Do Firms Learn by Exporting or Learn to Export? Evidence from Small and Medium-Sized Enterprises (SMEs) in Swedish Manufacturing

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Abstract

Using a matching approach, we compare the productivity trajectories of future exporters and matched and unmatched non-exporters. Future exporters have higher productivity than do unmatched non-exporters before entry into the export market, which indicates self-selection into exports. More interestingly, we also find a productivity increase among future exporters relative to matched non-exporters 1-2 years before export entry. However, the productivity gap between future exporters and matched non-exporters does not continue to grow after export entry. Our results suggest that learning-to-export occurs but that learning-by-exporting does not. In contrast to previous studies on Swedish manufacturing, we focus particularly on small and medium-sized enterprises (SMEs).

Keywords: productivity, learning-to-export, learning-by-exporting, matching.
JEL: D24, F14.

1 Introduction

Numerous studies have documented that exporters enjoy higher productivity than do non-exporters within the same industry, controlling for observed factors that may affect productivity.[1] In the literature, two non-exclusive explanations have been put forward to explain such export productivity premia: self-selection and learning-by-exporting.

Self-selection means that only the more productive firms can afford the higher cost of exporting. This implies that future exporters have significantly higher productivity than do non-exporters before they start exporting; productivity for future exporters is higher ex-ante. Most previous empirical studies have found support for self-selection.

Learning-by-exporting, on the other hand, should result in superior post-entry productivity performance in new export entrants relative to non-entrants. The reason might be that exporters are exposed to knowledge flows from international buyers and competitors and to more intense competition in international markets, which lead to larger opportunities and incentives to improve productivity than firms that sell only on the domestic market experience. Moreover, the exploitation of economies of scale and improved capacity utilization in connection with export entry could also be manifested in better post-entry productivity performance in new export entrants than in non-exporters.[2] However, in contrast to self-selection, the empirical evidence for any positive post-entry effects of exports and for learning-by-exporting are mixed.[3]

An interesting possible explanation for the self-selection pattern identified by most previous empirical studies has been proposed by Alvarez and Lopez (2005). They argue that firms consciously increase their productivity by investing in physical and human capital and new technology with the explicit purpose of becoming exporters. The investments involve pre-entry improvements in productivity among future export entrants; they learn to export rather than learning by exporting, and those learning effects are neither inevitable nor automatic.

Distinguishing between learning-by-exporting and learning-to-export among new export entrants is an important aim of this paper. Toward that end, we exploit a large-scale panel dataset including all Swedish manufacturing firms with one employee or more during the period between 1997 and 2006. Access to detailed longitudinal firm-level data allows us to use modern econometric matching techniques, which means that we can solve potential endogeneity problems and evaluate the casual effect of export activities on firm performance.

According to the learning-by-exporting hypothesis, one would expect that the effect of exporting on productivity should occur at the time when firms enter international markets and should then give rise to a widening productivity gap between export entrants and continuing non-exporters. In a standard matching approach, like the one we carry out at first, the post-entry productivity of export entrants and that of non-exporters with similar pre-export productivity histories and similar values for other pre-export covariates are compared. Such an approach does not allow for learning-to-export, which implies that

[1] *Seminal articles are Bernard and Jensen (1995, 1999). The literature has been surveyed by Greenaway and Kneller (2007) and Wagner (2007).*

[2] *See e.g. Van Biesebroeck (2005) and Damijan and Kostevc (2006).*

[3] *The surveys by both Greenaway and Kneller (2007) and Wagner (2007) arrive at that conclusion.*

preceding the entry into the export market, productivity increases for new export entrants relative non-exporters. To test the learning-to-export hypothesis requires a different matching strategy where the baseline for similar pre-export productivity (and other covariates) instead is set several years before the period of export entry, thus permitting the effect on productivity of exporting to appear even before the new export entrants enter international markets.

Matching methods have been employed with Swedish data before. Greenaway et al. (2005) use a panel of manufacturing firms spanning almost 20 years from 1980-1997. However, their data include only firms with 50 employees or more.[4] Export participation among such firms is quite high in Swedish manufacturing (more than 80 percent). Therefore, it is not surprising that they found that "in Sweden productivity growth of exporters on entry does not appear to differ significantly from non-exporters either in the periods leading up to or after entry." (Greenaway et al. 2005, p. 578). We obtain similar result for this group of firms for a more recent period. However, the outcome appears to differ considerably for smaller – and from a policy perspective – perhaps more interesting, firms.[5] The fact that the export participation rate is significantly lower in smaller firms and that productivity is higher in exporting firms than in non-exporting firms[6] is occasionally presented as a motive for intensified export promotion, particularly in small and medium-sized enterprises (SMEs).

To preview our findings, we observe an instantaneous productivity increase at export entry among the entering firms relative to non-entering firms and that thereafter, in subsequent periods, the productivity gap is constant. If we allow for different productivity trajectories before export entry for future export entrants and for firms not entering the export market, we notice a significant productivity differential between them even before export entry. Our results are largely driven by the smaller firms and are consistent with the learning-to-export hypothesis but to a lesser extent with the learning-by-exporting hypothesis.

The remainder of the paper is organized as follows. Section 2 presents our dataset and gives some descriptive facts and preliminary evidence regarding exports and productivity by Swedish firms. Section 3 describes our econometric strategy. Section 4 reports the results of the analysis. Section 5 concludes.

[4] In addition, Hansson and Lundin (2004) use a panel of Swedish manufacturing firms with 50 employees or more, but for the period from 1990 to 1999. When they employ a matching approach, they find no impact of exporting on productivity in export entrants after export entry.

[5] Export promotion of SMEs and, in general, the question of how to support the internationalization of SMEs are subjects that seem to attract significant policy interest on the national as well as on the EU level. See e.g. SOU (2008) and EC (2007).

[6] See Tables 1 and 3 in section 2.1.

2 Data and description

2.1 Exporting and exporters in Swedish manufacturing

The data on firms' export of goods comes from Statistics Sweden. It provides information on which types of products, and to which countries, a given firm was exporting during the period 1997 to 2006. For exports to EU countries, there is a threshold value for the registration of exports, while all transactions are registered by Swedish Customs for exports to countries outside the EU. The threshold value has risen over the studied period; before 1998, the yearly value of exports to EU countries had to be larger than 0.9 million SEK; between 1998 and 2004, the requirement was 1.5 million SEK or more; and after 2004, it was 4.5 million SEK or more. Due to this threshold for the registration of goods exported to EU, and to avoid considering firms with very limited sales outside the EU during a single year as exporters, we define a firm as an exporter if it has an export value larger than 1.5 million SEK.

From Statistics Sweden's compilation of figures from the financial accounts of enterprises, we obtain balance sheet information such as sales, value added and employment. We link the data on the export of goods at firm level to the balance sheet information for firms with at least one employee operating in the Swedish manufacturing sector (NACE 15-36). This gives an unbalanced panel of firms that contains information on the included firms' export status at every point in time. This means that we can identify whether a firm is a domestic producer, an export entrant, a continuing exporter, or a firm that has quit exporting. Capital stocks are book values from the balance sheets. Value added is deflated with Swedish producer price indices (PPI) on industry level.

We have chosen to use labor productivity as our productivity indicator rather than a theoretically more well-founded TFP measure, for instance, by employing the newly developed estimation methods proposed by Olley and Pakes (1996) and Levisohn and Petrin (2003). The reason is that the balance sheet information for smaller firms (1-9 employees) – especially for capital stocks, investments and material costs – is of somewhat dubious quality.

Sweden is a small export-dependent economy. The aggregate export intensity (the share of exports in sales) for manufacturing was 64 percent in 2006. Nevertheless, there are large variations in export participation rates and export intensities between firms of different sizes. Table 1 shows that the share of exporters is considerably larger among the medium-sized and large firms (those with 50 employees or more, among which more than 80 percent of the firms are exporters) than among small and micro firms. This is one reason why we focus our analysis of export entry on firms that have less than 50 employees. A similar pattern appears for export intensity, the number of export destination countries and the number of export products; larger firms tend to have higher export intensity and to export more products to more destination countries.

Table 1 Share of exporters, export intensity, and number of export destination countries and export products among micro, small, medium-sized and large manufacturing firms in 2006.

Firm size class	Share of exporters	Export intensity	Number of export destinations	Number of export products
Micro (1-9 employees)	3.2	1.4	0.2	0.1
Small (10-49 employees)	31.2	11.3	3.6	1.9
Medium-sized and large (50-∞ employees)	80.7	32.5	19.3	10.0
All firms (1-∞ employees)	15.2	5.9	2.4	1.3

Notes: Exporters are firms that have a value of export larger than 1.5 million SEK. Export intensity is the average share of export in sales for the firms within each size class. Number of export destinations (export products) is the average number of destination countries (products) the firms in each size class is exporting to.

How important are firms with less than 50 employees in terms of employment and value added in Swedish manufacturing, and what is their contribution to the goods export? From Table 2, it appears that firms with fewer than 50 employees represent a quarter of the employment in the Swedish manufacturing sector and less than a fifth of the value added, while their share of goods export is significantly lower – not even 7 percent. Micro and small firms employ a fair share of those working in manufacturing, while their share of exports is quite low.

Table 2 Share of employment, value added and exports for firms of different sizes in 2006.

Firm size class	Employment	Value added	Export
Micro (1-9 employees)	8.6	5.4	0.5
Small (10-49 employees)	16.5	12.3	6.1
Medium-sized and large (50-∞ employees)	74.9	82.3	93.3

As pointed out in the introduction, a very robust result from most of the previous analyses of the relationship between export and productivity at firm level is that exporters are more productive than non-exporters. It is evident from Table 3 that our study is no exception. Including industry dummies and firm controls, as in specification (3), substantially reduces the exporter productivity premia in comparison to specifications (1) and (2). However, the premia is still larger than 10 percent and strongly significant.[7] If, as in specifications (4) to (6), we estimate the premia for different firm size classes, the value is highest for firms

[7] *We obtain the exporter productivity premia by transforming the estimate on* β_1 *in Table 3,* $100\left(\exp(\beta_1)-1\right)$*, which is the percentage differential in productivity between exporters and non-exporters (Halvorsen and Palmqvist 1980).*

with fewer than 10 employees (micro firms) and lowest, and actually insignificant, for firms with 50 employees or more. In addition, we find that, except in the case of the micro firms, the larger the firms' export intensity, the higher the firms' productivity.[8]

Table 3 Exporter productivity premia, 1997-2006.

Regressors	Number of employees					
		1-∞		1-9	10-49	50-∞
	(1)	(2)	(3)	(4)	(5)	(6)
EX_{jt} = 1 if firm j is exporter at t	0.281*** (0.005)	0.279*** (0.047)	0.105*** (0.049)	0.420*** (0.018)	0.102*** (0.006)	0.011 (0.010)
Export intensity EXS	0.166*** (0.011)	0.154*** (0.010)	0.112*** (0.010)	-0.134*** (0.036)	0.030* (0.016)	0.117*** (0.014)
Firm controls	no	no	yes	yes	yes	yes
Industry dummies	no	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes	yes
R^2	0.051	0.067	0.157	0.125	0.172	0.249
Observations	221,066	221,066	221,066	152,533	50,382	18,151

Notes: A firm is an exporter if the value of exports is more than 1.5 million SEK. We estimate the following model:

$$\ln LP_{jt} = \beta_0 + \beta_1 EX_{jt} + \beta_2 EXS_{jt} + \beta_k Firm_{jt} + \sum_{i=1}^{I} \gamma_i D_i + \sum_{t=1}^{T} \gamma_t D_t + \varepsilon_{jt} .$$

*LP_{jt} is labor productivity, value added per employee, in firm j at time t. $Firm_{jt}$ are firm control variables: $\ln(K/L)$, where K/L is physical capital per employee; H/L is share of employees with post-secondary education; $\ln(EMP)$, where EMP is employment; and MNE is a dummy variable that equals one if a firm is part of a multinational enterprise. Industry dummies are defined at 2-digit NACE level (21 industries). Standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively.*

2.2 The data set of analysis and descriptive statistics

An important aim of the study is to investigate the productivity trajectories of firms that start exporting before and after they enter the export market and compare them with the trajectories of firms not entering the export market. Toward this end, we use the unbalanced panel of manufacturing sector firms with at least one employee to construct a balanced panel of export entrant and non-export entrant firms observed for every year during a seven-year time window. The seven-year time window is used because we want to be able to examine all firms three years before and three years after potential export entry. We define export-entrants as firms that exported in year t but did not export in the years $t-3$ to $t-1$, whereas non-entrants are defined as firms that did not export in any of the years $t-3$ to t. Given that our data cover the period from 1997 to 2006, the first year of potential export entry is 2000 (where export data for the period 1997 to 2000 are used to classify firms). The last year of potential export entry is 2003 (which allows for a three-year follow-up period during 2004 to 2006).

With these conditions, we end up with a balanced panel of firms made up of four cross-sections with potential export entry in 2000, 2001, 2002 and 2003 and with time windows of seven years for each cross-section. In the analysis, we compare firms entering the export market (treated firms) in a given year with firms not entering the export market (untreated

[8] Andersson et al. (2008) and ISGEP (2008) have recently estimated similar labor productivity export premia for Swedish manufacturing using the same type of data.

firms) in the same year, and we follow the firms during the seven-year time window. In our panel, the total number of observations of export-entrants is 724, and the total number of observations of non-entrants is 44,120. The 724 observations of export-entrants represent unique firms. With the seven-year time window and the conditions applied, there is no possibility that a firm classified as an export-entrant in, for example, 2000 will subsequently reappear as an export-entrant. Only 14,483 of the 44,120 observations of non-entrants represent unique firms. The reason is that if a firm is identified as a non-entrant in 2000, it might once again be classified as a non-entrant in 2001, and so on. In section 4.4, we refine the classification of export-entrants and non-entrants depending on the firms' export status not only in the years $t-3$ to t but also in the years $t+1$ to $t+3$. This will enable us to study the importance of whether export-entrants' continue to export or later on leave the export market and, similarly, whether non-entrants eventually enter international markets or continue not to export. Table 4 presents some descriptive statistics for our dataset, where we divide the firms into different size classes and classify them as either export-entrants or non-entrants.

Table 4 shows that export-entrants enjoy higher capital intensity (physical as well as human capital intensity) than do non-entrants the year before potential export entry. This holds true for micro and small firms, i.e. firms with fewer than 50 employees, but not for medium-sized and large firms. Furthermore, export-entrants are larger, have more employees, and are more often parts of multinational enterprises (MNEs).

Regarding our outcome variable, labor productivity, Table 4 indicates that export-entrants have higher productivity than do non-entrants even three years prior to potential export entry, which implies that more productive firms appear to become exporters (self-selection). Moreover, the productivity gap tends to widen during the seven-year time window. In other words, export-entrants are inclined to improve their performance relative to non-entrants in connection with their export entry. However, if we divide the firms into different size classes, these patterns are valid only for micro and small firms, not for medium-sized and large firms. Hence, the descriptive statistics in Table 4 produce some interesting distinctions in terms of productivity differentials and productivity trajectories between export-entrants and non-entrants, especially for firms with fewer than 50 employees. Nevertheless, to obtain more direct and reliable evidence regarding the relationship between export entry and firm productivity requires a careful econometric analysis.

Table 4 Sample means for export-entrants and non-entrants in different firm size classes.

	All firms (1-∞ employees)			Micro firms (1-9 employees)			Small firms (10-49 employees)			Medium-sized and large firms (50-∞ employees)		
Variable	Entrants	Non-entrants	Diff.	Entrants	Non-entrants	Diff.	Entrants	Non-entrants	Diff.	Entrants	Non-entrants	Diff.
$(K/L)_{t-1}$	298	204	95***	306	196	111***	298	229	69***	271	256	15
$(H/L)_{t-1}$	0.15	0.11	0.04***	0.20	0.12	0.08***	0.12	0.10	0.02***	0.13	0.17	-0.04**
EMP_{t-1}	32.1	8.6	23.5***	5.3	3.8	1.5***	21.8	18.0	3.8***	186.6	113.7	72.9***
MNE_{t-1}	0.12	0.02	0.09***	0.04	0.01	0.03***	0.12	0.06	0.07***	0.38	0.27	0.11*
LP_{t-3}	483	416	67***	510	407	103***	466	444	21	470	484	-15
LP_{t-2}	488	427	62***	513	419	94***	475	448	27**	465	486	-21
LP_{t-1}	502	429	73***	567	423	144***	467	445	22**	449	478	-28
LP_{t}	531	432	99***	603	424	179***	495	454	41***	455	528	-73
LP_{t+1}	541	427	114***	628	418	210***	496	454	43***	462	529	-68
LP_{t+2}	541	428	113***	620	417	202***	499	458	41***	479	538	-59
LP_{t+3}	539	430	109***	607	420	187***	503	463	40**	483	495	-12
Obs	724	44,120		268	34,264		384	9,097		72	759	

Notes: ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively. *LP* is labor productivity, *K/L* is physical capital per employee, *H/L* is share of employees with post-secondary education, *EMP* is employment and *MNE* is a dummy variable that equals one if a firm is part of a multinational enterprise. *t-x* and *t+x* refer to years before and after the year of potential export entry, *t*.

3 Econometric strategy

One main purpose of this paper is to estimate the causal effect on firm productivity of starting to export. The majority of studies focusing on this question has been dominated by different types of regression-based methods.[9] Recently, some papers have been published that employ matching methods.[10] While regression and matching approaches are both based on conditional independence for drawing casual inference, there are a few differences between the approaches that are more than cosmetic. First, matching does not rely on the type of functional form assumptions that regression typically does. Second, matching is more explicit in assessing whether or not comparable untreated observations are available for each treated observation. Current econometric research suggests that avoiding functional form assumptions and imposing a common support condition can be important for reducing selection bias in studies based on observational data.[11] In this section, we give a brief sketch of how matching solves the evaluation problem and discuss some specific features when implementing matching in our particular context.[12]

To begin, let t^- and t^+ indicate time periods before and after a period of potential export entry t^0. Furthermore, let $D_{t^0} = 1$ denote that a firm starts to export in period t^0 and $D_{t^0} = 0$ indicate that a firm do not start to export in period t^0 (starting to export is equivalent to receiving "treatment" in the typical evaluation terminology). Moreover, let LP_{1t^+} be the potential labor productivity in period t^+ for firms that start to export in period t^0 and LP_{0t^+} be the potential labor productivity in period t^+ for firms that do not start to export in period t^0. Finally, let X_{t^-} denote a set of observed covariates affecting both export entry and productivity.

The main parameter of interest is the average treatment effect on the treated, *ATT*, which can be defined as:

$$ATT = E(LP_{1t^+} - LP_{0t^+} \mid D_{t^0} = 1) = E(LP_{1t^+} \mid D_{t^0} = 1) - E(LP_{0t^+} \mid D_{t^0} = 1) \qquad (1)$$

In this specific context, *ATT* corresponds to the average effect on labor productivity of export entry for firms that actually start to export. The fundamental evaluation problem is that we only observe LP_{1t^+} or LP_{0t^+} for each firm, but never both. $E(LP_{1t^+} \mid D_{t^0} = 1)$ can be estimated directly from the observed data. Missing is the information required to estimate $E(LP_{0t^+} \mid D_{t^0} = 1)$, referred to as the counterfactual outcome. If export entry is non-random and we substitute the unobservable $E(LP_{0t^+} \mid D_{t^0} = 1)$ for the observable $E(LP_{0t^+} \mid D_{t^0} = 0)$

[9] *See the surveys of this literature by Greenaway and Kneller (2007) and Wagner (2007).*
[10] *See e.g. Girma et al. (2004) and De Locker (2007).*
[11] *Heckman, Ichimura and Todd (1997), Heckman, Ichimura, Smith and Todd (1998), Dehejia and Wahba (1999, 2002) and Smith and Todd (2005).*
[12] *For a more detailed and technical presentation of matching methods, see e.g. Heckman, Ichimura and Todd (1998), Imbens (2004) and Smith and Todd (2005).*

when estimating *ATT*, we end up with selection bias equal to $E(LP_{0t^+}|D_{t^0}=1)-E(LP_{0t^+}|D_{t^0}=0)$.

In experimental studies, randomization in a sense makes the counterfactual a factual. In observational studies, some assumptions must be made to eliminate the selection bias. The method of matching solves the evaluation problem by assuming that, conditional on X_{t^-}, LP_{0t^+} is independent of D_{t^0}:

$$LP_{0t^+} \perp D_{t^0} | X_{t^-} \tag{2}$$

This is referred to as the conditional independence assumption (CIA). The intuition behind this crucial assumption is that it makes treatment assignment random conditional on X_{t^-}, which in a sense ex post reproduces the essential feature of a randomized experiment. When CIA holds, we can therefore use the productivity of firms not making export entry as an approximation of the counterfactual outcome (the productivity firms making export entry would have experienced had they not started to export). Heckman, Ichimura and Todd (1998) show that for an unbiased estimation of *ATT*, it is only necessary to assume mean conditional independence:

$$E(LP_{0t^+}|X_{t^-},D_{t^0}=1)=E(LP_{0t^+}|X_{t^-},D_{t^0}=0) \tag{3}$$

The type of cross-sectional matching estimator described above assumes that conditioning on the set of observed covariates X_{t^-} is sufficient to remove selection bias. However, if there are unobserved characteristics affecting treatment assignment and outcomes, this will violate the identification conditions that justify cross-sectional matching. It has been shown that under these circumstances, the time invariant portion of the remaining selection bias can still be eliminated by using a conditional difference-in-differences (DID) matching estimator.[13] The conditional DID matching strategy requires that:

$$E(LP_{0t^+}-LP_{0t^-}|X_{t^-},D_{t^0}=1)=E(LP_{0t^+}-LP_{0t^-}|X_{t^-},D_{t^0}=0) \tag{4}$$

Whereas the cross-sectional matching estimator assumes that conditioning on the observed covariates is sufficient to remove bias in the post-treatment period, the conditional DID matching estimator assumes the same cross-sectional bias in the pre- and post-treatment period, so that by differencing the before-after differences for export entrants and non-export entrants, the time-invariant bias will be removed. The conditional DID matching strategy extends the conventional matching method because it does not require that

[13] *Heckman, Ichimura and Todd (1997) and Heckman, Ichimura, Smith and Todd (1998).*

selection bias is eliminated by conditioning on the observed covariates, only that the bias is the same in the pre- and post-treatment period.[14]

Furthermore, both the conventional and the DID matching method rely on a common support or overlap condition that for *ATT* can be formally stated as:[15]

$$\Pr(D_{t^0} = 1 | X_{t^-}) < 1 \tag{5}$$

This condition prevents X_{t^-} from being a perfect predictor of treatment status. In our context, this ensures that for every X_{t^-}, there are firms choosing to start to export and firms choosing not to start to export, which means that for every X_{t^-}, we will be able to construct the counterfactual outcome. When X_{t^-} has high dimension (i.e. includes continuous variables or discrete variables with many values), it becomes difficult to find comparables observations along all dimensions of X_{t^-}. Rosenbaum and Rubin (1983) have shown that if matching on X_{t^-} is valid, so is matching on the conditional probability of receiving treatment, referred to as the propensity score. The propensity score reduces the dimensionality of the matching problem by allowing us to match on a scalar function of the covariates rather than the entire covariate space.

All matching estimators are weighting estimators in the sense that they take a weighted average of the outcomes of the untreated observations to construct an estimate of the unobserved counterfactual for each treated observation. For *ATT*, the cross-sectional (CS) and the DID version can be written in the form:

$$ATT_{CS} = \frac{1}{n_1} \sum_{i \in \{D_{t0_i}=1\}} \left[LP_{1t^+i} - \sum_{j \in \{D_{t0_j}=0\}} w(i,j) LP_{0t^+j} \right], \tag{6}$$

$$ATT_{DID} = \frac{1}{n_1} \sum_{i \in \{D_{t0_i}=1\}} \left[(LP_{1t^+i} - LP_{1t^-i}) - \sum_{j \in \{D_{t0_j}=0\}} w(i,j)(LP_{0t^+j} - LP_{0t^-j}) \right] \tag{7}$$

where n_1 is the number of treated observations and $w(i, j)$ is the weight placed on the *j*th comparison observation in constructing the counterfactual for the *i*th treated observation. The primary difference between alternative matching estimators is how they construct the

[14] *Although the cross-sectional and the conditional DID matching estimator are presented as quite distinct, their similarity becomes apparent when considering how pre-treatment outcomes can be employed in both approaches. In the conditional DID case, pre-treatment outcomes are used in calculating the before-after differences, whereas in the cross-sectional version, they are used as right-hand-side conditioning variables. In a regression context, LaLonde (1986) refers to the latter approach (including pre-treatment outcomes as right-hand-side variables) as an unrestricted DID estimator.*

[15] *For the DID approach, this condition must hold in both the pre- and the post-treatment period.*

weight, which typically involves a trade-off between bias and variance. For instance, in single nearest neighbor matching, each treated observation *i* is matched to the in terms of the propensity score nearest comparison observation *j*, with the weight given by $w(i, j) \in \{1,0\}$. Single nearest neighbor matching trades reduced bias for increased variance (using additional neighbors would raise bias due to increasingly poorer matches but decrease variance because more information would be used to construct the counterfactual for each treated observation). In the empirical work, we will consider two alternative weighting regimes: single nearest neighbor matching and kernel matching based on the Epanechnikov kernel. For the latter, we will employ different bandwidths covering a fairly wide interval. Increasing the bandwidth will generally increase bias and reduce variance because heavier weight will be put on more distant observations when constructing the counterfactual for each treated observation (i.e. the effect of increasing the bandwidth is similar to that of using additional neighbors in nearest neighbor matching).

There are a few specific circumstances to consider when implementing matching in our particular context. The first is related to the aforementioned two principal explanations for why export firms enjoy higher productivity. According to the learning-by-exporting hypothesis, the effect of exporting on productivity should occur once the firms enter international markets, not before. To test this hypothesis, we either compare post-export productivity for export-entrants and non-entrants with similar pre-export productivity histories and similar values for other pre-export covariates (the cross-sectional case) or compare the before-after differences in productivity for export-entrants and non-entrants conditional on other pre-export covariates (the conditional DID case). This approach is rather typical from an evaluation perspective in the sense that the causal effect of the treatment appears after the treatment.

The alternative learning-to-export hypothesis is somewhat unorthodox from an evaluation viewpoint because the effect of exporting on productivity can occur before firms actually enter international markets – i.e. the causal effect, in fact, may precede the treatment. The argument for the alternative learning-to-export hypothesis is that firms make a deliberate effort to increase their productivity by investing, for instance, in human and physical capital and new production technologies and products with the explicit intention of becoming exporters. Here, initial productivity is not treated as exogenous (as in the typical self-selection hypothesis); instead, it is regarded as endogenous with respect to the decision to enter international markets. A test of the learning-to-export hypothesis requires a matching strategy where the base line for pre-export productivity (and other covariates) is set some time before the period of export entry. With this approach, the effect of exporting on productivity may appear even before firms actually enter the export market.

Consequently, in our empirical work, we will consider model specifications where (i) export is allowed to affect productivity at the time of firms' export entry and thereafter and (ii) export is permitted to influence productivity even before firms enter international markets.

A second circumstance that warrants special attention has to do with dynamics in firms' export status. Some of the firms that enter the export market will continue to export (entrant-stayers), while others will cease to export (entrant-stoppers). Similarly, some of the non-entrants will continue not to export (never-entrants), while others will eventually enter international markets (not-yet-entrants). In the empirical section, we will examine how robust our results are with regard to changes in firm export status.

Although the analysis of different types of sub-groups is uncomplicated as such, it is important to recognize how the construction of the various samples may change the interpretation of the results from an econometric perspective. For instance, if we anticipate a positive effect of export entry and choose to narrow the treatment group to entrant-stayers (instead of using all export-entrants, including entrant-stoppers) this will induce an upward bias in the estimated treatment effect. All firms that for one reason or another fail to endure as exporters will be disregarded, even though export failure should be viewed as part of the overall causal effect of export entry rather than being considered as exogenous with regard to the treatment. Similarly, if we refine the comparison group to consist of never-entrants (instead of using all non-entrants, including not-yet-entrants) and continue to expect a positive effect of entering the export market, we will once again end up with upward bias in the estimated treatment effect. The problem here is that we try to transform what is actually a process of dynamic treatment assignment (where some firms choose to enter the export market early, others decide to go in later, and some prefer to never enter) into a static one (where firms once and for all decide whether or not to enter).

In both cases above, the definition of the treatment and comparison group involves conditioning on the future and therefore produces samples that are selective in terms of the outcome of interest. It is beyond the scope of this paper to present any formal methodological solutions to these problems.[16] We merely want to emphasize that the conditioning in the sub-sample analysis introduces bias with regard to the typical treatment parameter in question and actually leaves us with a set of different treatment parameters with slightly different interpretations.

[16] *For a discussion of the methodological implications of dynamic treatment assignment and suggested solutions, see Fredriksson and Johansson (2008) and Crépon et al. (2009).*

4 Empirical results

We begin the presentation of our results in section 4.1 and discuss the estimates of the propensity scores used in the following matching analyses. Among other things, these estimates indicate whether firms self-select into the export-market. Then, in sections 4.2 and 4.3, we report estimates of the causal effects of export entry on firm labor productivity. In section 4.2, we use specifications that restrict productivity to be affected at the time of export entry and thereafter, whereas in section 4.3, we employ specifications that allow productivity to be influenced even before export entry takes place. Finally, in section 4.4, we show the outcome of some robustness checks where we refine the export-entrant and non-entrant groups.

4.1 Propensity scores and self-selection

In this section, we present estimates of the propensity scores (i.e. the probability of starting to export) that will be used in the matching analyses to follow. The covariates included in the propensity scores are standard variables suggested by theory and previous empirical literature to affect both export entry and future productivity. These include physical capital per employee (*K*/*L*), share of employees with post-secondary education (*H*/*L*), size in terms of employment (*EMP*), a dummy variable indicating whether a firm is part of a multinational enterprise (*MNE*), 2-digit NACE industry dummies (21 industries) and dummies for the year of potential export entry. In addition, the propensity scores for the cross-sectional specifications include pre-export labor productivity (*LP*). For the conditional DID specifications, labor productivity prior to potential export entry is not included as a covariate in the propensity scores but is instead used to construct the before-after potential export entry differences.

The specification of the propensity scores further differs for the matching models focusing on the learning-by-exporting and learning-to-export hypotheses. In the former case, we are seeking to find export entrants and non-export entrants that are as similar as possible all the way up to the period of potential export entry. These sets of propensity scores therefore include labor productivity for a three-year period prior to potential export entry ($t-3$ to $t-1$), while the other covariates refer to the year prior to potential export entry ($t-1$). In the specifications focusing on the learning-to-export hypothesis, all covariates refer to the third year prior to potential export entry ($t-3$).[17] The latter specifications thus allow for export entrants and non-export entrants to experience divergent development in terms of labor productivity and other firm attributes during the years up to potential export entry (i.e. during $t-2$ and $t-1$).

In all cases, we use a probit model to estimate the propensity scores. To the extent that interactions and higher orders of the covariates improved the balancing between export entrants and non-export entrants, they were included. For brevity, we will focus on the

[17] *In the conditional DID specifications, pre-export labor productivity is used to calculate the before-after potential export entry differences. For the learning-by-exporting case, this means that before refers to* LP_{t-1} *while before for the learning-to-export case refers to* LP_{t-3}.

linear terms for the most important variables and further restrict the presentation to the cross-sectional specifications.[18]

Table 5 presents estimates of the propensity scores pertaining to the cross-sectional learning-by-exporting specification. Beginning with the first column, which gives the results for all firms irrespective of size, we find that the probability of becoming an export entrant seems to increase with pre-export labor productivity. However, this result only holds in $t-1$. Due to high correlation between productivity in the different years, it is difficult to obtain precise estimates for each year. To avoid the problem of multicollinearity, we have experimented with a specification that instead includes average labor productivity over the years $t-3$ to $t-1$. The result (not reported in the table) indicates a highly significant and positive effect of pre-export labor productivity on the probability of export entry. These results are thus in line with the self-selection hypothesis: that more productive firms enter international markets. Furthermore, the results show that more capital-intensive firms (in terms of physical capital as well as human capital) tend to become exporters, and that the same applies to larger firms and firms that are part of multinational enterprises.

However, if we look at the results for firms of different sizes, the positive effect of pre-export labor productivity on the probability of becoming an exporter appears to be valid only for micro firms (firms with less than 10 employees).

Table 5 Estimated propensity scores for the cross-sectional learning-by-exporting specification.

	Number of employees			
	1-∞	1-9	10-49	50-∞
$\ln(LP)_{t-3}$	0.055	0.003	0.077	0.554
	(0.053)	(0.067)	(0.089)	(0.427)
$\ln(LP)_{t-2}$	-0.024	-0.096	0.116	0.444
	(0.060)	(0.073)	(0.109)	(0.374)
$\ln(LP)_{t-1}$	0.237***	0.490***	-0.099	-0.821***
	(0.061)	(0.077)	(0.104)	(0.314)
$\ln(K/L)_{t-1}$	0.082***	0.049**	0.122***	0.238***
	(0.015)	(0.020)	(0.025)	(0.086)
$(H/L)_{t-1}$	0.566***	0.607***	0.813***	-0.040
	(0.099)	(0.114)	(0.245)	(0.709)
$\ln(EMP)_{t-1}$	0.398***	0.458***	0.471***	0.270**
	(0.017)	(0.045)	(0.059)	(0.129)
MNE_{t-1}	0.192***	0.290*	0.252***	0.230
	(0.069)	(0.161)	(0.090)	(0.166)
Observations	42,630	32,607	9,150	775
Pseudo R^2	0.155	0.118	0.080	0.182

*Notes: The propensity scores are estimated using a probit model, and all specifications include 2-digit NACE industry dummies and dummies for the year of potential export entry. Standard errors in parentheses. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively.*

Turning to Table 6, which shows estimates of the propensity scores for the cross-sectional learning-to-export specification, we find more or less similar results. One notable

[18] *A complete list of estimated propensity scores for all matching models applied is available on request.*

difference is that the positive effect of pre-export labor productivity on the probability of export entry also seems to hold for small firms (firms with 10 to 49 employees).

In sum, our estimates of the propensity scores reveal some interesting patterns in terms of self-selection of firms into international markets. Our results indicate that the self-selection hypothesis – that more productive firms enter the export market – primarily applies to micro firms and to some extent to small firms, but not to medium-sized and large firms.

Table 6 Estimated propensity scores for the cross-sectional learning-to-export specification.

	Number of employees			
	1-∞	1-9	10-49	50-∞
ln(*LP*)$_{t-3}$	0.207***	0.251***	0.164*	1.355
	(0.044)	(0.052)	(0.084)	(4.388)
ln(*K*/*L*)$_{t-3}$	0.086***	0.066***	0.106***	0.321***
	(0.015)	(0.019)	(0.026)	(0.095)
(*H*/*L*)$_{t-3}$	0.553***	0.611***	0.483*	-0.551
	(0.094)	(0.102)	(0.272)	(0.761)
ln(*EMP*)$_{t-3}$	0.363***	0.347***	0.455***	0.265**
	(0.017)	(0.039)	(0.061)	(0.126)
MNE_{t-3}	0.155**	0.214	0.207**	0.184
	(0.075)	(0.174)	(0.099)	(0.187)
Observations	42,602	33,132	8,669	719
Pseudo R^2	0.135	0.085	0.079	0.198

*Notes: The propensity scores are estimated using a probit model, and all specifications include 2-digit NACE industry dummies and dummies for the year of potential export entry. Standard errors in parentheses. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively.*

4.2 Learning-by-exporting

In this section, we continue by presenting the propensity score matching estimates of the causal effect of export entry on labor productivity. The estimates are obtained using both cross-sectional (see equation (6)) and conditional difference-in-differences (DID) matching (see equation (7)). In both cases, we have applied two different weighting regimes: single nearest neighbor matching and kernel matching based on the Epanechnikov kernel. For the latter, we have used bandwidths in the interval [0.001, 0.01]. For brevity, we will only report results based on the Epanechnikov kernel using a bandwidth of 0.005.[19] Details regarding the specification of the propensity scores are provided in the previous section.

To begin, we focus on model specifications pertaining to the learning-by-exporting hypothesis. The estimates are thus based on export-entrants and non-entrants with similar pre-export entry firm attributes up to year $t-1$, and which we follow during the years t to $t+3$. Table 7 presents the differences in log labor productivity between export-entrants and matched non-entrants. These estimates can be interpreted as the approximate percentage effects of export entry on labor productivity.

[19] In general, the results show little sensitivity depending on the exact weighting regime. Estimates based on single nearest neighbor matching and different bandwidths for the Epanechnikov kernel are available on request.

Table 7 Matching estimates of the effect of export entry on labor productivity. Learning-by-exporting specification.

	Number of employees							
	1-∞		1-9		10-49		50-∞	
Effect at time:	CS	DID	CS	DID	CS	DID	CS	DID
t	0.054***	0.042***	0.138***	0.072***	0.028	0.035*	0.050	0.048
	(0.017)	(0.016)	(0.032)	(0.028)	(0.021)	(0.021)	(0.042)	(0.037)
t+1	0.062***	0.053***	0.139***	0.062*	0.033*	0.052***	0.019	0.033
	(0.018)	(0.017)	(0.037)	(0.035)	(0.018)	(0.019)	(0.045)	(0.047)
t+2	0.042**	0.027	0.106***	0.022	0.013	0.029	0.026	0.066
	(0.020)	(0.020)	(0.040)	(0.040)	(0.024)	(0.024)	(0.043)	(0.047)
t+3	0.059***	0.042**	0.132***	0.049	0.018	0.034*	0.056	0.069
	(0.018)	(0.018)	(0.036)	(0.039)	(0.020)	(0.020)	(0.047)	(0.048)
Balancing indicators								
Mean bias before	16.1	14.1	17.6	15.2	12.6	12.4	17.5	18.4
Mean bias after	1.1	1.3	1.8	1.2	1.3	1.1	4.9	3.7
Pseudo R^2 before	0.155	0.151	0.118	0.098	0.080	0.079	0.182	0.171
Pseudo R^2 after	0.001	0.001	0.003	0.002	0.001	0.001	0.017	0.007
Untreated on support	41,944	42,092	32,361	32,489	8,781	8,800	704	705
Treated on support	684	685	244	248	367	369	63	64
Observations	42,628	42,777	32,605	32,737	9,148	9,169	767	769

*Notes: The estimated parameters are based on cross-sectional (CS) and conditional difference-in-differences (DID) propensity score matching using an Epanechnikov kernel with a bandwidth of 0.005. For details on the specification of the propensity scores, see section 4.1. Approximate standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively.*

In Table 7, we can see that firms that become exporters increase their productivity by the time of export entry *t* relative to matched firms that do not enter as exporters at *t*. The percentage effect on labor productivity of export entry is 5.4 percent or 4.2 percent depending on the estimator (CS or DID). Interestingly, the effect is fairly stable over time and is about the same at year $t+3$. When we look at the results for different firm sizes, it becomes apparent that the productivity effect of export entry is larger and statistically more significant for smaller firms. Furthermore, the estimates based on cross-sectional matching tend to be larger than those based on DID matching.

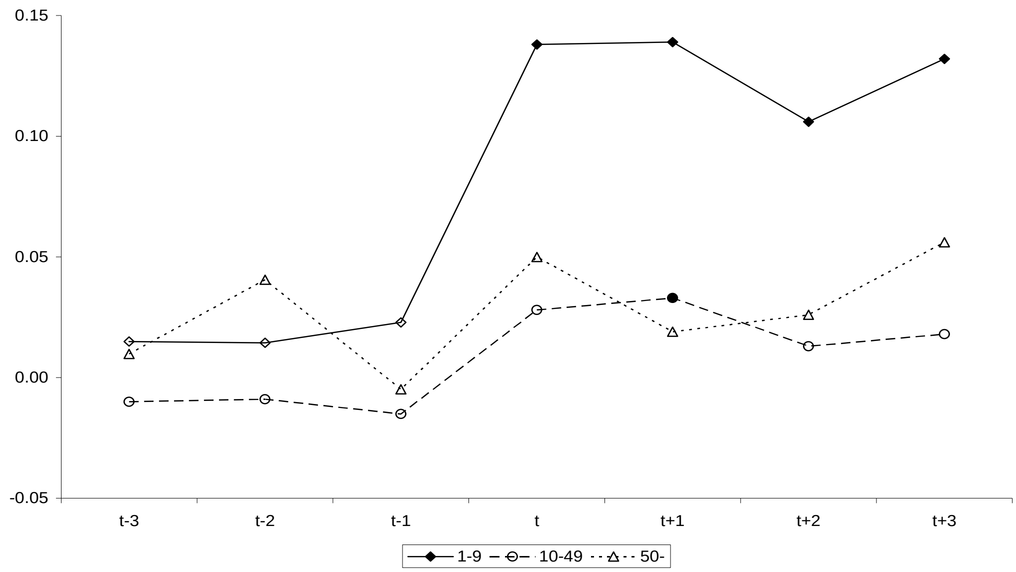
Table 7 also report some aggregate balancing indicators that give a sense of how successful the matching has been in terms of balancing differences in the covariates between export-entrants and non-entrants. The first is the mean standardized bias over all covariates used in the propensity scores, which is between 12 and 18 percent before matching and between 1 and 5 percent after matching.[20] On average, the matching generates a reduction in mean bias by roughly a factor of ten. The other indicator is the pseudo R^2 before and after matching. This statistic indicates how well the variables in the propensity score explain the probability of receiving treatment. After matching, the pseudo R^2 should be fairly low because there should be no systematic differences in the distribution of covariates between the treatment and the comparison group. Before matching, this statistic is between 0.08 and 0.18. After matching, it drops to virtually zero. In sum, the balancing indicators suggest that the matching has been fairly successful in terms of balancing differences in the covariates between the treatment and the comparison group. In fact, after matching, there remain no statistically significant differences in the means for the pre-export firm attributes of export-entrants and non-entrants.

Figure 1 illustrates the results of the cross-sectional matching estimates for different firm sizes in Table 7. Here, we notice the instantaneous productivity increase at export entry *t* for export-entrants with less than 10 employees and the constant 10-15 percent productivity gap in the subsequent years relative to the matched firms that do not enter international markets at *t*. For the larger firms, the productivity increase is much smaller and, in most cases, statistically insignificant.

Figure 1 (and Table 7) indicates that there is a positive impact on productivity at the time of entry among smaller firms entering the export market. However, with the reservation that the post-export period is rather short (three years), there does not seem to be any evidence of continuous learning through export. For this, we would have expected to see a widening productivity differential over time. The fairly stable gap might instead indicate more of a static productivity effect due to increased potential for economies of scale following export entry. Finally, looking at the pre-export productivity differentials, they tend to be close to zero and are statistically insignificant for all firm sizes. This can be regarded as additional support for that we are actually comparing comparable export-entrant and non-entrant firms.

[20] *The standardized bias of a covariate is defined as the difference of the sample means in the treatment and the comparison group as a percentage of the square root of the average of the sample variance in the two groups. See Rosenbaum and Rubin (1985).*

Figure 1 Cross-sectional matching estimates of the effect of export entry on labor productivity. Learning-by-exporting specification.



Notes: Based on the cross-sectional estimates in Table 7. Filled data marker indicates effect significant at the 10 percent level or lower.

4.3 Learning-to-export

So far we have presented results that compare export-entrants at t with non-entrants at t with similar pre-export entry firm attributes up to $t-1$. As we pointed out before, this approach is primarily designed to test the hypothesis of learning-by-exporting. By definition, such a strategy preclude any impact of exporting on productivity taking place before firms enter international markets; any productivity differences prior to export entry between future exporters and firms not entering the export market are balanced in the matching. Export may only affect productivity at the time of export entry or after it has taken place. To test the hypothesis of learning-to-export, we have to allow for export-entrants and non-entrants to experience divergent development in terms of labor productivity and other firm attributes even before the time of potential export entry. In this section, we present estimates based on export-entrants and non-entrants at t that have similar labor productivity and other firm attributes at $t-3$ but for which the trajectories of these attributes may differ thereafter.

Table 8 reveals that there is a significant productivity differential already at $t-1$ between export-entrants and non-entrants at t with similar productivity and other firm attributes at $t-3$. Moreover, the productivity gap continues to grow to 8.8 percent (CS) or 5.7 percent (DID) at $t+1$, and thereafter, the gap is basically constant. When we focus on the results for different firm sizes, we again find that the rising productivity differential is driven by the smallest firms, those with less than 10 employees. Looking at the balancing indicators, we also find that the matching has been quite successful in terms of balancing differences in the covariates between export-entrants and non-entrants.

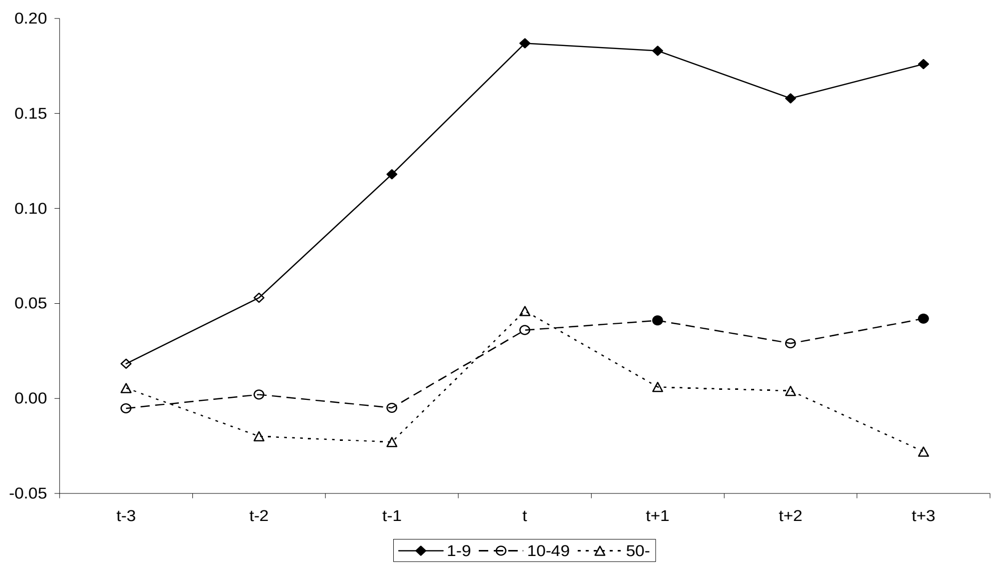
Table 8 Matching estimates of the effect of export entry on labor productivity. Learning-to-export specification.

	Number of employees							
	1-∞		1-9		10-49		50-∞	
Effect at time:	CS	DID	CS	DID	CS	DID	CS	DID
t–2	0.019	–0.005	0.053	–0.007	0.003	–0.011	–0.020	–0.009
	(0.017)	(0.017)	(0.033)	(0.034)	(0.018)	(0.018)	(0.063)	(0.051)
t–1	0.037**	0.012	0.118***	0.049	–0.005	–0.024	–0.023	–0.019
	(0.017)	(0.018)	(0.032)	(0.031)	(0.020)	(0.023)	(0.067)	(0.056)
t	0.079***	0.057***	0.187***	0.113***	0.036	0.015	0.046	–0.003
	(0.017)	(0.020)	(0.029)	(0.034)	(0.023)	(0.025)	(0.046)	(0.045)
t+1	0.088***	0.057***	0.183***	0.106***	0.041**	0.021	0.006	–0.006
	(0.018)	(0.021)	(0.033)	(0.041)	(0.020)	(0.023)	(0.050)	(0.051)
t+2	0.074***	0.044*	0.158***	0.084**	0.029	0.009	0.004	–0.034
	(0.020)	(0.023)	(0.034)	(0.042)	(0.026)	(0.028)	(0.052)	(0.047)
t+3	0.086***	0.055**	0.176***	0.098**	0.042**	0.018	–0.028	–0.040
	(0.018)	(0.021)	(0.033)	(0.041)	(0.020)	(0.023)	(0.053)	(0.049)
Balancing indicators								
Mean bias before	14.0	13.3	13.9	13.2	12.9	12.7	17.8	18.5
Mean bias after	1.1	1.1	1.0	1.0	1.0	0.7	7.0	7.9
Pseudo R^2 before	0.135	0.131	0.085	0.077	0.079	0.078	0.198	0.197
Pseudo R^2 after	0.001	0.001	0.001	0.001	0.001	0.000	0.024	0.014
Untreated on support	41,915	41,915	32,848	32,848	8,331	8,331	654	654
Treated on support	686	686	284	284	337	335	55	54
Observations	42,601	42,601	33,132	33,132	8,668	8,666	709	708

*Notes: The estimated parameters are based on cross-sectional (CS) and conditional difference-in-differences (DID) propensity score matching using an Epanechnikov kernel with a bandwidth of 0.005. For details on the specification of the propensity scores, see section 4.1. Approximate standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively.*

Figure 2 visualizes the estimates from the cross-sectional matching for different firm sizes in Table 8. Clearly, there is a considerable labor productivity differential before export entry between small export-entrants and small non-entrants, and the gap continues to widen until *t*. This is a phenomenon that we are not able to observe among the firms in the other size classes. Our interpretation of the pattern shown in Figure 2 (and of the findings in Table 8) is that smaller firms, at least, appear to prepare themselves for entering the export market by improving their productivity before entrance. In other words, they seem to learn to export.[21] However, one caveat is that the fairly high threshold value for the registration of exports (see section 2.1) means that some of the smaller entering firms in particular actually might have been exporters already in $t-2$ and $t-1$.

Figure 2 Cross-sectional matching estimates of the effect of export entry on labor productivity. Learning-to-export specification.



Notes: Based on the cross-sectional estimates in Table 8. Filled data marker indicates effect significant at the 10 percent level or lower.

4.4 Robustness to dynamics in export status

In this section, we will continue by examining how robust our results are with regard to changes in firms' export status. Remember that we defined export-entrants (treated firms) as firms that exported in year t but did not export in the years $t-3$ to $t-1$, whereas non-entrants (untreated firms) were defined as firms that did not export in any of the years $t-3$ to t. With this approach, we are most likely mixing export entrants that continue to export, often referred to as export successes, with those firms that cease to export, so called export failures. Similarly, we are mixing non-entrants that continue not to export with those that eventually enter international markets. In this section, we proceed by estimating

[21] *Alvarez and Lopez (2005) also provide some evidence for the learning-to-export hypothesis (conscious self-selection). They show that an increase in investment before entry raises the probability of exporting while controlling for other factors that might affect the probability of entry on the export market.*

productivity effects of export entry using a more detailed classification of firms' export status.[22]

We divide our treated firms into two subgroups: export-entrants that continue to export throughout the period $t+1$ to $t+3$ (entrant-stayers) and export-entrants that leave the export market during at least one of the years $t+1$ to $t+3$ (entrant-stoppers). We also split our untreated firms into two sub-groups: non-entrants that continue to stay out of the export market throughout the period $t+1$ to $t+3$ (never-entrants) and non-entrants that eventually enter the export market during the period $t+1$ to $t+3$ (not-yet-entrants).

Table 9 presents statistics on the export status types for the different firm size classes. The majority of our export-entrants exit the export market during at least one of the years following entry. The share of stoppers decreases with firm size. Two-thirds of the entrants in the micro firm category (1-9 employees) stop exporting, whereas four out of ten entrants stop in the medium-sized and large (50- employees) firm category. Looking at the non-entrants group, there seems to be considerably less dynamics going on, in particular in the smaller firm size classes. Only 1.5 percent of the non-entrants in the micro firm class eventually enter the export market (98.5 percent belong to the never-entrants category) compared to 19 percent of the non-entrants in the medium-sized and large firm class (81 percent belong to the never-entrants category). Note that due to the earlier mentioned threshold value for the registration of exports (see section 2.1), we are not able to assess to what extent the changes in export status type are a result of major swings in firms' export values or a consequence of smaller fluctuations around the threshold.

Table 9 Export status types by firm size.

	Number of employees			
Type	1-∞	1-9	10-49	50-∞
Export-entrants	724	268	384	72
Entrant-stayers	310	88	182	40
Entrant-stoppers	414	180	202	32
Non-entrants	44,120	34,264	9,097	759
Never-entrants	42,667	33,753	8,299	615
Not-yet-entrants	1,453	511	798	144

In this section, we are particularly interested in comparing the estimated effect of export entry on labor productivity for entrant-stayers relative to never-entrants to that of entrants-stoppers relative to non-entrants. In a sense, the former comparison is the most distinct classification of treated/untreated firms, whereas the latter is less clear-cut.

Before turning to the results, we would like to briefly recapitulate that the conditioning on the future used when constructing the different sub-samples implies that we are estimating a new set of treatment parameters that are actually biased in different respects. The entrant-stayers/never-entrants comparison excludes export failures and future entrants, which will result in an upward bias in the estimated treatment effect. Similarly, the entrant-stoppers/non-entrants comparison disregards export successes but includes future entrants, which will induce a downward bias in the estimated treatment effect. In both cases, the

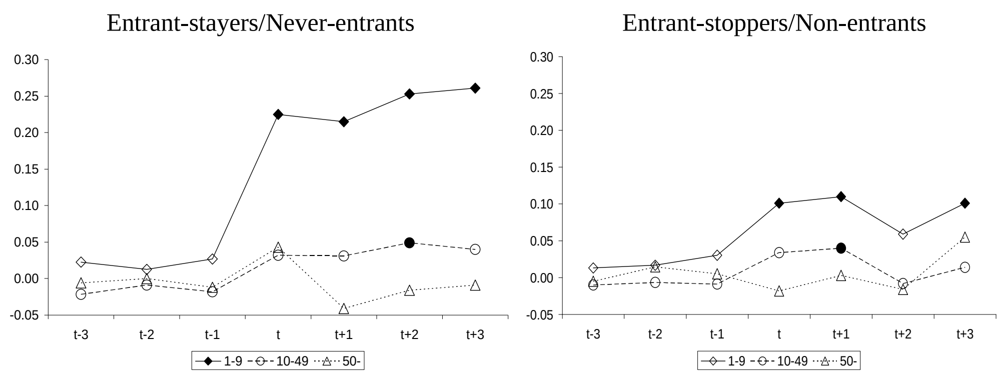
[22] *Similar divisions can be found in e.g. Bernard and Jensen (1999), Hansson and Lundin (2004) and Alvarez and López (2005).*

bias is a result of conditioning on future export status and therefore implicitly on future outcomes.

With these reservations in mind, Figure 3 illustrates the results based on cross-sectional matching for the two combinations in question.[23] Note that the specifications of the propensity scores are the same as in section 4.2 (i.e. the learning-by-exporting specification) and accordingly, the results should be compared to those in Figure 1 and Table 7.

In Figure 3, we observe that the effect of export entry for entrants-stayers relative to never-entrants in the micro firm category is considerably larger than the effect for entrants-stoppers relative to non-entrants in the corresponding class. For the former, the effect on labor productivity of export entry is between 22 and 26 percent and has a slight tendency to increase over time. For the latter, the productivity effect is between 6 and 11 percent but is not consistently statistically significant. The corresponding results from Table 7, in which we compare export-entrants to non-entrants, are between 11 and 14 percent. For the larger firms, there seem to be no differences in the estimated effects depending on the applied definitions of export status.

Figure 3 Cross-sectional matching estimates of the effect of export entry on labor productivity for different export status combinations. Learning-by-exporting specification.



Note: Based on the cross-sectional estimates in Table A1. Filled data marker indicates effect significant at the 10 percent level or lower.

In sum, we conclude that when we refine the export-entrants into entrant-stayers and the non-entrants into never-entrants, the positive productivity effect of export entry among micro firms becomes larger. Furthermore, we may discern a small increase in the productivity gap between export-entrants and non-entrants subsequent to entry.

[23] *Complete results can be found in Table A1 in the Appendix.*

5 Conclusions

The exporter productivity premia in Swedish manufacturing is larger in smaller firms, and while the export participation rate in general is high, it is still fairly low among the smaller firms. This means that policymakers might be particularly interested in whether, above all, smaller firms that enter the export market tend to improve their productivity performance relative to non-entering firms, i.e. whether they learn by exporting.

Using propensity score matching techniques, we found that there is an instantaneous productivity increase at the time of entry, especially for smaller firms, but that the productivity gap between entrants and non-entrants appears to be constant in the periods subsequent to entry. If the firms had learnt by exporting, we would have expected to see a widening productivity gap. However, when we look exclusively at smaller successful exporters – i.e. smaller firms that enter the export market and, after entrance, continue to be exporters – and compare their productivity trajectory after entry with that of firms that never enter the export market, we may see a tendency toward an increase in the productivity gap.

Ex ante (before export entry) labor productivity is significantly higher for smaller future exporters than for firms that do not enter the export market, which indicates that those firms self-select into export. Furthermore, if in our matching analysis we allow for different productivity trajectories before export entry, we observe that there is a significant productivity differential, at least for smaller firms, between export-entrants and matched non-entrants even before export entry. We interpret this as an indication of the fact that learning-to-export may exist.

References

Alvarez, R. and Lopez, R. (2005), Exporting and performance: evidence from Chilean plants. *Canadian Journal of Economics*, 38, 1384-1400.

Andersson, M, Lööf, H. and Johansson, S. (2008), Productivity and international trade: Firm level evidence from a small open economy. *Review of International Economics*, 144, 774-801.

Bernard, A. and Jensen, B. (1995), Exporters, jobs, and wages in U.S. manufacturing: 1976-1987. *Brookings Papers on Economic Activity*, 67-112.

Bernard, A. and Jensen, B. (1999), Exceptional exporter performance: Cause, effect, or both? *Journal of International Economics*, 47, 1-25.

Crépon, B., Ferracci, M., Jolivet, G. and van den Berg, G. J. (2009), Active labor market policy effects in a dynamic setting. Working Paper 2009:1, IFAU.

Dehejia, R. and Wahba, S. (1999), Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American Statistical Association*, 94, 1053-1062.

Dehejia, R. and Wahba, S. (2002), Propensity score matching methods for nonexperimental causal studies. *Review of Economics and Statistics*, 84, 151-161.

Damijan, J. and Kostevc, C. (2006), Learning-by-exporting: Continuous productivity improvements or capacity utilization effects? Evidence from Slovenian firms. *Review of World Economics*, 142, 599-614.

De Loecker, J. (2007), Do exports generate higher productivity? Evidence from Slovenia. *Journal of International Economics*, 73, 69-98.

EC (2007), *Supporting the internationalization of SMEs*. Directorate-General for Enterprise and Industry

Fredriksson, P. and Johansson, P. (2008), Dynamic Treatment Assignment – The Consequences for Evaluations using Observational Data. *Journal of Business & Economic Statistics*, 26, 435-445.

Girma, S, Greenaway, D. and Kneller, R. (2004), Does exporting increase productivity? A microeconometric analysis of matched firms. *Review of International Economics*, 12, 855-866.

Greenaway, D, Gullstrand, J. and Kneller, R. (2005), Exporting may not always boost firm productivity. *Review of World Economics*, 141, 561-582.

Greenaway, D. and Kneller, R. (2007), Firm heterogeneity, exporting and foreign direct investment. *Economic Journal*, 117, F134-F161.

Halvorsen, R. and Palmqvist, R. (1980), The interpretation of dummy variables in semilogarithmic equations. *American Economic Review*, 70, 474-475.

Hansson, P. and Lundin, N. (2004), Exports as an indicator or a promoter of successful Swedish firms in the 1990s. *Review of World Economics*, 140, 415-445.

Heckman, J, Ichimura, H. and Todd, P. (1997), Matching as an econometric evaluation estimator: Evidence from evaluating a job training program. *Review of Economic Studies*, 64, 605-654.

Heckman, J, Ichimura, H. and Todd, P. (1998), Matching as an econometric evaluation estimator. *Review of Economic Studies*, 65, 261-294.

Heckman, J, Ichimura, H, Smith, J. and Todd, P. (1998), Characterizing selection bias using experimental data. *Econometrica*, 66, 1017-1098.

Imbens, G. (2004), Nonparametric estimation of average treatment effects under exogenity: a review. *Review of Economics and Statistics*, 86, 4-29.

ISGEP (2008), Understanding cross-country differences in exporter premia: Comparable evidence for 14 countries. *Review of World Economics*, 144, 596-635.

LaLonde, R. (1986), Evaluating the Econometric Evaluations of Training Programs with Experimental Data. *American Economic Review*, 76:4, 604-620.

Levinsohn, J. and Petrin, A. (2003), Estimating production functions using inputs to control for unobservables. *Review of Economic Studies*, 70, 317-342.

Olley, S. and Pakes, A. (1996), The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64, 1263-1298.

Rosenbaum, P. and Rubin, D. (1983), The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70, 41-55.

Rosenbaum, P. and Rubin, D. (1985), Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. *The American Statistician*, 39:1, 33-38.

Smith, J. and Todd, P. (2005), Does matching overcome Lalonde's critique of nonexperimental estimators? *Journal of Econometrics*, 125, 305-353.

SOU (2008), Svensk export och internationalisering (Swedish export and internationalization). *Swedish Government Official Report 2008:90*.

Wagner, J. (2007), Exports and productivity: a survey of the evidence from firm-level data. *World Economy*, 60-82.

Van Biesebroeck, J. (2005), Exporting raises productivity in sub-Saharan African manufacturing firms. *Journal of International Economics*, 67, 373-391.

Table A1. Cross-sectional matching estimates of the effect of export entry on labor productivity for different export status combinations. Learning-by-exporting specification

	Number of employees							
	1-∞		1-9		10-49		50-∞	
Effect at time:	Entrants-stoppers/ Non-entrants	Entrants-stayers/ Never-entrants	Entrants-stoppers/ Non-entrants	Entrants-stayers/ Never-entrants	Entrants-stoppers/ Non-entrants	Entrants-stayers/ Never-entrants	Entrants-stoppers/ Non-entrants	Entrants-stayers/ Never-entrants
t	0.058**	0.078***	0.101***	0.225***	0.034	0.032	–0.018	0.043
	(0.023)	(0.026)	(0.037)	(0.063)	(0.032)	(0.029)	(0.061)	(0.056)
t+1	0.068***	0.076***	0.110**	0.215***	0.040	0.031	0.003	–0.041
	(0.024)	(0.025)	(0.046)	(0.062)	(0.025)	(0.028)	(0.066)	(0.064)
t+2	0.020	0.089***	0.059	0.253***	–0.008	0.049*	–0.016	–0.016
	(0.030)	(0.025)	(0.051)	(0.060)	(0.040)	(0.026)	(0.056)	(0.062)
t+3	0.047**	0.102***	0.101**	0.261***	0.014	0.040	0.055	0.009
	(0.023)	(0.026)	(0.042)	(0.066)	(0.027)	(0.029)	(0.062)	(0.065)
Balancing indicators								
Mean bias before	16.7	18.7	17.9	22.0	13.2	15.1	16.4	31.3
Mean bias after	1.2	2.4	2.1	3.8	0.9	2.8	5.4	7.9
Pseudo R^2 before	0.121	0.205	0.108	0.169	0.070	0.110	0.137	0.329
Pseudo R^2 after	0.001	0.006	0.006	0.021	0.000	0.004	0.028	0.134
Untreated on support	41,913	40,570	32,361	31,897	8,758	8,017	688	541
Treated on support	393	286	167	79	195	173	30	28
Observations	42,306	40,856	32,528	31,976	8,953	8,190	718	569

*Notes: The estimated parameters are based on cross-sectional propensity score matching using an Epanechnikov kernel with a bandwidth of 0.005. For details on the specification of the propensity scores, see section 4.1. Approximate standard errors in parenthesis. ***, **, and * indicate significance at the 1, 5 and 10 percent levels, respectively.*