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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. Overall I find that export entrants become more productive once they start exporting. The productivity gap between exporters and their domestic counterparts increases further over time. 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 towards high income regions.

Keywords: Exports; Production functions; Productivity dynamics; Learning by exporting; Export destination

JEL classification: L1; D24

1. Introduction

One of the main empirical regularities that characterizes exporters is that they are more productive than non exporters.[1] 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 the export status of a firm and its

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[1] Empirical contributions include Roberts and Tybout (1996), Clerides, Lach and Tybout (1998), Bernard and Jensen (1999), Van Biesebroeck (2006), Alvarez and Lopez (2004). Theoretical contributions include Melitz (2003) and Bernard et al. (2003).

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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 mechanism 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.[2] 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 and there has been a substantial evidence in favor of self-selection. However, recent studies by Aw, Chung and Roberts (2000) for Korea and Van Biesebroeck (2006) for Côte-d'Ivoire have documented that firms experience significant productivity increases after entering the export market.

This paper provides evidence for the learning by exporting hypothesis using a 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% 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 increased by 42%, 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. This significant entry into export markets over the various years within the sample period 1994–2000 allows me to identify the instantaneous and future productivity gains upon export entry controlling for the self-selection process. I find strong and significant productivity premium for firms that start exporting where the magnitude varies across the different industries of the manufacturing sector. The dynamics of the productivity gains are also explored and they are very different across industries.

In addition, I provide a potential channel through which the learning by exporting takes place by introducing the information on firm-level destinations of exports. Documenting and estimating positive productivity gains upon export entry does not provide enough information as to how these firms become more efficient. If there is scope for learning from foreign markets through contact with buyers and competitors, we would expect to find higher productivity gains for firms shipping their products to relative developed regions. This is exactly what I find for Slovenian manufacturing firms exporting to high income regions such as Western Europe and North America. However, the variance in the estimated productivity gains across industries cannot be solely attributed to differences in destination of exports.

To my knowledge this is the first paper that looks at productivity gains from entering export markets by distinguishing between various destinations. However, it is related to the work of Eaton and Kortum (2004, 2005) where export destination is used to understand the importance of fixed cost in entering export markets and to which extent they are market (country) specific. Related to this, I find that (at the firm level) the number of destinations and productivity are positively correlated. This is consistent with more productive firms being able to overcome higher fixed costs and in turn implies market specific fixed cost of export entry. The destination

[2] See Evenson and Westphal (1995), Westphal (1990), Grossman and Helpman (1991) and World Bank (1993).

information is only available to me as a cross section. Therefore I am not able to see firms entering new export destinations over time and identify the learning by exporting effect by market (country). Productivity gains from exporting to different regions (high and low income) are identified as there is sufficient variation in firm-level destinations across firms.

There has been a recent debate in the literature on the estimation of production functions. For a review of the latest contributions I refer to Ackerberg, Benkard, Berry and Pakes (in press). The choice of the appropriate estimation algorithm crucially depends on the application. My productivity estimates are obtained from a modified Olley and Pakes (1996) estimation algorithm where I explicitly allow for different market structures for exporting firms.[3] The method deals with both the simultaneity bias and the selection bias in estimating production functions. The latter is important for an emerging economy such as Slovenia where the least productive firms exit the market and are replaced by new more productive firms.[4] The introduction of exports in the estimation algorithm corrects for unobserved productivity shocks correlated with export status and filters out differences in market structures between domestic and exporting firms within a given industry such as the mode of competition, demand conditions, and exit barriers. These productivity estimates are then used to verify whether entering the export markets leads to productivity gains. Furthermore, I use matched sampling techniques based on an underlying selection model of self-selection into export markets as in Melitz (2003) to identify the productivity premium from entering export markets. I provide estimates for both the instantaneous and future productivity gains as export entry might not have an immediate effect on productivity.

I organize the paper as follows. In Section 2 I discuss the dataset and perform some preliminary analysis. In Section 3 I discuss the estimation procedure for getting reliable estimates of productivity. 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 4 I introduce firm-level information on the destination of exports and estimate the learning by exporting parameter for various groups of destination markets. Section 5 provides some robustness checks and collects concluding remarks. The last section concludes the paper.

2. Data and preliminary analysis

2.1. Data description

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 and 2000.[5] I have information on 7915 firms and it is an unbalanced panel with information on market entry and exit and export status. The export status – at every point in time – provides information whether a firm is a domestic producer, an export entrant or a continuing exporter. If I only take into account those (active) firms that report employment, I end up with a sample of 6391 firms or 29,804 total observations over the sample period.

[3] A similar approach has been used by Van Biesebroeck (2006).

[4] For more on this I refer to De Loecker and Konings (2006), where the role of entry and exit in productivity growth are analyzed for Slovenian manufacturing.

[5] The unit of observation is that of an establishment (plant). In the text I refer to this unit of observation as a firm. For more details on the data and the aggregate trade pattern I refer to Appendix A and to the working paper version for more detailed data description and results.

Table 1
Number of active firms and entry/exit rates in Slovenian manufacturing

	Annual average (1994–2000)
Number of active firms	4258
Number of exporters	1953
Number of starters	312
Entry rate	5.65%
Exit rate	3.21%
Domestic producers	2.90%
Exporters	0.30%

Table 1 shows the average number of firms that I observe and those that are exporting. While in 1994 about 1539 firms were exporting, by 2000 2335 did so or this represents an increase of 52%. The entire number of firms increased also over this period by 42% resulting in a net increase of the share of exporters in Slovenian manufacturing.

In row three I show the number of firms that started exporting. On average 16% of the exporting firms are new entrants in the export market and in total I observe 1872 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% of the export entrants are new firms entering the market. This leaves me with around 1700 export entrants – spread equally over the sample period – which I observe before entering the export market. It is this unique setting that allows me to verify the impact of *starting to export* on productivity by comparing (productivity of) export entrants with similar domestic firms in terms of past productivity shocks and other firm specific observables. The identification of the learning parameter is as such based on models like Melitz (2003) that indicate that more productive firms become exporters as I control for pre-export productivity shocks of new exporters.

Exports have gained importance in Slovenian manufacturing which is reflected by a 42% increase in total exports of manufacturing products over the sample period 1994–2000. In Fig. 1 I plot the evolution of total exports in the firm-level data and compare it with published aggregate export statistics. On average my firm-level data covers between 82 and 89% of total exports as reported by Nicita and Olarreaga (2006). It is also clear from Fig. 1 that the evolution of firm-level total exports and the aggregate follow each other very closely.[6] The industry composition of exports has been fairly stable over time where Chemicals (10%), Transport Equipment (12%), Machinery (9%) and Electrical Machinery (9%) comprise around 40% of total exports. However, the share of exports of the Wearing Apparel and Footwear industry in total manufacturing exports dropped from 9 to 4%. Slovenia exports to 180 different countries. However, as shown in Table A.2 in Appendix A, a large majority of manufacturing exports (80% on average across the sample period) is shipped to only 10 countries, with Germany receiving 29% of exports.

The structural change that has been going on in Slovenian manufacturing is also revealed by the patterns of enterprise turnover. In Table 1 I show the market entry and exit patterns in the data. Over the sample period I find an annual average exit rate of 3%, which is comparable to exit rates found

[6] In 1996 Slovenia signed the Europe Agreements by which EU candidate member states would have free access to the EU market with the exception of trade in some specific products such as steel and textiles. This was put into practice in 1998 once the actual accession process began with the initiation of the accession negotiations in the form of bilateral intergovernmental conferences. The timing of the trade agreement with the EU is clear in Fig. 1 where exports in manufacturing products peaked in 1998.

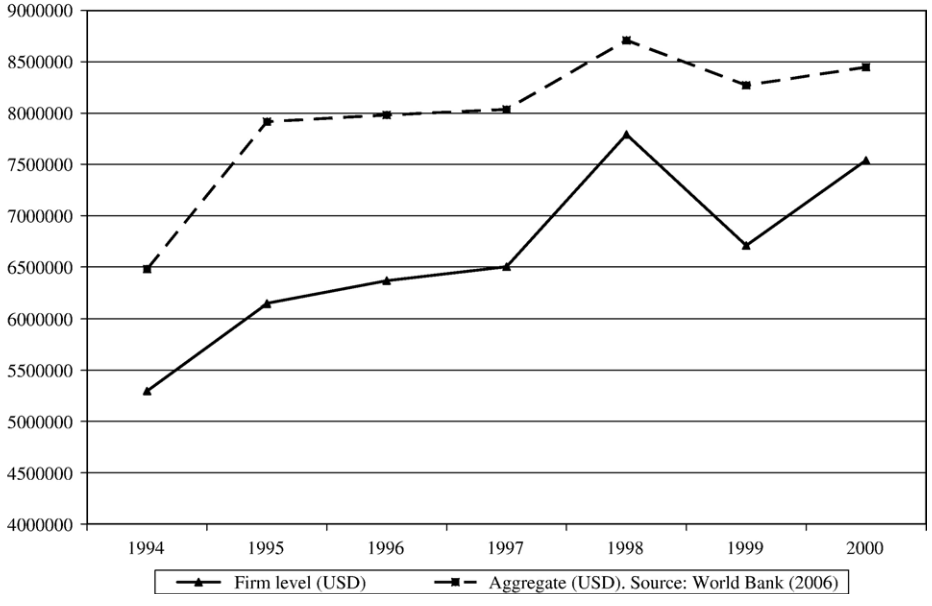

Fig. 1. Total export evolution: firm level versus aggregate trade statistics (in 1000 USD).

in other developing regions. For instance, Clerides, Lach and Tybout (1998) report annual average exit rates for Colombia of 1.7%, for Morocco of 3.7% and for Mexico of 1.5%. The entry rate in my sample is much higher, on average 5.65% per year. This compares to entry rates of 2.7%, 4.9% and 4.8% 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, 1998). Also the average firm size declined over the sample period and is close to the average size of manufacturing firms in Western economies. Furthermore real sales, value added and wages went up, 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 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

$$x_{ikt} = \alpha + \beta EXP_{ikt} + \gamma l_{ikt} + \sum_j \delta_j Time_j + \sum_k \lambda_k Ind_k + \varepsilon_{ikt} \tag{1}$$

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

Table 2
Firm characteristics differentials between non exporters and exporters

Firm characteristic (x)	β	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).

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 β 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 2 shows the results of estimating Eq. (1). It is clear that exporters differ significantly from non exporters.

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 USA, Bernard and Wagner (1997) for Germany, Isgut (2001) for Colombia and Van Biesebroeck (2006) for sub-Saharan Africa among others.

Using labor productivity as a rough measure for productivity, I find that exporting firms are on average 29.59% more productive. This paper is exactly about disentangling this stable correlation between export status and productivity. In addition my methodology allows me to test whether future productivity (and the productivity trajectory) changes after entering the export market. The next section presents the estimation strategy to obtain a reliable measure for productivity, total factor productivity, using the estimates of industry specific production functions parameters taking the export status of a firm into account.

3. Export entry and productivity gains

In this section I discuss the estimation strategy for getting estimates of the production function.[7] Secondly, I present the econometric model to identify the learning by exporting parameters and I discuss the results.

3.1. Productivity dynamics and export status

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: Firstly, it allows us to control for the simultaneity bias when estimating production functions, without having to rely on

[7] I rather estimate a value-added generating production function since I do not observe physical output. However, I interpret productivity in a broad sense: conditioned on the level of inputs how much more value added does a firm generate.

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 productivity.

I extend the Olley and Pakes (1996) framework by allowing market structure (factor markets, demand conditions, etc.) to be different for exporting firms by introducing export into the underlying structural model. In Appendix B I discuss the estimation algorithm in more detail. By introducing export in the estimation procedure 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 1), i.e. 2.9% versus 0.3% 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 that 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.

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 and the form of conduct in the industry (Ackerberg et al., in press). All these factors are now allowed to be different and evolve different over time for exporting firms as the investment function depends on export status.

Furthermore, I deflate value added with a Slovenian producer price index (PPI). This is not enough to control for the fact that output and factor prices might be different and/or evolve different over time for exporting firms. Incorporating the export dummy in the Olley and Pakes (1996) estimation algorithm results in estimates for productivity that are conditioned on differences in market conditions according to the firm's export status.[8] However, these conditions are still assumed to be common to all exporters within a given industry.

In terms of verifying whether entering export markets makes firms more productive, export specific shocks (like demand conditions, factor markets, exit barriers, etc.) are not attributed to productivity gains for exporters. On a more conceptual level, these market conditions might just be one of the driving forces behind the learning by exporting process. If I still find significant productivity gains for exporters it implies that additional firm-specific factors play a role.

Since the proportion of input factors and input prices may differ across different industries, I estimate the production function for each 2-digit sector separately. 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 industry dummies to control for different subsectoral (unobserved) shocks within a given industry, both in the production process and in the output market.

With the coefficients of the production function in hand, I recover a productivity measure ω_{ijt} of firm i active in industry j at time t and I calculate it in the following way

$$\omega_{ijt} = y_{ijt} - b_{lj} l_{ijt} - b_{kj} k_{ijt} \tag{2}$$

[8] Exporters might experience faster technological change. Therefore, I check whether technological change was different for exporters by interacting the time trend with export status, in addition to the full interacted polynomial.

where y, l, k denote the log of output as measured by value added, labor and capital, respectively. The parameters b_{lj} and b_{kj} denote the OP-EXP estimators for labor and capital respectively for industry j. 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.[9]

Overall mean productivity increases in every industry and there is considerable variance across 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. To get at the importance of exporters I construct a conventional productivity index where I weight a firm's 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 find that the productivity index increased by 16% for exporters and only by 10% for non exporters by 1999. De Loecker and Konings (2006) show that the increase in aggregate productivity in Slovenian manufacturing is largely due to the average firm becoming more productive (within productivity growth) and the net entry process. The next section provides a framework to evaluate the importance of increased export participation in within productivity growth.

3.2. Identification of productivity gains from exporting

The method I suggest below aims to control for the self-selection process while testing 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). The aim of this methodology is to evaluate the causal effect of exporting on productivity or productivity growth by matching *export starters* with non exporters. The identifying assumption in estimating the treatment effect (exporting) 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. 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. In the analysis I do not incorporate firms that export over the entire sample period 1994–2000 as their decision to export is not observed and consequently makes it impossible to identify the learning by exporting parameter.

3.2.1. Productivity trajectories

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. Fig. 2 shows 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

[9] 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. However, I find that both are highly correlated. I therefore opted for using the usual measure of TFP as it allows me to use all firm observations in stead of only firms with positive investment.

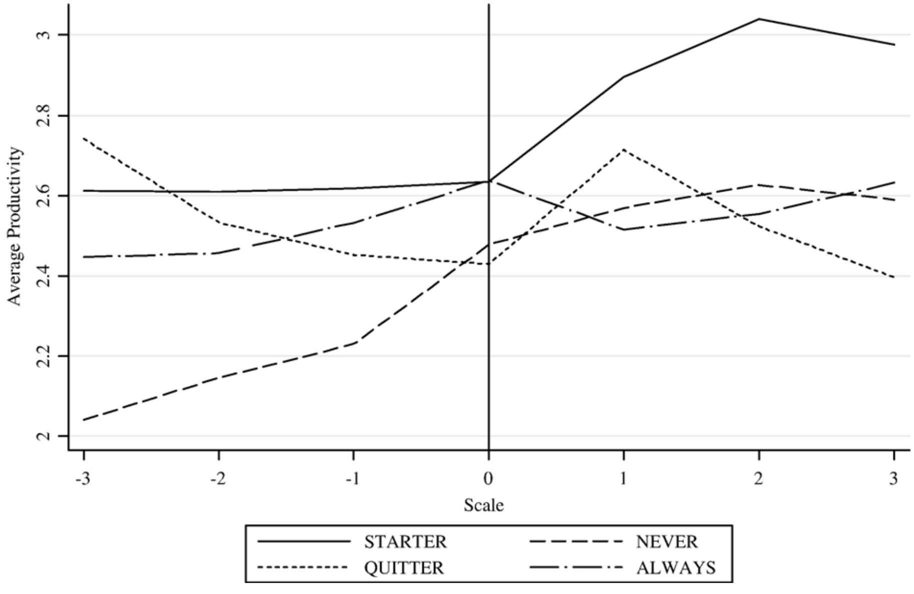

Fig. 2. Productivity trajectory for different groups: Wearing Apparel Industry (18).

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 productive than the rest. Fig. 2 provides some evidence of learning by exporting in the Wearing Apparel industry: average productivity of the firms that start exporting increases drastically. The latter is merely based on graphical inspection and I check whether my econometric results confirm these priors.

3.2.2. Econometric model

I rescale the time periods in such a way that a firm starts exporting at $s=0$. Let ω_{is} be the outcome at time s – productivity of firm i at period s – following entry in export markets at $s=0$ and the variable $START_i$ takes 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 ω_{is}^0 is not observable. I follow the micro-econometric evaluation literature (Heckman et al., 1997) and I define the average effect of export entry on productivity as

$$E\{\omega_{is}^1 - \omega_{is}^0 | START_i = 1\} = E\{\omega_{is}^1 | START_i = 1\} - E\{\omega_{is}^0 | START_i = 1\} \tag{3}$$

The key difficulty is to identify a counterfactual for the last term in Eq. (3). This is the productivity effect entrants in export markets would have experienced, on average, had they not exported. 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-export productivity of a firm. 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 (1983). This boils down to estimating a probit model with a dependent variable equal to 1 if a firm starts exporting and zero elsewhere on lagged observables including productivity.[10]

I model the probability of starting to export as follows. *START* is a dummy variable that is 1 at the time a firms *starts* exporting. This is in contrast to the variable *EXP* which is 1 when a firm exports. The difference in interpretation is that one is modelling the probability of *continuing to export* rather than *starting to export*. The probability model of starting to export (the propensity score) can be represented as follows

$$\Pr\{START_{i,0} = 1\} = \Phi\{h(\omega_{i,-1}, k_{i,-1}, PRIVATE_{i,-1})\} \tag{4}$$

where $\Phi(.)$ is the normal cumulative distribution function.[11] 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 $h(.)$ as to free up the functional form and improve the resulting matching (Woolridge, 2002). The most important variable in estimating the propensity score estimation clearly is the productivity variable ω_i. Differences in productivity will be conditioned on pre-export levels of productivity, capital and other relevant firm-level co-variates.[12] Furthermore I include an ownership variable, *PRIVATE*, which is a dummy variable equal to 1 if the firm is privately 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.

To verify the learning by exporting effects I perform the following algorithm: (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 moments of the co-variates are not different for the treated and the control units (Balancing hypothesis).[13] If the latter test is rejected a less parsimonious functional form of $h(\omega_{it}, k_{it}, PRIVATE_i)$ is considered including higher order terms. The matching is based on the method of the nearest neighbor, which selects a non exporting firm j

[10] De Loecker and Konings (2006) show that the entry of more efficient firms contributed significantly to the sharp increase in total factor productivity in Slovenian manufacturing. I do not attribute the effect of more efficient firms entering the market to learning by exporting as only firms that switch from a domestic producer to an exporter are considered as *treated firms*.

[11] This is essentially what most studies do when testing the self selection hypothesis. In all specifications the coefficients on productivity are positive and highly significant.

[12] 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 versus start/continue). The effect of starting to export on TFP is much (at least twice as high) bigger than continuing to export. This 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. In addition, including the lagged export status introduces a correlation with lagged productivity and this no longer allows to control for the self selection into export markets.

[13] In this way I match on the probability to export controlling for firm characteristics captured by covariates and in addition I restrict the first moment of the distribution to be the same across both groups. 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 (Imbens, 2003).

which has a propensity score p_j closest to that of the export entrant.[14] This results in a group of matched exporting and non exporting firms needed in order to evaluate the causal impact of exporting on productivity. For more details on this matching procedure I refer to Becker and Ichino (2002).

I match within each 2-digit NACE sector and therefore create control groups within narrowly 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.[15]

Once I have this counterfactual in hand I use a difference-in-differences (*DID*) methodology to assess the impact of exporting on productivity. The estimator of the learning by exporting effect (β_{LBE}) is calculated in the following way. Assume N firms that started exporting and a set C of control firms and ω^1 and ω^c are the estimated productivity 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. The number of control firms that are matched with an observation i (starter) 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 a firm starts exporting and $s = \{0, 1, \ldots, S\}$ 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 (5) and a cumulative productivity effect (6). The estimator β^s_{LBE} at every period s after the decision to start exporting is given by

$$\beta^s_{\mathrm{LBE}} = \frac{1}{N_s} \sum_i \left(\omega^1_{is} - \sum_{j \in C(i)} w_{ij} \omega^c_{js} \right). \tag{5}$$

In words, I estimate the productivity premium of firms that started exporting at each period s compared with (a weighted average of) productivity of a control group based on nearest neighbor matching at every period s. However, we are also interested how the effects of starting to export impacts the productivity trajectory. Therefore I estimate the average cumulative treatment effect or the productivity gain *gathered* over a period S after the decision to start exporting. The estimator β^S_{LBE} is given by

$$\beta^S_{\mathrm{LBE}} = \frac{1}{N_S} \sum_i \left(\sum_{s=0}^{S} \omega^1_{is} - \sum_{s=0}^{S} \sum_{j \in C(i)} w_{ij} \omega^c_{js} \right). \tag{6}$$

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 (s) and the productivity

[14] I also experimented with other matching techniques: the Mahalanobis one-to-one matching and the bias-corrected matching estimator developed by Imbens et al. (2001). My results do not change, however, the one-to-one matching is more sensitive to the underlying probability to export model.

[15] 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 as this controls for the 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.

Table 3A
Estimated learning by exporting effects

s	0	1	2	3	4
(a) Outcome: productivity					
β_{LBE}	0.088*	0.099*	0.099*	0.130*	0.037
	(0.035)	(0.036)	(0.038)	(0.043)	(0.053)
Nr treated	1770	1694	1610	1519	1293
Nr controls	5239	4983	4539	3952	2956
(b) Outcome: productivity growth: year-to-year growth rate					
β_{LBE}	0.079*	0.026	0.028	0.025	−0.089
	(0.028)	(0.033)	(0.040)	(0.049)	(0.063)
(c) Outcome: productivity growth: pre-export level ($s=-1$)					
β_{LBE}	0.079*	0.092*	0.092*	0.124*	0.001
	(0.028)	(0.031)	(0.038)	(0.045)	(0.067)
(d) Outcome: cumulative productivity					
β_{LBE}	0.088*	0.177*	0.283*	0.434*	0.460*
	(0.035)	(0.062)	(0.092)	(0.133)	(0.195)

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 significance at 5% or stricter and at 10% with * and **, respectively. Standard errors are denoted in parentheses.

gain.[16] The estimate in Eq. (6) gives us the productivity premium new exporters have gathered over time. This implies that the entire productivity path of export entrants is compared to that of the control group, whereas the estimate in Eq. (5) estimates the productivity premium at each period s.

I look at both the effect of starting to export on the level of productivity as on productivity growth. Furthermore, I consider both 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. Exporting firms 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.

Finally, Blundel and Costa Dias (2000) mention that a combination of matching techniques and difference-in-differences (*DID*) 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. Tables 3A and B present the results for the different sectors and for the manufacturing as a whole under various specifications.[17]

[16] The cumulative estimator β_{LBE}^S is not exactly equal to the sum of the pure time estimator β_{LBE}^s due to the unbalanced data. Formally, $\sum_s\beta_{\mathrm{LBE}}^s\neq\beta_{\mathrm{LBE}}^S$ since N varies with s.

[17] 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.

Table 3B
Evidence on learning by exporting at industry level

Evidence on learning by exporting		No evidence
Immediate impact	Future	
Leather and Leather Products	Food Products and Beverages	Pulp and Paper
Publishing and Printing	Textiles	Basic Metals
Chemicals and Chemical Products	Medical, Precision and Optical	Furniture/Manufacturing n.e.c.
Rubber and Plastic Products	Electrical Machinery and Apparel	
Non-Metallic Mineral Products	Wearing Apparel	
Machinery and Equipment	Wood and Wood Products	
	Motor Vehicles, Trailers	
13 sectors		3 sectors

3.3. Productivity gains upon export entry in Slovenian manufacturing

3.3.1. Results at manufacturing level

I now turn to the main results as shown in Table 3A where I present various specifications reflecting how entering an export market might impact productivity. Row (a) shows the impact on the *productivity level* at every period s. In row (b) I present the effect on *year-to-year productivity growth*, whereas row (c) presents the *productivity growth with respect to pre-export productivity* (ω_{i-1}) at every period s. Finally row (d) presents 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 rows (d) is different from specifications (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 to estimate 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.[18]

In the overall sample export has a positive and significant treatment effect on *productivity* and the magnitude of the coefficients are to be interpreted as percentages. Exporting firms become on average 8.8% more productive once they start exporting and the productivity gap widens further in later years. After 4 years of exporting ($s=3$) exporters are around 13% 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 as only firms that entered the export market in 1996 or before are considered.

Starting to export causes *productivity growth* to be significantly higher compared to the pre-export productivity level (7.9%) and exporters experience higher productivity growth in future periods. For instance, productivity of export entrants is 12.4% higher after 4 years of exporting. The *year-to-year* growth rates are estimated positively but insignificant. This implies that exporters become more productive 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.

Cumulative productivity also increased significantly upon export entry. I find that cumulative productivity is significantly higher for exporters in all the years following the export activity.

[18] 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 4 for more discussion on the potential selection bias. Furthermore, all results presented here are robust to an alternative underlying propensity score model where lagged productivity growth – instead of the level of productivity – is included.

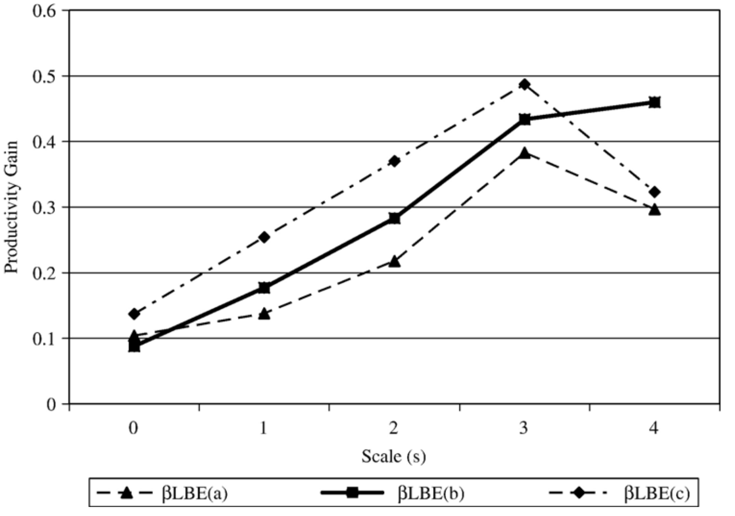

Fig. 3. Estimated productivity gains: (a) OP, (b) OP-EXP, (c) learning + (b).

Firms that started exporting became 17.7 (46)% more productive after two (four) years of exporting compared to their domestic counterparts.[19]

I plot the cumulative productivity trajectory in Fig. 3 (β_{LBE}(b)) next to the base-line result using the standard OP estimator (β_{LBE}(a)). Introducing the extra control – export status – in the estimation of productivity leads to somewhat higher effects on future productivity. However, the results are quite similar, except that I do not find a decrease in the productivity gap after 5 ($s=0$) years of exporting. It is a robust finding that firms that initiated in export activities will have a significantly higher level of productivity than their matched counterpart that did not started exporting in the years following their export decision. From this graph it is also clear that exporters increase the productivity gap with respect to their domestic counterparts, however at a decreasing rate.[20]

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; World Bank, 1993; Evenson and Westphal, 1995). This suggests that the estimated productivity gain at $s=0$ is potentially 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 *preparing 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)

[19] Using the standard Olley and Pakes (1996) technique for estimating productivity, I also find evidence for learning by exporting although somewhat higher. Exporters become on average 10.4% more productive once they start exporting as opposed to 8.8%. 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. One of those potential factors is the destination market of the exports and I address this in the next section.

[20] This would be consistent with spillover (productivity) effects to domestic producers which are the control group in estimating the productivity premia.

than the productivity growth effect at $s=0$ (0.079) suggesting that additional productivity gains take place from exporting.

Finally, since a relatively small share of firms 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 groups do not overlap. Therefore I check every specification by restricting it to a common support on the propensity score. The results are invariant suggesting that the control group is appropriate to evaluate the learning effect.[21]

3.3.2. Industry specific results

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. I now estimate the effect within narrow defined industries (NACE 2 digit) and I find that there is quite some heterogeneity across the various industries both in the magnitude and in the timing of the estimated productivity gains.

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. 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.[22] There is a wide range in the effects of starting to export on productivity across the industries. I can identify sectors where starting to export does not have an initial effect on productivity, however, productivity increases in later periods following the decision to export.

Finally, the productivity gains from shipping products to foreign markets – if any – may well take some time. Therefore I look at the difference in cumulative productivity between exporting firms and their matched counterfactual in future periods. 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 3B 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.

4. Productivity gains and export destination

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 productivity gains 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. I provide a potential channel through which the learning by exporting takes places by introducing the information on firm-level destinations of exports.

[21] In the following sections I prefer the results obtained without imposing the common support constraint, since I can use more observations to estimate the learning by exporting parameters.

[22] If I rank industries according to the number of firms active in industry (see Table A.1 in Appendix A) I find that the productivity premia is (mostly) estimated significantly for industries with more firm observations.

Documenting and estimating positive productivity gains upon export entry does not provide enough information as to how these firms become more efficient. If there is scope for learning from foreign markets through contact with buyers and competitors, we would expect to find higher productivity gains for firms shipping their products to relative developed regions. To my knowledge this is the first paper that looks at productivity gains from entering export markets by distinguishing between various destinations. However, it is related to the work of Eaton and Kortum (2004, 2005) where export destination is used to understand the importance of fixed cost in entering export markets and to which extent they are market (country) specific. Related to this, I find a positive correlation (at the firm level) of the number of destinations and productivity.[23] This is consistent with more productive firms being able to overcome higher fixed costs and in turn implies market specific fixed cost of export entry.

In addition, including export destination also takes into account that export prices (for a given product) are 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.[24] 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 allowing market structures to be different between exporters and domestic producers within a given industry. However, if output prices differ across foreign markets within an industry, my productivity estimates are potentially biased. Including the destination information controls for this to the extent that differences in destinations pick up differences in output prices.

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 and provide estimates for the learning by exporting parameter for different export destinations.

4.1. Pattern of firm-level export destinations

I first present the destination structure of the exporters in my sample. The dataset used until now has no firm-level information on destination of exports. I add extra information for a sub sample of exporters listing the regions they export to. The data were made available by the Slovenian Chamber of Commerce and Industry under the label of SLO*EXPORT*. 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, and company size.[25] I match this information with the firm-level dataset and this results in 1090 firms having information on the destination of export, covering around 50% of exporting firms. I group 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

[23] The coefficient on the number of destinations is highly significant and positive when running a simple OLS regression of productivity on export status and the number of destinations a firm supplies controlling for firm size, year and time dummies.

[24] For more on this I refer to De Loecker (2006) 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, they perform better and can be ranked accordingly. However, as mentioned in Katayama et al. (2003), the implications for welfare crucially hinge upon the correct productivity estimates, controlled for price setting power.

[25] An online version of this data is available at www.gzs.si/sloexport. The destination information is time invariant and therefore I cannot identify separate parameters by destination.

Table 4
Destination pattern and portfolio of exporters (year and industry averages)

	Africa	Asia	N-America	S-America	W-Europe	S-Europe	CEE	Others
Mean	11%	38%	36%	8%	88%	89%	92%	7%
Std	0.07	0.14	0.13	0.07	0.08	0.10	0.07	0.06
Africa	**10%**	8%	8%	4%	10%	10%	10%	3%
Asia		**35%**	23%	7%	34%	35%	35%	6%
N-America			**33%**	7%	31%	33%	32%	6%
S-America				**8%**	8%	8%	8%	3%
W-Europe					**84%**	76%	83%	7%
S-Europe						**89%**	81%	7%
CEE							**89%**	7%
Others								**7%**

Note: *CEE*: Central and Eastern European countries including countries of former Soviet Union, *Others*: Australia and New Zealand and the Caribbean.

Union (CEE) and Others (Australia and New Zealand). On average firms export to around 3 to 4 different destinations.

In Table 4 I present the destination portfolio and the destination pattern for the entire manufacturing. On average 90% of the firms export towards Western, 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 which in itself sheds light on the industry specific learning by exporting estimates: the differences across industries cannot solely be explained by differences in destination of exports. This table clearly shows that a large majority of the exporters ship their products to high income countries (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.

Finally, I present the destination portfolio providing information on which destination markets firms tend to sell. The numbers have to be interpreted as follows: 8% 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 first row of Table 4.

4.2. Estimating productivity gains by destination

I verify whether the learning effects found in Section 3 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 destination market and I estimate the learning parameter β_{LBE}, separately for firms (who start) exporting to high and low income countries. Note that here I restrict it to firms exporting to only high or only low income regions. This is important since both markets are often served by the same firm. The reason for observing relatively few 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.[26] I follow the exact same approach as before and now estimate the productivity gains from export entry

[26] See Table 4 where e.g. 83% of the firms that export to Western Europe also export to Central and Eastern Europe.

Table 5
Learning by exporting by destination: (a) baseline, (b) market structure control and (c) market structure and learning

	All	High income	Low income
β_{LBE}(a)	0.104*	0.129**	0.078*
s.e.	(0.038)	(0.080)	(0.037)
β_{LBE} (b)	0.088*	0.202*	0.095*
s.e.	(0.035)	(0.080)	(0.037)
β_{LBE} (c)	0.147*	0.174*	0.099*
s.e.	(0.039)	(0.081)	(0.041)
# starters	1770	250	1520

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 ** denote significance at 5% or stricter and 10%, respectively. Results in row (c) are based on the methodology discussed in Appendix B.

separately for high and low income regions. The data covering matched firm-level data and destination information have 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 and estimate the instantaneous productivity gain since the destination information is only cross sectional. The latter implies that I estimate an average productivity gain both over countries within a destination group and over time.

On the full sample the estimated instantaneous effect of starting to export on productivity is 8.8%. Table 5 shows the results (of the instantaneous effect) for the various destination regions and compares it with the results from Section 3. 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. 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%). Firms (only) exporting towards high income regions experience a higher productivity gain than the overall sample of export entrants (20 versus 8.8%).[27]

These results shed light on the self-selection into export markets. If it were only the more productive firms that are able to export, export destination would not matter that much. However, I find that the productivity premia are considerably higher for firms shipping products to more developed regions and this is consistent with learning from buyers and can help explain why some authors did not find strong evidence using data on developed economies.

5. Robustness checks and concluding remarks

From the previous sections a robust result emerges that entering export markets has a positive impact on the productivity trajectory. These results were obtained by restricting the sample to firms having at least $s+2$ consecutive observations which potentially introduces a sample selection bias. In this section I verify to what extent my results depend on sample selection and discuss the importance of the methodology suggested in this paper in establishing the results. Finally I collect some concluding remarks.

[27] As noted by a referee, the breaking up of Yugoslavia potentially forced some firms to export as part of the production chain (input suppliers and/or final product market) is now located outside Slovenia. We can then reinterpret the results for exporting to high income regions as excluding potential forced exporting as the low income region includes countries from former Yugoslavia.

5.1. Future productivity gains and sample selection

The results on cumulative productivity gains in Tables 3A and B were obtained by restricting the sample to firms having at least $s+2$ consecutive observations. Given this restriction, I check whether the effects attributed to exporting are not driven by the selection process over time. 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 6 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 3A. 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 3A, one has to 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. 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.

5.2. One-time level or continuous 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 3A. 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. Exporters have grown by 12.4% after 4 years of exporting compared to 9.2% 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 Fig. 4. 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 (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 samples of firms discussed above.

Table 6
Cumulative productivity gains: detailed results

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

Note: I denote significance 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.

5.3. The importance of methodology in establishing results

A key assumption in identifying the causal effect from entering export markets to productivity gains is that all differences between export entrants and domestic producers are captured by observables including estimated productivity. The estimated productivity gains for new exporters could well be driven by unobservables that are highly correlated with export status and hence not directly by starting to export. Ultimately, this cannot be tested within my framework. However, including (estimated) productivity in the underlying matching adds strength to the identification strategy. Productivity is the residual from an industry specific production function and therefore captures all (firm specific) unobservables generating additional value added conditional on inputs. The fact remains that the export status of a firm can be correlated with the unobservable truly causing productivity to increase. Independent of their being such an unobservable, the results indicate that the drastic reorientation of trade in Slovenian manufacturing leads to significant productivity gains for the entire economy. Whether or not these firms had the ability to raise their productivity before becoming an exporter, they were not able to do so. It was only with the transition to a market economy and trading with more developed regions that the productivity gains were realized.

One way to evaluate the importance of my methodology is to apply techniques used in the literature – that find no strong evidence for learning by exporting – on the Slovenian data. Bernard and Jensen (1999) suggest the following regression to estimate the causal impact of export entry on productivity.

$$\frac{1}{T}(\omega_{iT} - \omega_{i0}) = \alpha_0 + \alpha_1 start_{iT} + \alpha_2 stop_{iT} + \alpha_3 continue_{iT} + controls + \varepsilon_{iT} \tag{7}$$

where $start_{iT}=1$ if a firm did not export at 0 but exports at T, $stop_{iT}=1$ if a firm exported at 0 but no longer at T and $continue_{iT}=1$ if a firm exports both at T and 0. Their estimate for productivity is the residual from an OLS production function without controlling for the simultaneity bias, selection bias and the export status of a firm. It is clear from Eq. (7) that the self-selection into export markets is not controlled for and that new exporters are not compared to similar non exporting firms in terms of pre-export productivity, capital, ownership. In addition, firms that switch export status over the sample period might blur the results in particular when the window [0–T] becomes larger.[28] I now run regression (7) on my dataset and compare the results with those obtained using my suggested methodology and the results are presented in Table 7.[29] The first row shows that there is little evidence for productivity gains upon export entry using the Bernard and Jensen (1999) framework. However, once I run (7) using my productivity estimates and exclude switching exporters, significant productivity gains are estimated for all three windows (short, medium and long run). The last row shows the implied average annual productivity growth rates using my suggested method (Table 3A row c). Finally, the effect of starting to export on productivity is assumed to be constant across the sectors of the manufacturing sector and over time. I showed that the productivity gains upon export entry varies greatly across industries (Table 3B). Both the methodology suggested in this paper and the unique setting of drastic trade

[28] Bernard and Jensen (1999) find a positive estimate on *start* but only in the short run using US plant-level data. The estimates for medium and long run are insignificant.

[29] Note that this method provides me with estimates of (average) annual productivity growth rates and should be compared to my results as shown in row (c) of Table 3A. In addition, my results are not sensitive to the inclusion of export switchers.

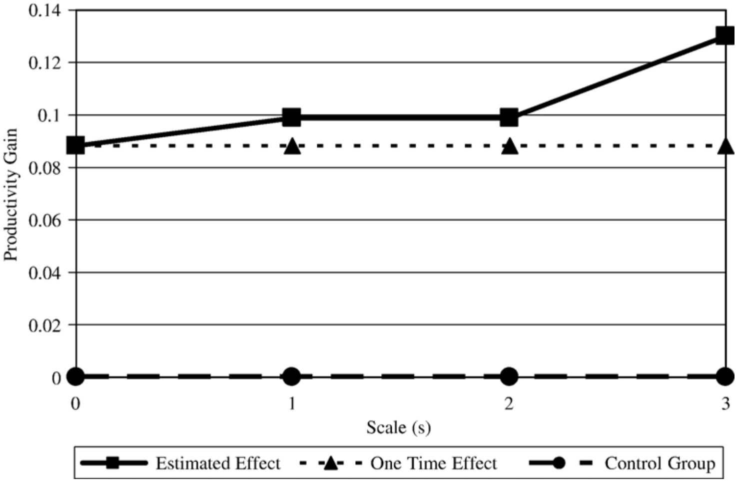

Fig. 4. Estimated time effect versus hypothetical one-time effect.

reorientation to more developed regions appear crucial in establishing robust evidence for productivity gains from entering export markets.[30]

5.4. *Productivity gains after exporting: summing up*

There might be reasons why other authors have not found support for the learning by exporting hypothesis. 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 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.[31] In addition, the biggest productivity gains take place from exporting to developed regions which is consistent with the lack of evidence for developed regions such as the US (Bernard and Jensen, 1999). The latter shows the importance of dissecting the destination of exports.

Secondly, my results indicate that *starting to exports* leads to higher productivity levels and that exporters remain more productive upon export entry which is confirmed by the positively estimated productivity growth rates (with respect to the pre-export productivity level). The immediate productivity effect is also what previous studies find, although using a different

[30] In addition, in Appendix B I allow the productivity process to depend on past export experience – as opposed to just following an exogenous Markov process – and all my results go through.

[31] The Slovenian Times (2005) reported that "*Slovenia used this same opportunity to learn from its trading partners. Because 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 of goods that were subsequently exported to the southern markets*."

Table 7
Evaluating methodology of estimating learning by exporting parameters

	Short run	Medium run	Long run
Bernard and Jensen (1999) approach	**0.057***	0.019	0.015
	(2.86)	(1.74)	(1.60)
Bernard and Jensen (1999) modified	**0.141***	**0.042***	**0.032****
	(4.49)	(2.66)	(1.83)
Table 3A (c) implied annual rates	**0.079***	**0.046***	**0.034***
	(2.82)	(2.97)	(2.42)

Note: All regressions include size, year dummies and industry dummies and t-statistic is shown in parentheses, * and ** denote significance at the 1 and 3% level, respectively. Modified Bernard and Jensen (1999) approach is based on my productivity estimates (OP-EXP) and excludes export switchers as they introduce noise especially as time window [0–T] increases.

framework which only allows average productivity to depend on export status. My methodology allows to check whether the entire productivity trajectory is different. I show that 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 (2000), there are a number of other explanations besides the learning by export story as to why exporters widen the productivity gap with non exporters. 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 path and this clearly reduces the problem of observational equivalence.

Finally, in order to put the estimated – instantaneous – effect of exporting on productivity in perspective, I ran a simple OLS regression as suggested in Eq. (1) using my various estimates for productivity. This regression only captures a simple correlation between export status and productivity controlling for ownership, size, industry and year dummies. I find highly significant coefficients of around 0.2 using various estimates for productivity and it implies that the (estimated) learning by exporting effect explains roughly half of the export productivity premium.

6. 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 of 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 datasets 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 suggest an estimation algorithm to estimate total factor productivity allowing me not only to estimate productivity consistently, but also to take into account potential selection of firms. This is important in economies – like Slovenia – undergoing a lot of structural change where significant simultaneous entry and exit takes place.

I introduce a matched sampling technique to construct a counterfactual control group to test whether export entrants become more productive. My findings suggest that firms that enter export markets increased their performance significantly. I estimate that exporters become on average 8.8% more productive and also productivity increases in future years following the decision to export. The magnitude and timing of the learning effects are quite different across sectors, however in 13 out of 16 sectors I find evidence for learning effects.

Finally, using a unique data source with information on firm-level destination of exports, I find significantly higher productivity premia for firms exporting their products to high income regions. These results shed light on the self-selection into export markets. If it were only the more productive firms that are able to export, export destination would not matter that much. This suggests that the characteristics of the destination export market matter which is consistent with learning from foreign markets. However, the variance in the estimated productivity gains across industries cannot be solely attributed to differences in destination of exports.

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Appendix A. Data description

In this appendix I describe the firm-level data used more in detail. The data are taken from the Slovenian Central Statistical Office and are the full annual company accounts of firms operating in the manufacturing sector between 1994 and 2000. 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. (2004) and Konings and Xavier (2002). I have information on 7915 firms and it is an unbalanced panel with information on market entry and exit and export status. The export status – at every point in time – provides information whether a firm is a domestic producer, an export entrant or a continuing exporter. If I only take into account those (active) firms that report employment, I end up with a sample of 6391 firms or 29,804 total observations over the sample period.

All monetary variables are deflated by the appropriate two digit NACE industry deflators and investment is deflated using a one digit NACE investment deflator. The industry classification NACE rev. 1 is similar to the ISIC industry classification in the USA and the various industries with corresponding code are: Food Products (15), Tobacco Products (16), Textiles (17), Wearing Apparel (18), Leather and Leather Products (19), Wood and Wood Products (20), Pulp, Paper and Paper Products (21), Publishing and Printing (22), Coke and Petroleum Products (23), Chemicals (24), Rubber and Plastic Products (25), Other non-Metallic Mineral Products (26), Basic Metals (27), Fabricated Metal Products (28), Machinery and Equipment n.e.c. (29), Office Machinery and Computers (30), Electrical Machinery (31), RTv and Communication (32), Medical, Precision and Optical Instruments (33), Motor Vehicles (34), Other Transport Equipment (35), Furniture and Manufacturing n.e.c. (36) and Recycling (37).

I observe all variables every year in nominal values, however, investment is not reported accurately so I calculate it from the other information. Value added is obtained using sales and material costs in thousands of Tolars, employment is measured by the number of full-time equivalent employees in a given year. Capital is proxied by total fixed assets in book value in thousands of Tolars. As opposed to commonly used data sources like the LRD data or US census data I observe the capital stock every year. Investment is calculated from the yearly observed capital stock in the following way $I_{ijt}=K_{ijt}+1-(1-\delta_j)K_{ijt}$ where δ_j is the appropriate depreciation rate (5%–20%) varying across industries j.

The firm-level dataset has information on the ownership of a firm, whether it is private or state owned. The latter is very important in the context of a transition country such as Slovenia. In my sample around 85 (5333 in 2000)% of firms are privately owned and a third of them are exporters (1769 in 2000). 917 firms are state owned and 690 of them are exporters. The ownership status of a firm serves as an important control by comparing productivity trajectories of exporting and non exporting firms with the same ownership status (private or state). I refer to Konings and Xavier (2002) for a discussion of private ownership in Slovenia.

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: there is not enough variation to identify the production function parameters and select appropriate counterfactuals.

Table A.1: Average number of firms and change 1994–2000 per industry

Industry	Average	Change (%)	Industry	Average	Change (%)
15	273	43	27	55	61
16	1	0	28	757	39
17	160	37	29	340	44
18	236	14	30	78	24
19	58	68	31	215	28
20	311	44	32	115	2
21	75	22	33	163	30
22	447	104	34	62	38
23	4	33	35	24	55
24	110	21	36	327	47
25	275	53	37	31	12
26	144	28	Total	4262	42

Table A.2: Top destinations of Slovenian exports in manufacturing

Destination country	Average share	Cumulative share
Germany	29.281	29.281
Italy	13.840	43.121
Croatia	9.025	52.147
France	7.470	59.617
Austria	6.792	66.409
USA	3.189	69.598
Russia	3.121	72.719
Bosnia and Herzegovina	3.010	75.730
UK	2.236	77.965
Macedonia	2.163	80.129
Poland	1.929	82.058
Czech Republic	1.684	83.742
Netherlands	1.524	85.266
Hungary	1.519	86.785
Belgium and Luxembourg	1.201	87.986
Republic of Serbia	0.949	88.935
Switzerland	0.886	89.820
Sweden	0.720	90.541
Spain	0.711	91.252
Denmark	0.710	91.962

Source: Own calculations based on World Bank's "Trade, Production and Protection 1976–2004" database and for an accompanying paper see Nicita and Olarreaga (2006). I report the share of a given destination in percentages and these are averaged over the sample period 1994–2000.

Appendix B. Estimating productivity

In this appendix I discuss the estimation algorithm for getting reliable estimates of the production function in more detail. Furthermore, I check whether my results are sensitive to the assumption that productivity follows an exogenous Markov process.

Estimation algorithm: introducing export status

As in the standard Olley and Pakes (1996) 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 (ω). Factor prices are assumed to be common across firms and they evolve according to a first order Markov process. At every period the firm faces three decisions: It has to decide 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 i 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 $k_{it+1}=(1-\delta)k_{it}+i_{it}$ where t denotes the time index. Productivity is assumed to be determined by a family of distributions conditional on the information set at time t, J_t. This set includes the past productivity shocks. Given this distribution, both the exit and investment decision will crucially hinge upon the firm's perception of the distribution of future market structure given their current information (past productivity). The decision that the firm takes will in turn generate a distribution for the future market structure.

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 by allowing the investment function to depend on export status. Formally this means that the investment equilibrium relation can be represented as follows (8)

$$i_{it} = i_{e,t}(\omega_{it}, k_{it}) \Longleftrightarrow \omega_{it} = h_{e,t}(i_{it}, k_{it}) \tag{8}$$

where e denotes the export dummy. Exporting firms face different operating conditions and this is captured by allowing the coefficients of the polynomial $h(.)$ to be different for exporting firms, which is denoted by subscript e.[32] Furthermore, the survival decision (9) depends on export status through the productivity shock at t and through the capital accumulation process (investment) as exporting firms tend to be more capital intensive and therefore remain active with a lower productivity shock compared to a non exporter.

$$\Pr(\chi_{it+1} = 1|I_t) = \Pr(\chi_{it+1} = 1|\omega_{it}, \underline{\omega}_{it+1}(k_{it+1})) = \tilde{p}_{e,t}(i_{it}, k_{it}) \tag{9}$$

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. The first stage of the estimation algorithm is in fact almost identical to introducing export as an input, however, it is now also interacted with all terms of the polynomial in capital and investment as given in Eq. (10)

$$y_{it} = \beta_0 + \beta_l l_{it} + \tilde{\phi}_{e,t}(i_{it}, k_{it}) + \eta_{it} \tag{10}$$

where $\tilde{\phi}_{e,t}(i_{it}, k_{it}) = \beta_k k_{it} + h_{e,t}(i_{it}, k_{it})$. 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 heterogeneous process across firms. In addition, it also implies that the effect is time-invariant or that every year exporting raises output (conditioned on labor and capital) by the coefficient estimated on the export dummy.

The last stage is now a non linear least square estimation on Eq. (11)

$$y_{it+1} - b_l l_{it+1} = \beta_0 + \beta_k k_{it+1} + g((\hat{\tilde{\phi}} - \beta_k k_{it}), \ \hat{\tilde{P}}_{it+1}) +_{it+1} \tag{11}$$

where '~' reflects that export status is also controlled for. The error term (υ_{it+1}) is decomposed into the i.i.d. shock (η_{it+1}) and the news term in the Markov process (ξ_{it+1}). 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 ($\tilde{\phi}_{e,t}(i_{it}, k_{it}) - \beta_k k_{it} = h_{e,t}(i_{it}, k_{it}) = \omega_{it}$) 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 υ_{t+1} in Eq. (11). 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 υ_{t+1}

[32] For a similar setup where lagged export status is incorporated as a state variable in Olley and Pakes (1996) I refer to Van Biesebroeck (2006).

that still captures some variation in productivity correlated with the export status violating the identifying assumption. When correcting for the export status $\widetilde{\phi}_{it}$ 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 2 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.

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*). Including the export variable into the OP framework leads to different estimates of the production function.[33] As expected, the labor coefficient is estimated – if anything – lower. The sign of the bias of the capital coefficient is less clear since it works both through the productivity shock and the exit decision.

Levinsohn and Petrin (2003) suggest a modification of the Olley and 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, in recent work Ackerberg et al. (2004) discuss both proxy estimators. 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 becomes hard. The OP estimator for labor is identified under a plausible data generating process. A crude and indirect test within the OP framework is to verify whether the polynomial $\phi_t(.)$ is well specified by running the following regressions in the final stage and test whether β_{cl} is different from zero.

$$y_{it+1} - b_l l_{it+1} = c + \beta_k k_{it+1} + \sum_{j=0}^{s-m} \sum_{m=0}^{s} \beta_{mj} (\widehat{\widetilde{\phi}}_{it} - \beta_k k_{it})^m \widehat{P}_{it+1}^j + \beta_{lc} l_{it} + e_{it+1}$$

In all cases, I found β_{lc} to not be significantly different from zero, confirming that the non parametric approximation $\widetilde{\phi}_t(.)$ is well specified and hence no variation in labor is left.

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 Appendix A).

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

[33] I compared my estimates (OP-EXP) with different estimation methods. As expected the OLS typically over-estimates the labor coefficient and underestimates the capital coefficient, however there is some variation across industries. 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. The estimated production function coefficients for the various specifications can be found in the working paper version.

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. 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) compares different methods for estimating productivity on data characterized by known measurement errors and he finds that the semi-parametric methods (like OP) are least sensitive to measurement error when estimating *TFP*. In fact, he shows that the correlation between estimated and true productivity when using semi-parametric methods remained high even in the case of measurement error.

Allowing for the productivity process to depend on 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. 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. I checked whether my results are sensitive to this by including past export experience in the information set of the productivity process. Essentially the estimation algorithm is extended by decomposing the productivity shock in two (independent) terms: one following an exogenous Markov process and the other follows an endogenous Markov process determined by past export experience. I proxy the unobserved productivity component related to learning by exporting by a non parametric function in past export experience as measured by the share of exports in total sales and the number of years exported up till t.[34] Note that the latter is firm specific and implies that the impact of past export experience on productivity is firm specific.[35] Note that I cannot directly estimate the productivity gains from *entering export markets* directly from

[34] I also estimated the production function based on the model suggested in this appendix excluding the number of years exported T in $l(.)$ as the number of years exporting is only available for firms born after 1994. The estimated coefficients of the production functions do not change. I would like to thank an anonymous referee for this suggestion.

[35] 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). 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 ω_{t-1} depends on current ω_t and past productivity ω_{t-1}.

the production function as it pools new exporters with continuing exporters. The effect of starting to export on cumulative productivity does hardly change; it is estimated somewhat higher (for $s=1, 2, 3$ estimates are 14.7, 27.3, 41.4, 30.6%, respectively). In Fig. 3 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 5. 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%), however, lower than firms selling on a market with high income consumers (18.5%).

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