning parameter  $\beta_{LBE}$  separately for firms (start) exporting towards high and low income countries. However, the data covering matched firm-level data and destination information has a lower number of observations, having an impact on the power of the test. Therefore I only run the regressions on the entire manufacturing level in order to identify the parameter.

I follow the exact same approach as outlined in section 4., however, I estimate it separately for high and low income exporters.<sup>32</sup> Remember that on the full sample the estimated instantaneous effect of starting to export on productivity was 8.8 percent. Table 7 shows the results (of the instantaneous effect) for the various destination regions and compares it with the results from section 4. It is clear that the positive learning effect is robust over the different destinations, with differences in the precision of the estimates due to the lower number of observations (observing a firm starting to export having information on the destination). It is interesting to note that firms exporting only to low income regions get additional productivity gains ,however, lower than their counterparts exporting to high income countries (20 versus 10 percent). As expected firms only exporting towards high income regions experience a higher productivity gain than

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<sup>32</sup>Note that here I restrict it to firms only exporting to a high or low income region. This is important since both markets are often served by the same firm and as to control for export price differences among exporters. The reason for observing 75 firms that start exporting *only* to high income regions, is because firms only exporting to high income countries is a relatively small share of the sample. See Table 6B where e.g. 83 percent of the firms that export to Western Europe also export to Central and Eastern Europe.

the overall sample of export entrants, i.e. 20 versus 8.8 percent.

Using the additional information on the destination of exports, I have showed that the results are not driven by specific export regions and hence specific destination market characteristics potentially including prices and quality. The fact that I still find significant productivity gains for exporters shipping their products to relatively similar income regions (compared to Slovenia) suggests that the productivity gains found in the overall sample are not driven by higher output prices for exporters. Even when I only consider the export entrants shipping their products towards Central and Eastern European countries (CEEs), I still find that productivity increases significantly. It is however interesting to note that using the standard OP estimates for productivity I find no significant effects for exporters only shipping their products to CEEs. The latter demonstrates the importance of controlling for the export status when estimating productivity.

## 5.2 Allowing for Learning in Productivity by Export Status

So far when estimating productivity I have assumed that productivity follows a first order Markov process and hence productivity shocks are exogenous to the firm. However, this implies that productivity is potentially miss-measured in the presence of learning effects. The self-selection into export does not introduce this problem since future productivity is not endogenously determined. The key assumption in the Olley and Pakes (1996) model is that future productivity is given by expected productivity and some unexpected shock ( $\xi$ ). If productivity depends on the past export experience - learning by exporting - then part of the unobservable is not captured by the polynomial in investment, capital and current export status.

In terms of the production function, think of the productivity shock  $\omega$  to be decomposed in two (independent) terms, one following an exogenous Markov process ( $\omega^E$ ) and the other follows an endogenous Markov process determined by past export experience ( $\omega^L$ ). However, I have no explicit model in mind how the latter process is governed as opposed to controlled productivity improvements like R&D (Buettner; 2004). Therefore I just proxy the unobserved productivity component related to learning by exporting to a non parametric function  $l(\cdot)$  in past export experience  $z_{it}$  and the number of years exported  $T$  up till  $t$ . If the learning process would be controlled I could use an indicator to estimate  $\omega^L$  in a first stage as in Akerberg and Pakes (2005). However, there is no prior sensible indicator for the learning experience. Therefore I assume that learning is captured by output conditioned on the inputs and the exogenous unobserved productivity shock. The first stage now has an additional term capturing the learning effects from

exporting in previous periods (12).

$$y_{it} = \beta_0 + \beta_l l_{it} + \tilde{\phi}_t(i_{it}, k_{it}, e_{it}) + l(z_{it-1}, T_{it-1}) + \eta_{it} \quad (12)$$

Now consider the production function at  $t + 1$  based on information at time  $t$

$$y_{it+1} = \beta_0 + \beta_l l_{it+1} + \beta_k k_{it+1} + E(\omega_{it+1} | I_t, \chi_{it+1} = 1) + \xi_{it+1} + \eta_{it+1} \quad (13)$$

and Olley and Pakes (1996) assume that  $\omega_{it+1} = E(\omega_{it+1} | I_t, \chi_{it+1} = 1) + \xi_{it+1} = g(\omega_{it}, \underline{\omega}_{it+1}) + \xi_{it+1}$ . If learning effects are present then export status or other variables capturing export experience should enter in  $g(\cdot)$  as well. Therefore I now allow export experience and other variables proxying export experience ( $z_{it}$ ) to impact future productivity.

$$\begin{aligned} \omega_{it+1} &= E(\omega_{it+1}^E | I_t, \chi_{it+1} = 1) + E(\omega_{it+1}^L | I_t, \chi_{it+1} = 1) + \xi_{it+1} \\ &= E(\omega_{it+1}^E | \omega_{it}, \underline{\omega}_{it+1}) + E(\omega_{it+1}^L | \underline{\omega}_{it+1}, z_{it}, T_{it}) + \xi_{it+1} \\ &= \tilde{g}_1(\omega_{it}, \underline{\omega}_{it+1}) + \tilde{g}_2(\underline{\omega}_{it+1}, z_{it}, T_{it}) + \xi_{it+1} \end{aligned}$$

where  $\xi = \xi^E + \xi^L$ . Now the information set at time  $t$  also includes the export experience of the firm ( $z, T$ ). I assume that the survival decision is a before. I use a crude and simple proxy for this export experience, i.e. I combine the export status  $e_{it}$  and the share of export sales in total sales into one variable  $z_{it}$  and I include the number of years exported so far,  $T$ . The latter should proxy the relative importance of the foreign market and hence the scope for learning.<sup>33</sup> This leads to the following regression equation (14)

$$y_{it+1} - b_l l_{it+1} = \beta_0 + \beta_k k_{it+1} + \tilde{g}_1((\tilde{\phi}_{it} - \beta_k k_{it}), \tilde{P}_{it+1}) + \tilde{g}_2(z_{it}, T_{it}, \tilde{P}_{it+1}) + v_{it+1} \quad (14)$$

where  $v = \eta + \xi$  and  $\tilde{\phi}$  and  $\tilde{P}$  are as in the pervious section controlled for export status.<sup>34</sup> Now additional variables  $z$  and  $T$ - capturing the potential learning effects - enter the non parametric function since future productivity is now allowed to depend on export experience. Note that the latter is firm specific and implies that the impact of past export experience on productivity is firm specific.<sup>35</sup> The unobservable  $\omega^L$  capturing the

<sup>33</sup>I also experimented with including other variables like the destination of the exports, ownership and results were similar.

<sup>34</sup>Formally, export status enters the information at time  $t$  to decide whether to exit the market at  $t + 1$ . However, since export status enters through the productivity shock as well, the survival regression remains the same.

<sup>35</sup>In addition I implicitly allow for productivity to follow a second order Markov process, however, investment is only a function of current productivity ( $i_{it} = i_t(\omega_{it}, k_{it})$ ), even when assuming no differences in market structure. By making future productivity depending on past export status, I also pick up some variation in productivity at  $t - 1$  through the self-selection into export markets (as in Melitz; 2003). Remember that if  $EXP_{it} = 0$ , also  $z_{it} = 0$ . Formally,  $\Pr(EXP_{it} = 1 | I_{t-1}, \chi_{it} = 1) = \Pr(\omega_{it} \geq \bar{\omega}_{it} | \omega_{it-1}, EXP_{it-1}, \underline{\omega}_{it}(k_{it}))$  and therefore  $\Pr(EXP_{it} = 1 | I_{t-1}, \chi_{it} = 1) = \rho_{t-1}(\omega_{it-1}, P_t, EXP_{it-1})$ . The latter shows that future productivity depends on current  $\omega_t$  and past productivity  $\omega_{t-1}$ , through  $z_{it}$ .

learning effects cannot be subtracted away in the third stage given the estimates from the first stage ( $l(z_{it-1}, T_{it-1})$ ) since the expectation also depends on the probability of survival at  $t + 1$ .

I can proceed from here as before, i.e. perform a propensity score and estimate the treatment effect. Note that by just introducing the export dummy in the production function (as in Van Biesebroeck; 2005), one only models the productivity effect of exporting directly into the production function and does not allow exports to work through the unobserved component of productivity. The methodology suggested here does allow for firm specific impact of export experience on productivity and has a flexible functional form assumption (non parametric). Note that the way productivity is estimated in section 3. conditions on the export status of a firm and implicitly controls for past export experience through  $\tilde{\phi}_{it}$  in equation (6). Here I am more explicitly by introducing additional variables potentially capturing the scope of learning (export share in sales and number of years exported).

I now verify whether the I still find significant productivity gains from exporting. I include the share of export sales in total sales in the non parametric function  $\tilde{g}(\cdot)$  to proxy for the export intensity of a firm. This share  $z_{it}$  is zero for firms that did not export at time  $t$  and therefore no learning effects are present. For firms that exported at  $t$  there can be learning effects and I assume these effects to increase with the share of export sales in a firm's total sales. Note that this proxy incorporates the export dummy and in addition allows for a more flexible functional form. The coefficient on labor is now identified controlling for both the exogenous and endogenous unobserved productivity shock. In addition the estimated productivity will change through a differently estimated capital coefficient. If learning effects are present some variation in output that before was attributed to capital, will now be attributed to export experience. The latter is most likely also positively correlated with the level of capital stock since exporters tend to be more capital intensive. If learning effects are not controlled for, the capital coefficient might be overestimated and hence lead to a bias in my productivity estimates.

The additional non parametric function  $\tilde{g}_2(\cdot)$  turns out to be significant and changing the capital coefficients. The direction of the change differs across industries and is hard to predict. It seems that for sectors where I found strong learning effects (e.g. Chemicals) that the capital coefficient is estimated somewhat lower confirming my prior. The reverse is true for the sectors with no or even negative learning effects (e.g. Furniture). Overall, my results are very similar as before. Panel B of Table 5 shows the learning effects. The effect of starting to export on cumulative productivity does hardly change; it is estimated some what higher (14.7 percent). In Figure 4 I plot the estimated cumulative productivity gains for my three productivity estimates: (a) the standard OP, (b) corrected for market

structure differences and (c) correcting for learning. The sign and path of the learning effect is not sensitive to the corrections, however, the magnitude of the coefficients varies somewhat across the three measures of productivity.

Finally I present the results by destination allowing for learning effects in the unobserved productivity shock and these are shown in the last row of Table 7. Correcting for potential miss-measurement of productivity when learning effects are present, confirms the result that exporting towards low income regions leads to a productivity gain (11.8 percent), however, lower than firms selling on a market with high income consumers (18.5 percent).

### **5.3 The Effect of Exporting on Productivity: Selection Bias and Level Increase versus Continuing Future Gains?**

From the previous sections a robust result is that entering into the export market has a clear positive impact on the productivity level immediately after entering. Are the future effects due to the selection process, i.e. a specific sample of firms? What if starting to export only raises the productivity level immediately and that the gap between exporters and non exporters remains constant after that. Do firms really benefit from exporting then? This answer has been largely dealt with by estimating the productivity growth with respect to the pre-export level and cumulate future productivity gains of starting to export. I now discuss each of these concerns.

#### **5.3.1 Future Productivity Gains and Sample Selection**

The results on cumulative productivity gains in Table 5 were obtained by restricting the sample to firms having at least  $s + 2$  consecutive observations. Given this restriction, I now check whether the effects attributed to exporting are not driven by the selection process over time.<sup>36</sup> I now verify the effects of export entry at every period  $s$  for the various groups based on the number of years I observe the firm after the decision to start exporting. Table 8 shows the complete results of the cumulative productivity gains after initiating into export markets. The figures in bold are the effects based on the sample restriction as shown in row (d) in Table 5A. In the first column the number of consecutive observations are given. In order to verify whether the results are sensitive to the sample I have used in Table 5A, one has compare the figures within a column. For instance after three years of exporting (at  $s = 2$ ) the cumulative productivity gain is 0.283 restricting it to the sample of firms that have at least 4 consecutive observations in the sample.

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<sup>36</sup>Note that my productivity estimates are already corrected for the selection bias, less productive firms (given their capital stock) exit the market.

For firms having 5 consecutive observations the estimated cumulative productivity gain is 0.260. It is clear that the effects at all future periods  $s$  are significant and very similar across the various groups, confirming that the future results are not driven by the selection of a specific sample of firms.

### 5.3.2 One-Time Level Effect versus Continuing Productivity Gains

I have found rather strong immediate productivity effects of starting to export. This might raise the question whether exporting just raises productivity levels one time and that no future productivity improvements occur from continuing to export. The answer to this question has been largely dealt with in the various specifications of Table 5A. If exporting only raises productivity instantaneously, productivity growth in future years should never be higher than that of the first year. It is clear from row (c) that additional productivity growth is realized in future years, i.e. exporters have grown by 12.4 percent after 4 years of exporting compared to 9.2 percent after 3 years, indicating additional gains from exporting. The same reasoning holds using the results from the impact of export on productivity levels as illustrated by Figure 5. I plot the pure time effects at each point in time  $s$ . In addition, I plot the hypothetical case where no additional future productivity gains from exporting take place, represented by the horizontal line at the level of the immediate productivity impact ( $s = 0$ ), 0.088. Furthermore, the combination of the matched sample techniques and the *DID* methodology implies that the horizontal axis coincides with the matched domestic control group. It is clear that the estimated productivity gains lie well above the hypothetical case and that the productivity gap increases over time. This same picture emerges for the various sample of firms discussed above.

## 6 Productivity Gains after Exporting: Summing Up

There might be reasons why other authors have not found support for the learning by exporting evidence. The first and most obvious reason is the specific country that is studied. In Slovenia the transition process was a clear exogenous shock that changed trade patterns and trade activity drastically. The fact that I find evidence for the learning by exporting hypothesis (LBE) in the context of a transition economy is not surprising. There has been a substantial reorientation of trade flows during the sample period that I analyze. Furthermore, before the transition started there was not much chance to gain experience in terms of doing trade with market economies, due to the CMEA trading system. After the collapse of communism the only possibility for many firms to survive was often to reorient their activities towards the Western markets, irrespective of their



initial conditions, so that the learning scenario is more likely for a transition country like Slovenia. As suggested in Van Biesebroeck (2005), exporters can overcome the lack of demand by selling on foreign markets and hence exploiting returns to scale. The latter seems to be a plausible scenario for Slovenia where trade reoriented towards high income regions. However, my methodology controls for the returns to scale by including the export status as a state variable in the underlying structural model. To the extent that the productivity gains are only driven by a larger market and thus exploiting returns to scale, I also find a positive effect of exporting on productivity in industries with no significant increasing returns to scale.

Most of the studies look at *TFP* growth and not at levels, exporting might not be increasing *TFP* growth but can still lead to an increase in the level of productivity. Bernard and Jensen (1997) look at productivity growth between the first year of the sample and later periods and verify whether exporters grow faster in productivity. They find no evidence for this. However, their approach does not compare exporters with *matched* non exporters in terms of pre- export productivity, capital stock and ownership structure. It is therefore crucial to compare *export entrants* to non exporters which are *similar* in terms of observables that are correlated with the decision to start exporting.

My results indicate that *starting to exports* leads to higher productivity levels and that exporters remain more productive after the entry to the export market, which is confirmed by the positively estimated productivity growth rates (with respect to the pre-export productivity level). This is also what Blalock and Gerlter (2003) and Van Biesebroeck (2005) find, although using a different framework. They include the export dummy into the Olley and Pakes (1996) framework as an input in the production function and only allow the average productivity to be depending on export status, i.e. in a deterministic way. The latter makes it impossible to allow for heterogenous effects of export status since one estimates one parameter that captures the effect of exporting on the mean of the future productivity distribution. I relax this by allowing future productivity to depend on current and past export experience. If I would only find evidence for a productivity increase in levels the first year a firm starts exporting, no learning takes place. My methodology allows to check whether the productivity trajectory is different, even years after starting to export. I have shown that indeed in some industries the productivity gain only comes in some years after the initial export period, suggesting that export does more than leading to a one time productivity gain at the time of starting to export. In addition, using the estimates for the entire sample (manufacturing) I have shown that the productivity gains lie well above the theoretical case of a one-time jump in productivity levels.

As suggested by Aw, Chung and Roberts (1998), there are a number of other expla-

nations besides the learning by export story as to why exporters widen the productivity gap with non exporters. Differences in technology, increasing returns to scale are other explanations as to why exporters widen the productivity gap after entering the export market. Note that my methodology - at least partly - controls for these since I estimate the coefficients of the production function controlling for export status. They note that essentially any factor that results in positive serial correlation in productivity can generate productivity gains from exporting. Firms with positive shocks to their productivity are more likely to self select into the export market and if these positive shocks continue over time the productivity of exporters will continue to diverge from the non exporters. However, if I would not find productivity to be significantly different for exporters once they enter the export market, the learning by exporting explanation (as any of the other explanations) is not valid. In addition, the matching is based on the pre-export productivity level and therefore conditions on the pre-export productivity path. In order to find an effect from entering in the export market, productivity has to significantly change after this decision since I compare exporters with non exporters that experienced similar productivity shocks in the past, which clearly reduces the problem of observational equivalence noted by Aw, Chung and Roberts (1998).

Finally, in order to put the estimated - instantaneous - effect of exporting on productivity in perspective, I ran a simple OLS regression as suggested in (1) using my various estimates for productivity. Remember this regression only captures a simple correlation ( $\beta$ ) between export status and productivity controlling for ownership, size, industry and year dummies. I find (highly significant) coefficients of 0.2035, 0.1877 and 0.2061 using the standard OP, controlling for market structures and learning, respectively. The estimated learning by exporting effect explains roughly half of this export productivity premium.

## 7 Conclusion

The transition from plan to market in many of the formerly planned economies offers us a unique natural experiment to evaluate a number of fundamental economic questions. This paper analyzes the effects of exports on the economic performance of one the most successful transition economies, Slovenia. In a period of 6 years exports have more than doubled, the number of firms that started exporting over this period has increased dramatically. The observed correlation between exports and firm performance begs the question whether the best firms select themselves in export markets or whether exporting leads to productivity improvements. The question has been analyzed before, however, both the nature of the underlying dynamics in export status in the various data sets at hand and the empirical methodologies that were used have not led to a clear picture on

which hypothesis to support.

I start my analysis by showing that exporters have different characteristics than non-exporters. I then introduce a new estimation technique to estimate total factor productivity based on Olley and Pakes (1996). This method allows us not only to estimate *TFP* consistently, but also to take into account potential selection of firms. This may be important in economies undergoing a lot of structural change where significant simultaneous entry and exit takes place. I find that the modified Olley-Pakes estimates yields different estimates for labor and capital, which suggests that an analysis of *TFP* just using OP may result in biased estimates. I then introduce a matched sampling technique to construct a counterfactual control group to test whether exporting firms if they had not entered the export market would had performed equally well. I match firms within narrow defined industries and I condition on the ownership and the state variables of the dynamic problem where the most important one is productivity. The latter captures the entire pre-export productivity path, i.e. I condition on the self selection mechanism that might occur prior to the decision to export.

My findings suggest that exports have contributed to the better performance of exporting firms. They become on average 8.8 percent more productive, which gives support to the learning by exporting hypothesis. Also exporting raises productivity in years following the decision to export. Once I perform the analysis at more disaggregated level, I can identify sectors where learning by exporting is present suggesting that controlling for industry specific unobservables is crucial. The magnitude and timing of the learning effects are very heterogeneous across the different sectors, however in 13 out of 16 sectors I find evidence for learning effects. Starting to export also increases *TFP* growth in future years with respect to the pre-export level of productivity. Furthermore, my results are robust to potential miss-measurement of productivity in the presence of learning effects and the characteristics of the destination of exports capturing different demand conditions.

Finally, my findings suggest that the good economic performance of the Slovenian manufacturing - and consequently of the entire economy - can be partly explained by the entry into export markets and suggests that policy aimed at promoting exports may be beneficial.

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## Appendix A: Data Description

In this appendix I describe the variables used more in 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. I observe all variables every year in nominal values, however, investment is not reported or accurately so I calculate it from the other information.

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

I 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. As opposed to commonly used data sources (e.g. LRD data, Olley and Pakes (1996), various census data (Chile, Levinsohn and Petrin (2003)) I observe the capital stock every year.
- Investment: calculated from the yearly observed capital stock in the following way with the appropriate depreciation rate (5%-20%) varying across industries, i.e.  $I_t = K_{t+1} - (1 - \delta)K_t$ .

The industry classification NACE rev. 1 is similar to the ISIC industry classification in the U.S.A. and the level of aggregation is presented in the table below.

**Table A.1.: Industry Classification**

Nace 2-Digit	Description
15	Food Products
16	Tobacco Products
17	Textiles
18	Wearing Apparel
19	Leather and Leather Products
20	Wood and Wood Products
21	Pulp, Paper and Paper Products
22	Publishing and Printing
23	Coke and Petroleum Products
24	Chemicals
25	Rubber and Plastic Products
26	Other Non-Metallic Mineral Products
27	Basic Metals
28	Fabricated Metal Products
29	Machinery and Equipment n.e.c.
30	Office Machinery and Computers
31	Electrical Machinery
32	RTv and Communication
33	Medical, Precision and Optical Instr.
34	Motor Vehicles
35	Other Transport Equipment
36	Furniture/ Manufacturing n.e.c.
37	Recycling

I now present the number of active firms by industry over the sample period. It is clear that some sectors have very few observations and do not provide us with enough information to verify the learning by exporting experience, i.e. there is not enough variation to identify the production function parameters and select appropriate counterfactuals.

**Table A.2.: Number of Active Firms per Industry (1994-2000)**

NACE	1994	1995	1996	1997	1998	1999	2000	Growth
15	216	241	271	287	289	301	308	43%
16	1	1	1	1	1	1	1	0%
17	131	146	157	165	171	173	180	37%
18	216	230	239	249	231	238	246	14%
19	41	52	58	62	59	64	69	68%
20	247	282	301	315	328	346	356	44%
21	64	70	76	78	79	78	78	22%
22	307	345	401	429	456	566	625	104%
23	3	3	5	5	5	4	4	33%
24	98	101	109	109	114	118	119	21%
25	215	245	261	274	292	307	328	53%
26	124	130	140	145	154	157	159	28%
27	41	48	54	58	57	63	66	61%
28	619	690	740	779	797	812	862	39%
29	263	293	363	345	353	386	379	44%
30	66	68	80	81	83	84	82	24%
31	187	193	217	221	224	226	240	28%
32	111	128	116	111	115	114	113	2%
33	142	153	157	167	167	171	185	30%
34	50	57	60	61	67	72	69	38%
35	20	22	19	21	24	29	31	55%
36	258	295	319	340	347	355	378	47%
37	25	27	35	36	34	30	28	12%

Figure 1:



## Appendix B. Estimating Productivity

Levinsohn and Petrin (2003, LP) suggest a modification of the Olley-Pakes (1996) approach by using intermediate inputs, such as electricity or fuel usage instead of investment, which has the advantage that the data can be used more efficiently. In my data, however, I have no information on electricity or fuel usage so I could not pursue this. Additionally, the LP methodology suffers from potential collinearity problems in the first stage of the estimation algorithm. The OP estimator, however, is not fully protected against this. However, using investment instead of materials has the advantage that labor is less likely to be correlated with the non-parametric function, crucially depending on the timing of the various inputs in the production process. For more on this I refer to Akerberg, Caves and Frazier (2004). They argue that depending on the timing of the inputs and the extent to which labor is freely chosen, the identification of the labor coefficient is no longer possible in the regular OP framework. In order to verify whether the polynomial  $\phi_t(\cdot)$  is well specified I run the following regressions in the final stage

$$y_{t+1} - b_l l_{t+1} = c + \beta_k k_{t+1} + \sum_{j=0}^{s-m} \sum_{m=0}^s \beta_{mj} (\hat{\phi}_t - \beta_k k_t)^m \hat{P}_{t+1}^j + \beta_{lc} l_t + e_{t+1}$$

and I test whether  $\beta_{cl}$  is different from zero, respectively. In all cases, it is not significantly different from zero, confirming that the non parametric approximation  $\phi(\cdot)$  is well specified and hence no variation in labor is left. In addition the Olley and Pakes (1996) method does not rely on the assumption of perfect competition in the output market, whereas the LP does, i.e. every positive productivity shock leads to more input use and hence higher output and leaves no room for positive mark-ups.

All three estimations have in common that I use series estimators to proxy for the unknown functions, instead of using kernel estimators. I experimented with the order of the polynomials used and I found that there is almost no change when moving from the 4th to the 5th order polynomial. The use of a series estimator in the first stage yields an estimator with known limiting properties (Andrews, 1991). However, the use of the series estimator yields an estimator that does not have a well-defined limiting distribution (Pavcnik, 2002). Pakes and Olley (1995) proof asymptotic results in the case of using a kernel estimator, however, not when a series estimator is used. Despite this shortcoming, there are several advantages of using a series estimator instead of a kernel estimator. Firstly, it is easier and faster than any kernel approximation. Secondly, Pakes and Olley (1995) show that the results are very similar. I use bootstrapping methods to come up with the correct standard errors for the series estimator of the capital coefficient, where I use 1,000 replications as in Pavcnik (2002). The standard errors on the capital coefficient tend to be overestimated when using bootstrap methods (see Pakes and Olley (1995)) and this is what I find for some industries.

Some critical considerations related to this method are worth mentioning. First, one potential concern of the OP approach is the positive investment requirement, which is enforced by the estimation algorithm. As in Pavcnik (2002) I experimented with both restricted and unrestricted samples, the latter including all firms. However, the results were very similar, despite the theoretical assumptions of the model. Nevertheless, I excluded a small number of sectors from the analysis, mainly due to the limited number of available observations. For instance, the tobacco industry is not included as this is a monopoly in Slovenia (see Table A.2 in the Data Appendix).

A second concern in the estimation of  $TFP$  is the assumption of perfect competition in the factor market. In a recent paper, Katayama, Lu and Tybout (2003) point out how  $TFP$  measures can be biased in the presence of imperfect competition in the product market and in the labor market. The limiting nature of the assumption of perfect competition in estimating  $TFP$  is indirectly taking into account in the second step of the empirical

analysis, where I apply a difference-in-difference approach to analyze the learning-by-exporting controlling for the self-selection process. If the bias in the estimates of  $TFP$  due to the presence of imperfect competition is roughly the same for similar sectors we can control for that by differencing it out when I compare exporting with non-exporting firms in section 4. Despite this drawback of productivity estimates, the reassuring part is that in the Katayama et al. (2003) paper, the correlation between the traditional  $TFP$  estimate, and the alternative measure suggested by the authors which consists of estimating consumer and producer surplus, turns out to be relatively high.

Another caveat is the possibility of measurement error that may plague my analysis. In particular for the labor input in my production function, I use number of employees. Although number of hours worked would have been an input with less measurement error and more truly reflect the actual use of labor input, this was not available to me. In terms of capital, I used the book value of fixed tangible assets, but I have no information on capacity usage or periods of idle capacity. However a recent paper by Van Biesebroeck (2004) comparing different methods for estimating productivity on data characterized by known measurement errors, finds that the semi-parametric methods, like the OP one I use here, is least sensitive to measurement error when estimating  $TFP$ . In fact, Van Biesebroeck (2004) shows that the correlation between estimated and true productivity when using semi-parametric methods remained high, even in the case of measurement error.

## Appendix B: Productivity: Estimated Coefficients and Index

Table B.1: Coefficients of the Production Function

Sector	OLS	FE	OP	OP-EXP	OP-LBE	OLS	FE	OP	OP-EXP	OP-LBE
15) Food Products and Beverages	0.9105	0.8228	0.8804	0.8811	0.8233	0.1928	0.1911	0.2651	0.0943	0.1077
17) Textiles	0.8077	0.6336	0.7782	0.7705	0.7602	0.1728	0.1015	0.1491	0.2411	0.2328
18) Wearing Apparel	0.8723	0.8224	0.8459	0.8033	0.7973	0.1734	0.1392	0.2003	0.2972	0.2011
19) Leather and Leather Products	0.7945	0.4215	0.6712	0.5837	0.5318	0.2059	0.1163	0.2349	0.2544	0.2339
20) Wood and Wood Products	0.7946	0.6805	0.7673	0.7545	0.7443	0.1914	0.2459	0.1831	0.1789	0.1763
21) Pulp, Paper & Paper Products	0.7952	0.5788	0.6724	0.6957	0.6516	0.2236	0.1814	0.2409	0.3445	0.2466
22) Publishing and Printing	0.7986	0.6717	0.6882	0.6727	0.6609	0.2711	0.1849	0.2072	0.2017	0.2469
24) Chemicals and Chemical Prod.	0.8089	0.6963	0.5668	0.5674	0.7682	0.2694	0.1380	0.4340	0.4772	0.2026
25) Rubber and Plastic Prod.	0.7276	0.7757	0.6923	0.6788	0.6344	0.2791	0.2403	0.1295	0.2933	0.3036
26) Non-Metallic Mineral Prod.	0.8027	0.7800	0.7340	0.7718	0.7711	0.2192	0.1193	0.2177	0.2155	0.1989
27) Basic Metals	0.6525	0.7433	0.6796	0.6928	0.5763	0.2715	0.2502	0.2484	0.2314	0.3643
29) Machinery and Equipment	0.7495	0.7793	0.7665	0.7593	0.7800	0.2328	0.2336	0.2421	0.1781	0.2345
31) Electrical Machinery & App.	0.7629	0.8593	0.7325	0.7059	0.7196	0.2737	0.3035	0.2118	0.2380	0.1906
33) Medical, Precision & Optical	0.7723	0.6616	0.7213	0.7045	0.7127	0.2349	0.2802	0.2719	0.1926	0.2673
34) Motor Vehicles, Trailers	0.7584	0.8517	0.7214	0.7342	0.7905	0.2077	0.2365	0.2185	0.0770	0.1308
36) Furniture and N.E.C. Manuf.	0.8105	0.7675	0.7878	0.7829	0.8245	0.2131	0.2226	0.3191	0.2554	0.2021

**Note:**

1/All coefficients are significant at the 1 percent level. 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 1,000 replications. The standard errors on the capital coefficient tend to be overestimated due to limiting distribution, see Pakes and Olley (1995). I estimate the production function at the industry (2 digit) and include 3 digit industry dummies. I include a time trend throughout the entire estimation algorithm, i.e. in all three stages of the estimation and it turns out to be an important control variable and this is also what Olley and Pakes (1996) find in their dataset.

2/ **FE**: fixed effects estimator, **OP**: standard Olley and Pakes (1996), **OP-EXP**: **OP** + export status and **OP-LBE**: **OP-EXP** + export experience

Table B.2: Productivity Index

year	Index	Index Exporters	Index Domestic
1994	1.0000	1.0000	1.0000
1995	1.0230	1.0213	1.0484
1996	1.0661	1.0627	1.1162
1997	1.1118	1.1107	1.1263
1998	1.1245	1.1229	1.1484
1999	1.1623	1.1661	1.1082
2000	1.1847	1.2006	0.9537
Total	1.1008	1.1028	1.0720

Table 1: Number of Active and Exporting Firms

Year	# active firms	# exporters	# starters
1994	3,445	1,539	.
1995	3,820	1,738	407
1996	4,152	1,901	263
1997	4,339	1,960	285
1998	4,447	2,003	273
1999	4,695	2,192	302
2000	4,906	2,335	342

Table 2: Entry and Exit Rates in Slovenian Manufacturing

Year	Number of Firms	Exit Rate	Entry Rate	Exit Rate <i>Exporters</i>	Exit Rate <i>Domestic</i>
1995	3,820	3.32	13.14	0.4	2.9
1996	4,152	2.60	5.44	0.3	2.3
1997	4,339	3.43	4.47	0.4	3.0
1998	4,447	3.94	4.14	0.3	3.6
1999	4,695	3.26	3.30	0.4	2.9
2000	4,906	2.69	3.38	0.2	2.5
Average	4,393	3.21	5.65	0.3	2.9

Note: One could also consider the pool of exporting firms and look at exit rate within that pool and compare it to the exit rate for the non exporting firms. I find that (on average) the exit rate for exporting firms is 19.2 percent and 33.4 percent for non exporting firms. The exit rates are not comparable to those presented in the table above but the same message is clear, i.e. exporting firms have a much lower exit rate, in both cases around 10 to 15 percent lower.

Table 3: Summary Statistics

Year	Size	Value Added	Wage	Capital pw	Sales	Value Added pw
1994	40.93	580.2	7.93	30.36	1,978	14.03
1995	41.31	591.5	8.99	32.18	2,105	14.71
1996	37.75	621.5	10.49	37.13	2,132	16.45
1997	35.17	676.2	10.63	42.85	2,282	18.22
1998	34.15	669.3	11.33	38.62	2,363	18.81
1999	33.43	727.2	12.56	41.03	2,397	21.02
2000	33.60	778.5	13.26	41.99	2,730	21.26
Mean	36.39	668.4	10.93	38.19	2,300	18.07

Note: -All monetary variables are expressed in thousands of Slovenian Tollars and in real terms, using a two digit PPI to deflate. The exchange rate is roughly 200 Tollars to the euro.  
- pw: per worker

Table 4: Firm Characteristics Differentials between Non- and Exporters

Firm characteristic ( $X$ )	$\beta$	$R^2$
Average wage	0.1614	0.31
Value Added per worker	0.2959	0.14
Sales per worker	0.5863	0.15
Capital per worker	0.3655	0.09
Investment per worker	0.3749	0.06
Employment	1.8532	0.31
Observations (min / max)	18,106 (*) / 29,804	

Note: All coefficients are significant at the 1%. All regressions include a size effect except for the employment regression. All monetary variables are deflated by the appropriate industry-deflator, (\*): Number of observations for the investment regression, it drops due to the definition of investment, i.e. I construct investment from the yearly observable real capital stock and thus I lose the first year of observation (1994).

Table 5: Learning by Exporting

A. Controlled for Market Structure ( $i=i(k,e,\omega)$ )

s	0	1	2	3	4
<b>(a) Outcome: Productivity</b>					
$\beta_{LBE}$	0.088*	0.099*	0.099*	0.130*	0.037
	(0.035)	(0.036)	(0.038)	(0.043)	(0.053)
Nr treated	1,770	1,694	1,610	1,519	1,293
Nr controls	5,239	4,983	4,539	3,952	2,956
<b>(b) Outcome: Productivity Growth: <i>year-to-year growth rate</i></b>					
$\beta_{LBE}$	0.079*	0.026	0.028	0.025	-0.089
	(0.028)	(0.033)	(0.040)	(0.049)	(0.063)
<b>(c) Outcome: Productivity Growth: <i>pre-export level (s = -1)</i></b>					
$\beta_{LBE}$	0.079*	0.092*	0.092*	0.124*	0.001
	(0.028)	(0.031)	(0.038)	(0.045)	(0.067)
<b>(d) Outcome: Cumulative Productivity</b>					
$\beta_{LBE}$	0.088*	0.177*	0.283*	0.434*	0.460*
	(0.035)	(0.062)	(0.092)	(0.133)	(0.195)
<b>(e) Outcome: Cumulative Productivity : Common support restriction</b>					
$\beta_{LBE}$	0.086*	0.177*	0.277*	0.431*	0.426*
	(0.032)	(0.062)	(0.098)	(0.144)	(0.204)

Note: - Imposing the balancing constraint I am left with  $n$  blocks ensuring that the mean propensity score is not different for treated and controls in each block. The matching procedure puts equal weight on the forward and backward neighbor in the searching algorithm. The number of treated and controls decreases as I estimate future productivity effects ( $s$ ) since I restrict the sample of firms to be included in the estimation

- I denote significant at 5% or stricter and at 10% with \* and \*\*, respectively.

B. Controlled for Market Structure ( $i=i(k,e,\omega)$ ) & Learning Effects

s	0	1	2	3	4
<b>(a) Outcome: Productivity</b>					
$\beta_{LBE}$	0.147*	0.149*	0.105*	0.083**	-0.006
	(0.039)	(0.042)	(0.042)	(0.047)	(0.056)
<b>(b) Outcome: Productivity Growth: <i>pre-export level</i> (<math>s = -1</math>)</b>					
$\beta_{LBE}$	0.137*	0.148*	0.121*	0.137*	0.003
	(0.031)	(0.036)	(0.040)	(0.051)	(0.065)
<b>(c) Outcome: Cumulative Productivity</b>					
$\beta_{LBE}$	0.147*	0.273*	0.414*	0.306*	0.182
	(0.039)	(0.068)	(0.099)	(0.141)	(0.192)

Note: - Imposing the balancing constraint I am left with  $n$  blocks ensuring that the mean propensity score is not different for treated and controls in each block. The matching procedure puts equal weight on the forward and backward neighbor in the searching algorithm. The number of treated and controls decreases as I estimate future productivity effects ( $s$ ) since I restrict the sample of firms to be included in the estimation

- I denote significant at 5% or stricter and at 10% with \* and \*\*, respectively.



### C. Industry Specific Results

Outcome : Productivity and cumulative productivity					
<i>s</i>	<i>0</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>
15) Food Products & Beverages	-0.007	0.155	0.513*	0.829*	1.217*
17) Textiles	-0.059	0.007	0.297	0.883*	1.787*
18) Wearing Apparel	0.037	-0.02	0.309	0.973*	0.528*
19) Leather & Leather Products	0.881*	0.005	1.518*	4.610*	4.573*
20) Wood & Wood Products	0.070	0.195	0.395*	0.240	0.493*
21) Pulp, Paper & Paper Products	0.100	0.201	0.361	0.474	-0.136
22) Publishing & Printing	0.205*	0.278*	0.039	-0.113	0.163
24) Chemicals & Chemical Prod.	0.526*	0.636*	1.430*	2.589*	3.791*
25) Rubber & Plastic Prod.	0.363*	0.523*	0.469*	0.640*	1.159*
26) Non-Metallic Mineral Prod.	0.175**	0.321**	0.137	0.432	0.285
27) Basic Metals	0.124	0.240	-0.095	-0.878	-1.639
29) Machinery & Equipment	0.212*	0.278**	0.278	0.921*	0.517*
31) Electrical Machinery & App.	0.185**	0.226	0.745*	0.709*	1.623*
33) Medical, Precision & Optical	0.055	0.329	0.580*	0.670*	2.826*
34) Motor Vehicles, Trailers	0.252	0.328	0.909*	1.747*	0.533
36) Furniture/ Manufacturing n.e.c.	-0.043	-0.025	0.035	-0.019	0.192

Note: I only report the estimated coefficient and whether it is significant, \*: significant at 5% (or stricter) level I drop the industry Other Transport Equipment due to the lack of observations of performing the DID estimation. The number of starters by year and industry are quite low in some sectors making identification hard and reduces the power of my test considerably.

### D. Evidence on Learning by Exporting: Industry Classification

Evidence on Learning by Exporting		No Evidence
Immediate Impact	Future	
Leather & Leather Products	Food Products & Beverages	Pulp & Paper
Publishing & Printing	Textiles	Basic Metals
Chemicals & Chemical Prod	Medical, Precision & Optical	Furniture/ Manuf. n.e.c
Rubber & Plastic Prod	Electrical Machinery & App	
Non-Metallic Mineral Prod	Wearing Apparel	
Machinery & Equipment	Wood & Wood Products	
	Motor Vehicles, Trailers	
13 sectors		3 sectors



Table 7: ‘Learning By Exporting’ by Destination

(a) baseline, (b) market structure control and (c) market structure and learning

	All	High income	Low income
$\beta_{LBE}$ (a)	0.104*	0.129**	0.078*
s.e.	(0.038)	(0.080)	(0.037)
$\beta_{LBE}$ (b)	0.088*	0.202*	0.095*
s.e.	(0.035)	(0.080)	(0.037)
$\beta_{LBE}$ (c)	0.147*	0.174*	0.099*
s.e.	(0.039)	(0.081)	(0.041)
# starters	1,770	250	1,520

Note: - The high number of starters for ‘Low income’ compared to ‘High income’ is due to the inclusion of Central and Eastern European regions in the ‘Low income’ category.

- \* and \*\* significant at 5% or stricter and 10%, respectively.

Table 8: Cumulative Productivity Gains: Detailed Results

<i>s</i>	0	1	2	3	4
Consecutive observations from starting to export					
5: [<1997]	0.087*	0.119*	0.260*	0.406*	<b>0.460*</b>
4: [<1998]	0.088*	0.153*	0.290*	<b>0.434*</b>	
3: [<1999]	0.077*	0.169*	<b>0.283*</b>		
2: [<2000]	0.086*	<b>0.177*</b>			
1: [all starters]	<b>0.088*</b>				

Note: - I denote significant at 5% or stricter and at 10% with \* and \*\*, respectively.  
 - Between square brackets in the first column the implied sample of starters is given. Exporters having 5 consecutive observations from the point they export capture firms that started exporting before the year 1997, i.e. in 1995 and 1996.

Figure 1: Evolution of real export sales and domestic sales

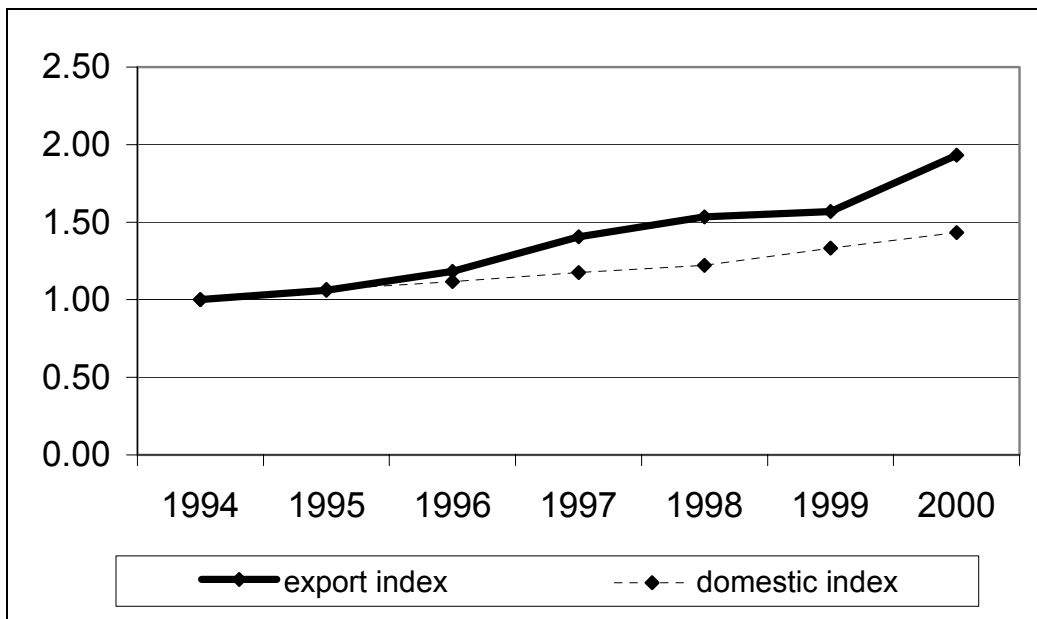




Figure 2: TFP Trajectories for Different Groups (Wearing Apparel)



Figure 3: TFP Trajectories for Different Groups (Furniture and NEC)

Figure 4: Cumulative Productivity (Manufacturing)

(a) OP, (b) market structure (OP-EXP), (c) learning + (b) (OP-LBE)

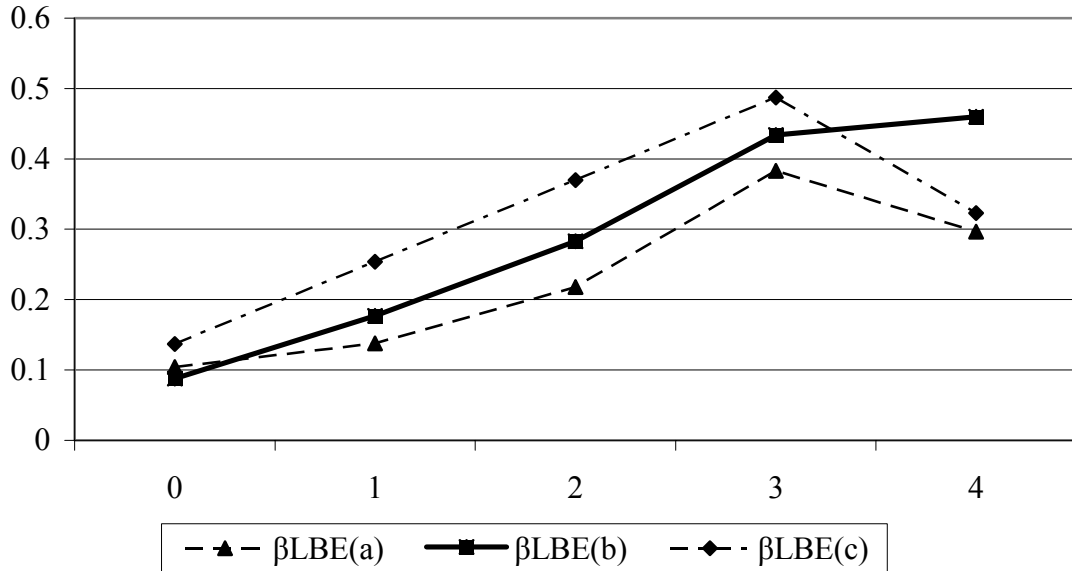


Figure 5: Estimated Time Effect versus Hypothetical One-Time Effect

