Do Portuguese manufacturing firms learn by exporting?*

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Abstract

Using a longitudinal database (1996-2003) at the plant level, this paper analyses the causal nexus between international trade engagement and productivity in Portugal. By applying the Propensity Score Matching and a differences-in-differences estimator, the learning-by-exporting hypothesis is particularly analysed. A higher growth of labour productivity and total factor productivity is found for new exporting firms. To uncover the channels through which the learning effects are driven, the same methodology to some sub-samples is applied. Learning effects are higher for new exporters that are also importers or start importing at the same time. Other factors affecting learning ability are found in firms exporting to more developed markets, in those that achieve a certain threshold of export intensity and mainly for those firms that belong to sectors where Portugal has comparative disadvantage.

Keywords: Exports, Imports, Self selection, Learning-by-exporting, Matching.

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1. Introduction

Since the 60s, cross-country macroeconomic literature has established a positive correlation between trade and growth. However, there is still an on-going debate on the relationship between trade and firms' performances, namely productivity. Pioneered by Bernard and Jensen (1995) and Aw and Hang (1995), several recent works have been analysed this issue. There are two theses to explain the high correlation between trade and firms' productivity: the self-selection (SS), assuming that most productive firms become exporters and the learning-by-exporting (LBE), claiming that firms become more efficient as they start exporting and experience acceleration in productivity growth when compared with similar non-exporters.

SS thesis is based on the existence of important fixed costs of foreign market entry (e.g., Jovanovic, 1982; Roberts and Tybout, 1997). In this line, only the most productive firms would self-select to foreign markets. LBE is still often taken as a black-box with an unclear learning effect behind the productivity growth. However, there are several mechanisms that could fill that gap: (i) exporting positively affects innovation (e.g., Salomon and Shaver, 2005); (ii) large and more competitive markets could give the necessary boost to exporters to be more efficient (competition effect); (iii) the wider network of contacts with several sources (e.g., clients, suppliers, competitors or even professional and scientific institutions) could also enhance the generation of efficiency advances or innovations; (iv) the wider dimension of international markets could more likely offer the essential scale economies. Thus, the absence of a coherent theory that supports and explains the LBE thesis may occur due to the difficulty in controlling the learning effects in empirical works and this may block theoretical advances.

A growing body of empirical literature has been claiming that exports produce learning effects, resulting from an adjustment in the process governing firm's productivity growth. LBE is then assumed to be a channel or a set of channels, beyond the use of economies of scale, generated or enhanced by wider foreign markets that are coupled with increased competition and technology transfers and which enable firms to improve goods,[1] processes and organization structures. LBE tests have been produced for several countries (e.g., Wagner, 2007, reports studies for 34 countries) but, in general, post-entry effects seem weak, mainly observed in less developed countries and are confined to sub-samples of exporters.[2] Moreover, the channels from which LBE could be generated are still not adequately studied. There is a general assumption that LBE is perhaps more easily detected in firms or countries operating far away from the technological frontier and also that export to more developed markets.

To contribute to this discussion, we tested the LBE thesis for Portuguese manufacturing firms, by using the largest available sample on both financial and international trade variables, for the period 1996-2003. Applying matching techniques with differences in differences estimators and other panel data techniques, we tried to uncover the effects on several variables (e.g., productivity, sales and wages) generated by the beginning of exports activity. We also analysed the connections between imports of Portuguese firms and LBE.

Assuming that post-entry mechanisms of exporting activity may be heterogeneous and may rely on several factors that work as transmission channels to LBE, we also tested the LBE thesis for some sub-samples: (i) technological differences between sectors; (ii) firms' initial size, wage and efficiency; (iii) firms' previous international trade status; (iv) types of markets firms trade with on export and import sides; (v) firms' exporting intensity.

The paper is organized as follows. Section 2 describes the data. In section 3, we begin to test LBE by using a Fixed Effects (FE) model and then we focus on post-entry effects, by implementing a matching approach that allows us to discuss in more detail if exports improve firms' performances or not. Section 4 presents some concluding remarks.

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[1] Some empirical studies have found positive effects of competition on productivity growth (e.g., Nickell, 1996).

[2] Overall, empirical literature seems to fully confirm only the self-selection thesis.

2. Data description

The empirical analysis relies on the same dataset and overall definitions used in Silva et al. (2010a, b). It combines two data sources of the Portuguese National Statistics Institute (INE): balance sheet information (IAE) and external trade information (ECE). Datasets are linked by firms' non revealed fiscal number. IAE provides information of firms' balance sheets,[3] and uses a survey sample of all manufacturing Portuguese firms, from 1996-2003. We used number of employees, turnover, value added, investment, labour cost, stock of capital assets, liabilities and earnings.[4] Firms are classified according to their main activity, as identified by INE standard codes (CAE), which are correlated with Eurostat Nace 1.1 taxonomy.

Despite being unbalanced, our database contains information for an average of 4,500 firms per year. Capital is proxied by tangible fixed assets at book value (net of depreciation). In turn, ECE provides information for each firm, on trade volume (exports and imports) aggregated by year and by country (destination of exports and origin of imports), and it also display information on the types of products/sectors traded for each transaction.[5] All nominal variables are measured in 1996 Euros and are deflated using 2 digit industry-level price indices provided by INE; for capital stock we use the same deflator for all sectors.

Firm-level productivity is measured using two concepts: value-added per employee (LP) and total factor productivity (TFP). Since it is probable that profit-maximizing firms instantly adjust their input levels, each time they notice productivity shocks, productivity and input choices are likely to be correlated and TFP estimation involves problems. Thus, in line with several authors (e.g., Sharma and Mishra, 2009; Maggioni, 2009), TFP is estimated using the

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[3] Since 2004, INE has changed its methodology and works with the universe of Portuguese manufacturing firms but before 2004 the only data available is the one we use. INE ensures the representativity of the sample used.

[4] Unfortunately, we do not have other data types that would have been useful, such as: innovation performance, workforce composition, workforce educational level or data about affiliates of Portuguese multinationals.

[5] Our data includes 14 different sectoral types of traded products.

semi-parametric method of Levinsohn and Petrin (2003). This method recognizes the simultaneity bias as firms observe the productivity shocks but econometricians do not. Thus, we compute TFP as the residual of a Cobb-Douglas production function where: the firm value added is the independent variable; capital, labour and unobservable productivity level are the dependent ones. Besides, this method assumes that intermediate inputs have a monotonic positive relationship with productivity and thus could be used as proxies. Given data availability, we use intermediate inputs as the deflated values of "supplies and services from thirds" at book value. We estimate production function for every 2-digit sector separately.[6]

3. Post-entry effects

The empirical prove of LBE requires that new exporters experience large, stable productivity improvements, compared with similar firms serving only the domestic market. Hence, starters must present productivity advances at a faster rate than similar non exporters due to: (i) advantages of higher competition in foreign markets (ii) benefits of knowledge sharing from foreign contacts which further enhance efficiency and innovative performances.

If in modelling terms there are few attempts to formally describe LBE (e.g., Kostevc, 2009), in empirical terms several methodologies have been used: Granger causality tests, random effects estimation, FE model, non-parametric techniques and Matching techniques using Propensity Score Matching with Differences in Differences estimators (PSM-DID).

3.1. Post entry effects assessed by Fixed Effects model

The FE model (e.g.,McCann, 2009) does not allow perfect treatment for the endogeneity related with LBE, as firms self-select to export, and thus the analysis of post-entry effects may be biased. However, it is useful as a first test of post-entry effects. Assuming that "starter" is a firm that initiates exports at time *t* and keeps doing it for at least 2 years, and

[6] Details on the Levinshon and Petrin's methodology are shown in Maggioni (2009).

does not export neither at t-2 nor at t-1; additionally assuming that a "non-exporter" is a firm that does not export during the observed period, we performed the following regression:

$$\Delta TFP_{i,t+\delta} = \beta_0 + \beta_1 Starter_{i,t} + \beta_2 Controls_{i,t} + \varepsilon_{i,t} \tag{1}$$

t is the year in which firms decides whether to become an exporter or remain domestic. The dependent variable may be taken as an average TFP growth rate, computed from t-1. We have five different cohorts of average growth rates. *Controls* refers to a vector including: size, a dummy for firms that possess skilled workers only devoted to R&D, a dummy for firms that report a share of foreign capital, a dummy for different sectors (CAE) and a time dummy.

Table 1. Learning effects of entry to exports on TFP, using FE model

	t / t-1	t+1 / t-1	t+2 / t-1	t+3 / t-1	t+4 / t-1
tfp change (of all starters)	0.136^{*} (0.005)	0.033^{*} (0.019)	0.073^{*} (0.022)	0.005^{+} (0.023)	-0.012^{+} (0.030)
tfp change (of starters which do not import): NT – OE[(a)]	0.011^{**} (0.066)	-0.019^{+} (0.038)	0.085^{*} (0.035)	-0.017^{+} (0.036)	-0.047^{+} (0.042)
tfp change (of starters already importers):OI – TWT[(b)]	0.143^{*} (0.05)	0.060^{**} (0.030)	0.087^{**} (0.027)	0.021^{+} (0.029)	0.024^{+} (0.042)

Source: Own calculations. Notes: [(a)] NT means non-trader becoming OE which means only exporter; [(b)] becoming TWT which means two-way trader and OI means only importer. Robust standard errors appear below the coefficients' estimates in parenthesis. * and ** mean statistical significance at 10% and 5%, respectively; $^{+}$ means not statistically significant; Estimations obtained with Stata 10 software.

Table 1 clearly shows that beginning to export is associated with a significant increase in the TFP growth rate, at least for a period of three years after the entry into foreign markets occurs, suggesting the presence of LBE. These effects are stronger when starters were already importers (OI) and become two-way traders (TWT), signifying that LBE may be enhanced by imports. In the case of firms that change from non-traders (NT) to only exporters (OE), the LBE effects are weaker and appear to be inconstant.

3.2. Post entry effects assessed by matching methods

Introduction to the use of matching methods in LBE assessment

Given that we confirmed that Portuguese firms with best performances are more likely to be exporters (Silva et al., 2010a) then, matching methods applied to LBE – pioneered by Wagner

(2002) for German firms and Girma et al. (2003) for UK – are regarded as a promising tool to cope with statistical problems stemming from endogenous decision to become exporter.

Ideally, the effects of becoming an exporter would be made by comparing the firms' performance, some years after they begin to export, with the performance, at the same time, if they never began to export. Under the impossibility of such scenario, matching methods aim to evaluate the Average Treatment effect on the Treated (ATT), which means in practice, we are considering the effects of a treatment model, where treatment is the export entry; however, we can only observe the outcome of exporters, provided that they had exported. Conceptually, we aim to measure the ATT, meaning the average effects of a "treatment"; i.e., the decision to start exporting on starters' performances, computing:

$$ATT = E\left[Y_{i,t}(1) - Y_{i,t}(0) \mid D_i = 1\right] = E\left[Y_{i,t}(1) \mid D_i = 1\right] - E\left[Y_{i,t}(0) \mid D_i = 1\right] \text{, where:} \qquad (2)$$

$Y_{i,t}(1)$ is the outcome of a firm *i* at *t* given it began exporting at a certain time; $Y_{i,t}(0)$ is the outcome of *i* at *t* given it did not begin exporting at the referred time; *D* is the decision made by *i* if it was starting to export (1) or not (0). In practise, we can only compute $E\left[Y_{i,t}(0) \mid D_i = 0\right]$[7] and the solution is to replace the unobservable $E\left[Y_{i,t}(0) \mid D_i = 1\right]$ by the observable $E\left[Y_{i,t}(0) \mid D_i = 0\right]$; i.e., we use $E\left[Y_{i,t}(0) \mid D_i = 1\right] - E\left[Y_{i,t}(0) \mid D_i = 0\right]$ thus originating a selection bias in ATT computation.

Matching techniques consider possible to select a suitable control group of firms, from non-starters, that will be used as counterfactuals for starters. Firstly, it would be crucial to select firms with the most identical features to the treated group; i.e., the control group should have *n*-1 (out of *n*) similar features to the starters group and differ only in the n^{th} feature, which would be their decision to export in that year. The reason of matching is thus to pair

[7] That is, the outcome for non-exporters provided that they have not exported, but we are unable to calculate the outcome of exporters if they had not started to export $E\left[Y_{i,t}(0) \mid D_i = 1\right]$

each new exporting firm, in each year – on the basis of some observable variables, named as covariates – with a larger control group of similar firms that stay non-exporters until that year.

Given the variety of observable variables that can be used to pair starters with non-starters (e.g., productivity, size, ownership, capital or sector), a problem of dimension of treatable variables arises. In line with Rosenbaum and Rubin (1983), this problem is solved by computing an average index: the "propensity score". Using this index from a large group of non-treated firms we can find the ones the most similar to starters in the pre-treatment period.

Two main conditions should be observed to adequately use matching methods: the conditional independence assumption (CIA) and the common support assumption (CSA). The former assumes that the covariables on which we match cannot be affected by the treatment, either ex-post or in anticipation of the treatment: if exports adjust their features in anticipation of the opening to export activity, then we would end up matching on endogenous variables.

The CSA assures that, relying on the chosen covariates, the potential outcome in the non-treatment case is independent of the treatment status. It is enough to assure "mean conditional independence" between the control group and the treatment (e.g., Heckman et al., 1998).[8] Besides, the CSA prevents the group of covariates from becoming a perfect predictor of the decision of a firm to begin exporting. Thus, we restrict matching to firms in "common support", meaning that we only "work" with firms where the propensity score belongs to the intersection of the supports of the propensity score of treated and controls (e.g., Becker and Ichino, 2002). Hence, we drop treated units that have a propensity score higher (lesser) than the maximum (minimum) propensity score of the controls.

The selection of Treated firms and Control firms

If we had chosen common exporters as the treatment group, it would not provide us with the needed dynamics, as the effects of starting to export may have dissipated some time before.

[8] We omit the study of other moments of the conditional-distribution probability between starters and controls.

Thus, treated units must be export starters in a certain year and controls must be firms that do not export in that year. There are however several criteria to identify and select each group. Eliasson et al. (2009, p. 19) describe the difficulties involved: “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)”.

The definition of treated and control firms may affect the computation of ATT and thus the LBE assessment. Defining starters as only “successful” new exporters (instead of all new exporters) and controls as never-exporters in the period (instead of firms that do not begin exporting in that year), we will probably generate a bias favouring LBE. Thus, it would be prudent to use as controls, in each year, all firm not-yet-entrants, despite the options they assume in the future (e.g., Eliasson et al., 2009). Overall, it must be recognized that the composition of the treatment and comparison group affects future results as it produces samples that are selective in terms of the outcome of our interest. To analyse more deeply the implications of such options we decided to consider a triple taxonomy of starters and controls.

For starters, we have used three concepts: (i) the more restricted assumes that starter is a firm that exports in t, but not in t-1, t-2 and t-3; (ii) the intermediate assumes that starter is a firm that exports in t, but not in either t-1 or t-2; (iii) the flexible assumes that a starter is a firm that exports in t, but not in t-1. For controls, we also tested three concepts: (i) the more restricted assumes that control is a firm that does not export in t, t-1, t-2 and t-3; (ii) the intermediate assumes that control is a firm that does not export in t, t-1 and t-2; (iii) the flexible assumes that control is a firm that does not export in t and t-1. We also require that both groups of firms are observed at least for one year, after the treatment begins.

In the next sections we adopt the more flexible concept of starter,[9] and of control; this option derives from the interest in using the widest sample possible. Considering other concepts of starters and controls, our main conclusions are not affected (Silva et al., 2010b).

3.3. Estimating the propensity score matching

The selection of covariates

The first step to apply PSM consists of estimating the propensity score. The chosen covariates to identify the probability of a firm beginning to export were:[10] TFP, Unit Labour Cost (ULC) of sales, size measured by employees, a dummy (Dsmall) controlling for small firms (with less than 50 employees), capital stock, investment, wages, sales, and dummies indicating if the firm has R&D workers (Skill), if the firm has a foreign share of capital (Forcap), if the firm imports (Imp), if the firm imports machines (ImpMac) and also sectoral dummies.[11] Such lagged variables seem to affect export entry decision and the outcomes of starters and controls.

Regarding the regression, the choice of the functional form seems to be robust since the binary treatment with logit and probit regressions yields similar results.

$$\begin{aligned} Pr(Start_{i,t}=1) = f(&TFP_{t-j}; N_{t-j}; Small_{t-j}; K_{t-j}; Invest_{t-j}; Wages_{t-j}; Sales_{t-j}; UCL_{t-j};\\ &Skill_{t-j}; Im\,p_{t-j}; Im\,pMac_{t-j}; Forcap_{t-j}; Other\ control\ Variables_{t-j}) \end{aligned} \tag{3}$$

To free up the functional form of the propensity score we also included higher order polynomials and interaction terms. In search for the proper specification of the probit model, we also tested the effect of other variables: level of profits, liquidity restrictions of firms (measured, at the end of each year, by firms' available cash balances and by firms' banking credit balances), weight of debt for each firm (measured by the ratio of banking debt to capital stock at the end of each year) and a dummy controlling for raw-materials imports. These variables were excluded as they harmed the quality of matching and the balancing tests that

[9] Using this definition of starter, on average for 1997-2002, 5% of the exporters are new entrants in each year.

[10] In line with several studies on determinants of firms' selection to exporting (e.g., Silva et al., 2010a).

[11] The detail of these dummies depends on the type of data used; if using data for each cohort we used five digits sectoral codes but when performing pooled data we used two digit sectoral codes.

are performed to ensure that the chosen specification balances the pre-treatment covariates between the treatment and the control group, conditional on the estimated propensity score.

Results of the ensuing matching performed on pre-treatment variables at *t*-3, *t*-2 and *t*-1 were similar. The risk of matching on the endogenous variable is very low as many starters' pre-treatment features at *t*-3 closely resemble those at *t*-1. Thus, to benefit from a larger sample we present results from matching on covariates at *t*-1. The chosen probit specification respects the balancing test (e.g., Rosenbaum and Rubin, 1983; Becker and Ichino, 2002).

Performing Propensity Score Matching (PSM)

The second phase consists of matching starters (treated firms) with controls (non-treated firms) by using the estimated propensity scores. There are several algorithms, which differ due to the different weighting regimes to assess the importance of each control for each treated firm. We tested two of those weighting schemes: kernel matching and nearest neighbour matching. Given their properties on variance, presented results are based on the Epanechnikov kernel.[12]

A crucial decision has to be made when performing the matching; to do it (i) separately in each year and for each sector (CAE) or (ii) pooling all time cohorts and all sectors. We performed both ways but when performing a pooled PSM we found that control-matches belong to same year and sector of starters only in 25% of all cases. The option of such pooled PSM could have potential drawbacks as the marginal effects of various variables on the probability to start exporting may differ greatly between different sectors and periods (e.g., De Loecker, 2007). This could be due to different technological and market conditions the firms face. This means that, conceptually, the separate estimation of the probability to start exporting for each sector and each year is a better procedure. On the other hand, given the narrowness of our database the use of a pooled PSM is of some interest.

[12] We use a 0.001 bandwith. Results are little sensible on the weighting regime used or on the bandwith interval.

Then, aware of the importance of both keeping an ample dimension of our database and of the advantages of estimating the PSM cohort by cohort,[13] we executed, as an intermediate solution, a data segmentation based on five group classification of sectors according to the technological sophistication, in line with Pavitt (1984) – e.g., Silva et al (2010b).

Hence, we estimated the PSM in two ways: (i) for each year and for each group of five sectors and (ii) by pooling all cohorts (years and sectors). By using (i), we ensure that the matches come from both the same year and the sector, but we cannot produce a LBE analysis for the period 1996-2003 and for the whole sector. By using the pooled PSM in (ii) we can exploit the information contained in the largest dataset and overcome the eventual loss of efficiency of (i), since the starters in every cohort is sometimes relatively low. However, when using (ii) we may obtain estimations of lower quality since the ideal matches are not ensured.[14] Thus, applying the matching to the pooled sample, additional precaution is needed and some compensatory "measures" must be taken, for example by using relative variables.

We also used another PSM performance where the propensity scores are initially obtained from each separate year and sector and then keeping those propensity scores and their corresponding weights, we perform the matching by pooling all cohorts of sectors and years but ensuring that matches come from the same year and sector of each starter. To distinguish the PSM applied to the two pooled datasets, we will name the latter as the "fine pooled PSM" and the former as the "general raw pooled PSM".

To sum up, we applied PSM to four samples: (i) we perform PSM for each cohort of different year and sector and then we implement matching on the pooled sample using three complementary ways: (ii.a) by pooling together the treated and matched control firms of different years and of different sectors – the general raw pooled PSM; (ii.b) by adding to the

[13] Now, meaning separately for each year cohort and also for each sector.

[14] There is no reason to believe that the same specification of the propensity score will balance the covariates in all samples (e.g., Serti and Tomasi, 2008; Dehejia and Wahba, 2002).

general raw pooled PSM the use of relative variables, computed as deviations from sector-year means, instead of absolute variable levels; (ii.c) by pooling together treated and matched controls but making sure to perform PSM on firms of the same year and sector (fine pooled PSM) using the methodology described. In all pooled samples we ensure that starters that repeat their status during the time span are only accounted for the first time they are starters (e.g., appendix B in Silva et al., 2010b).

3.4. Assessing matching quality

The basic assumption to evaluate matching quality is to compare the average level of the covariates before and after matching and look for differences between treated and control units. If there are differences for the matched sample, the matching was not fully successful.

To test our matching we implemented a balancing test proposed by Becker and Ichino (2002) and a standard *T*-test for equality of means. In the former test, we split the sample into intervals so that the average propensity score for the treated and the control does not differ in each interval. Then, within each interval, we checked that the means of each feature do not differ between treated and control units. We made sure that the balancing property is satisfied for every specification of the propensity score. Regarding the second test, we computed the *T*-test for the mean values at *t*-1.[15] Results in Table 2 make us confident that we have identified the appropriate matched control group.

Table 2. Assessing matching quality – comparison between treated and control at *t*-1

Unmatched sample

	TFP	Employees	Capital	Invest.	Wages	Pscore	Skill	Forcap	Imports Machine	All imports
Treated	1.052	102.7	6.062	0.645	10.489	0.256	0.072	0.059	0.355	7.90
Control	0.959	69.0	3.800	0.355	10.182	0.195	0.043	0.023	0.199	4.90
T-test	3.44	8.42	4.63	5.92	1.10	15.03	2.81	4.95	8.93	2.02

Matched sample

	TFP	Employees	Capital	Invest.	Wages	Pscore	Skill	Forcap	Imports	All

[15] Similar results are available for *t*-2., in Table 4b of Silva et al. (2010b). We have also assessed the matching quality for the other concepts of starters and controls (Appendix C1 and C2 of Silva et al. 2010b).

									Machine	imports
Treated	1.033	95.1	4,98	0.557	10.482	0.251	0.069	0.055	0.349	7.90
Control	1.050	92.3	5,08	0.554	10.601	0.247	0.067	0.051	0.343	7.01
T-test	-0.50	0.48	-0.31	0.05	-0.55	0.49	0.04	0.41	0.19	0.41

Source: Own calculations.

3.5. Propensity Score Matching with Differences in Differences estimator.

In spite of all precautions when performing PSM, the self-selection bias may still exist, due to the bias coming from unobservables. In fact, if there are unobservable variables affecting both "assignment" into exporting and the outcome variable simultaneously, a hidden-bias arises.

A method to deal with time-invariant unobservable bias is to add a differences-in-differences (DID) estimator to PSM; According to Blundell and Costa Dias (2000) this approach can improve the quality of non-experimental evaluation. Using DID,[16] we compare differences in outcomes before and after the treatment (i.e., export entry) for the treated group, starters, to the same differences computed for the untreated group, controls. From the previous assumptions, without the treatment, the differences across groups should not exist.

To finally evaluate the impact of exporting on new exporters' performances (ATT), we performed the PSM-DID estimator applying it to the database built on the more flexible concept of starters and controls, and at every period after the entry into the export markets with respect to the year prior to entry (t-1). The implemented estimator could be written as:

$$M^{PSM-DID} = \frac{1}{n_i}\sum_{D_i=1}\left[\left(Y_{i,Post}-Y_{i,pre}\right)-\sum_{D_j=0} w_{i,j}\left(Y_{j,Post}-Y_{j,pre}\right)\right] \qquad (4)$$

In (4), Y is the required outcome (in logarithms, *ln*, instead of absolute values to obtain differences in growth rates between starters and non-starters); *Post* and *pre* denote that the variable is at post-entry and pre-entry period; D_i=1 (D_j=0) denotes the group of starters (non-starters) in the region of common support; n_i is the number of treated units on the common support; $w_{i,j}$ is the weight of the j^{th} observation of controls in constructing the counterfactual to

[16] According to Heckman et al. (1997), the difference-in-difference (DID) matching estimator removes the effects of common shocks on treated and controls, providing a more accurate description of the exporting effect.

the i^{th} treated firm. When using nearest neighbour algorithm each treated firms is matched with a single control but using kernel means all controls, in the common support region, are weighted for matching each treated firm. We considered a maximum of six years after the starting year and thus we calculated ATT effects from *t* to *t*+6.

By using *ln*, values in Table 3 are percentual point differences in growth rates between starters and controls, for variables and observed cumulatively from *t*-1 to the end of that year. Standard errors are obtained by bootstrapping[17] the entire estimation framework, including the propensity-score computation stage. The PSM-DID was applied to the sample obtained by pooling all cohorts without special care for matches coming from sectors and years (general raw pooled PSM-DID). From Table 3, the effect of exports on TFP (and on LP) is positive and statistically significant since one year after export entry up to four years later. Results are in line with those obtained by the FE model and similar results arise using nearest neighbour algorithm (results are not reported for reasons of brevity.); LBE effects seem robust.

Table 3. ATT effects: PSM-DID estimations (raw version)

	t / *t*-1	*t*+1 / *t*-1	*t*+2 / *t*-1	*t*+3 / *t*-1	*t*+4 / *t*-1	*t*+5 / *t*-1	*t*+6 / *t*-1
TFP	0.008^{+}	0.026^{*}	0.045^{*}	0.039^{*}	0.059^{**}	-0.002^{+}	-0.071^{+}
	(0.018)	(0.013)	(0.025)	(0.027)	(0.027)	(0.044)	(0.067)
LP	0.003^{+}	0.036	0.029^{+}	0.038^{*}	-0.019^{+}	-0.039^{+}	-0.070^{+}
	(0.027)	(0.018)	(0.024)	(0.022)	(0.045)	(0.042)	(0.071)
Capital	0.009^{+}	0.058	0.048	0.358	0.064^{**}	0.009^{+}	-0.027^{+}
	(0.01)	(0.011)	(0.016)	(0.001)	(0.026)	(0.04)	(0.077)
Employees	0.006^{+}	0.028	0.052	0.035^{**}	0.046^{**}	0.071^{**}	-0.027^{+}
	(0.008)	(0.011)	(0.016)	(0.020)	(0.026)	(0.040)	(0.067)
Investment	0.014^{+}	0.081^{+}	-0.016^{+}	0.016^{+}	0.018^{+}	0.014^{+}	0.001^{+}
	(0.057)	(0.067)	(0.085)	(0.091)	(0.011)	(0.17)	(0.26)
Sales	0.022^{**}	0.032^{**}	0.053	0.054^{**}	0.076^{**}	0.017^{+}	-0.077^{+}
	(0.013)	(0.011)	(0.020)	(0.022)	(0.031)	(0.052)	(0.093)
Wages	0.001^{+}	-0.004^{+}	-0.014^{+}	0.002^{+}	0.007^{+}	-0.032^{+}	-0.034^{+}
	(0.012)	(0.072)	(0.013)	(0.011)	(0.023)	(0.026)	(0.045)
ULC	-0.015^{*}	-0.017^{*}	-0.014^{+}	-0.016^{+}	-0.022^{+}	0.021^{+}	0.016^{+}
	(0.011)	(0.012)	(0.022)	(0.024)	(0.026)	(0.037)	(0.042)
CI	0.004^{+}	0.022^{*}	0.041	0.275	0.018^{+}	-0.061^{+}	-0.002^{+}
	(0.011)	(0.012)	(0.013)	(0.012)	(0.032)	(0.048)	(0.076)
Earnings after taxes	-0.055^{*}	-0.071^{**}	-0.162^{**}	0.125	0.271	0.217^{*}	0.021^{+}

[17] The use of bootstrapping is justified as an improvement of the accuracy of standard errors computed by module *psmatch*2; in performing bootstrapping, we used 200 replications.

	(0.023)	(0.042)	(0.073)	(0.041)	(0.058)	(0.131)	(0.023)
R&D personnel [(a)]	-0.173^{+} (0.191)	0.078^{+} (0.271)	0.354^{**} (0.211)	0.423^{**} (0.242)	-	-	-
Number Treated	725	723	489	381	281	181	111
Number Controls	2,751	2,747	1,822	1,298	869	509	233

Source: Own calculations. Notes: We report bootstrapped standard errors (200 replications), the number of treated on the common support and the number of matched controls. If nothing mentioned coefficients are significant at 1%.**: mean significant at least at 5%. * means coefficients are significant at least at 10%. $^{+}$ means coefficients are not significant. [(a)]: PSM-DID for the quote in total employees of those designated exclusively to R&D activities.

The positive effects of exporting seem to spread to other variables such as capital, employees and sales, while wages do not present different growth rates between starters and non-starters. Starters also appear to become even more capital intensive than non-starters, mainly three and four years after the beginning of export. Moreover, starters do not present a higher growth of investment, which could be explained by the larger investment waves that they performed some years before internationalization. In addition, starters present, from two years after start to export, a notably higher growth rate of R&D employees (R&D personnel), indicating for those firms a superior attention to innovation activities; this, in turn, helps them to deal with the more competitive environment faced in foreign markets. Regarding profits (earning after taxes), in the first three years after exporting, starters perform worse than non-starters but then the growth rate of earnings for starters is much more higher which suggests that only after some time exporters are compensated for their option of internationalization.

Robustness of PSM-DID to different pooling methods

We performed a similar procedure for PSM-DID but using, as the base year for computing the LBE effects, two years before starting to export (instead of one year); general conclusions still hold, proving the robustness of our findings (for a details see Silva et al., 2010b, appendix D). Besides, previously we applied PSM-DID in a broad criteria, pooling all treated and controls across sectors and years. To overcome the limitations of this procedure, we computed ATT (LBE effects) using relative (instead of absolute) values; i.e., now variables are expressed as a deviation from their respective sector-year mean, to consider sectoral and time specificities.

Results (in Table 4), about LP and TFP, are quite similar to the previous ones, showing that applying PSM-DID estimators to general raw pooled sample is an acceptable procedure.

Additionally, we also estimated ATT effects ensuring firms strictly match with controls solely of the same year and sector. Thus, we performed thirty different PSM, using nearest neighbour algorithm and controlling for common support, for each of those 30 cohorts;[18] we saved the propensity scores and the weights, in each separate PSM, of the treated and controls; we eliminated all treated and controls that were out of the common support region and we also ignore all controls that were not used as matches in each separate PSM; we pooled all the remaining firms (treated and controls that were matched) and computed the ATT. Results in Table 5 are in line with the previously obtained with the raw pooled PSM.

Table 4. ATT effects: PSM-DID estimations using relative variables

	t / *t*-1	*t*+1 / *t*-1	*t*+2 / *t*-1	*t*+3 / *t*-1	*t*+4 / *t*-1	*t*+5 / *t*-1	*t*+6 / *t*-1
TFP	0.010^{+} (0.015)	0.026* (0.015)	0.052** (0.022)	0.044** (0.020)	0.055* (0.030)	0.021^{+} (0.015)	-
LP	0.013^{+} (0.015)	0.031* (0.015)	0.045* (0.022)	0.039* (0.021)	0.052* (0.031)	0.014^{+} (0.015)	-

<u>Source</u>: own calculations. <u>Notes</u>: See Table 3. Given data narrowness estimates for 6th year are impossible.

Table 5. ATT effects: PSM-DID "fine" estimations
(PSM performed cross-section by cross section and year by year)

	t / *t*-1	*t*+1 / *t*-1	*t*+2 / *t*-1	*t*+3 / *t*-1	*t*+4 / *t*-1	*t*+5 / *t*-1	*t*+6 / *t*-1
TFP	0.009^{+} (0.023)	0.077** (0.033)	0.031** (0.021)	0.045^{+} (0.043)	0.118* (0.056)	0.005^{+} (0.07)	-0.014^{+} (0.014)
LP	0.012^{+} (0.023)	0.072** (0.031)	0.025** (0.013)	0.035^{+} (0.042)	-0.037^{+} (0.07)	-0.045^{+} (0.067)	-0.061 (0.111)
Capital	0.003^{+} (0.023)	0.049 (0.019)	0.029^{+} (0.023)	0.572* (0.023)	0.024^{+} (0.023)	0.019^{+} (0.083)	-0.053^{+} (0.153)
Employees	-0.002^{+} (0.013)	0.040** (0.017)	0.056 (0.019)	0.028^{+} (0.023)	0.063* (0.023)	0.061^{+} (0.053)	-0.007^{+} (0.111)
CI	0.007^{+} (0.011)	0.008^{+} (0.021)	0.028* (0.013)	0.641 (0.013)	-0.047^{+} (0.043)	-0.042^{+} (0.053)	-0.047^{+} (0.131)
Sales	0.032** (0.016)	0.067 (0.025)	0.048* (0.028)	0.007^{+} (0.053)	0.107* (0.056)	0.016^{+} (0.088)	0.018^{+} (0.151)
Invest	-0.026^{+} (0.098)	0.031^{+} (0.017)	-0.129^{+} (0.146)	-0.119^{+} (0.221)	0.319* (0.019)	-0.057^{+} (0.311)	0.331^{+} (0.691)
Wages	0.008^{+} (0.008)	-0.017* (0.010)	-0.011^{+} (0.014)	-0.019* (0.091)	-0.025^{+} (0.020)	-0.057* (0.031)	-0.027^{+} (0.053)

[18] The 30 cohorts are the result of 6 years (1997 to 2002) multiplied by 5 groups of aggregated sectors.

ULC	-0.026* (0.015)	-0.043** (0.021)	-0.009+ (0.022)	-0.029+ (0.024)	-0.075** (0.037)	0.002+ (0.05)	-0.059+ (0.076)

Source: Own calculations. Notes: See Table 3. Number of firms: 944.

Therefore, we reconfirmed the LBE thesis for this sample of manufacturing Portuguese firms. Both LP and TFP growth of starters is higher than for non-starters, mainly two and three years after export starts. These results also mean that the general raw pooled database (Table 3) does not cause serious bias and in order to use the biggest possible sample of treated and control firm, we use henceforth the general raw pooling criteria.

Robustness of PSM-DID to firms' history

To test further the robustness of PSM implemented on the general raw pooled sample, we performed a PSM splitting treated and control firms along with the time span where they are observed, before and after the treatment year. Table 3 shows that the sample size drops when we focus on more distant periods from the export entry year, due to: some (the less successful) starters stop exports after some years; controls, starters or both exit the market; despite being in the market, controls or starters did not respond, in that year, to the INE query.

Assuming a time span of one year after export entry, to admit firms in our database, we cannot observe the whole history of firms after the export entry. This option enlarges our database but could bias results. Indeed, by imposing just a year of observation after export, we are ignoring that some starters quit after one year and so we could be biasing results against LBE, as we would be overweighting unsuccessful starters.

Following De Loecker (2007) and Maggioni (2009), to check on this possible sample selection effect, we recalculated the post-entry effects for different groups of firms according to the number of years we can observe firms after the export entry year (such years are not inevitably of exporting). Then, we studied LBE, splitting firms by years with complete data before exports start, thus adding firms' history to LBE assessment. Results show no substantial differences when compared with related cases in Table 3, indicating there is no systematic selection process of firms over time (See Silva et al., 2010b, for more details).

Robustness of PSM-DID to yearly computation

In line with De Loecker (2007) and Maggioni (2009), we could consider that in the entry year, firms reach a higher TFP path and then they stay on this efficiency level. If this is true, the annual growth rates would be higher for starters only in the entry period. To check this thesis we computed the ATT effects on yearly TFP growth rates, changing for each computation the year of comparison. Table 6 shows that starters present a higher annual TFP growth rate than non-treated only for the second complete year after export entry. Thus, we can argue that, even if exports have positive effects on firm performance and even if it lasts for some years following the export entry, it is not in the entry year that starters go on a higher TFP path.[19]

Table 6. ATT effects: PSM-DID estimations of yearly growth rates

	t / *t*-1	*t*+1 / t	*t*+2 / t+1	*t*+3 / t+2	*t*+4 / t+3	*t*+5 / t+4	*t*+6 / t+5
TFP	0.008^{+} (0.018)	0.017^{+} (0.015)	0.034^{**} (0.017)	0.019^{+} (0.019)	0.048^{**} (0.021)	0.044^{+} (0.031)	-0.005^{+} (0.067)

Source: Own calculations. Notes: See Table 3.

3.6. Learning channels and detailed Learning-by-Exporting analysis

The link between LBE and imports

As in other countries (e.g., Maggioni, 2009, for Turkey), empirical evidence on LBE reveals a close link between exports and imports: export starters often start importing in the same year; in our sample, about 40% of firms are simultaneously export and import starters (Table 7).

Table 7. Export and import starters

	1997	1998	1999	2000	2001	2002
Export starters	166	132	105	125	86	118
Import starters	253	236	179	203	178	194
Common starters	75	58	41	36	31	51

Source: Own calculations.

[19] Results are different from those found for Slovenian (De Loecker, 2007) and Turkish (Maggioni, 2009) firms.

We decided to perform a double test concerning the meaning of imports: (i) we tested if post-entry effects of exports are larger for firms start importing simultaneously with exporting; (ii) we checked for any difference in ATT effects between two groups: firms that change their international status from non-trader (NT), in the pre-entry year, to only exporters (OE); and firms that change from only importers (OI), in the pre-entry year, to two-way-traders (TWT). Concerning the first goal we split our database into two mutually exclusive groups:[20] (i) a group formed by common starters in each year, i.e., firms NT in *t*-1 that become TWT in *t*; (ii) group containing all export starters for each year, independently of being NT or OI before that moment.[21] Then, we applied the usual PSM-DID estimator to each group and checked the matching quality. Results, in Table 8, strongly suggest that imports enhance LBE effects.

Table 8. ATT effects: PSM-DID estimations on TFP controlling for import starters

	t / *t*-1	*t*+1 / *t*-1	*t*+2 / *t*-1	*t*+3 / *t*-1	*t*+4 / *t*-1	*t*+5 / *t*-1	*t*+6 / *t*-1
Import and export starters	0.116^{**} (0.022)	0.159^{**} (0.033)	0.215^{**} (0.069)	0.083^{*} (0.059)	0.109^{+} (0.092)	0.192^{+} (0.152)	-
Only export starters	-0.001^{+} (0.032)	0.014^{+} (0.034)	0.062^{+} (0.048)	0.063^{+} (0.051)	0.056^{+} (0.046)	0.048^{+} (0.049)	-0.097^{+} (0.089)

Source: Own calculations. Notes: See Table 3. Given the narrowness of each sub-sample it is impossible to compute both ATT for 6th year.

We also split the second group into two sub-groups: sub-group contains OI, i.e., firms that are also importers in the export starting year, independently of when those imports began, and sub-group composed by purely NT in the export starting year. Results, in Table 9, in line with McCann (2009) for Irish firms, suggest that LBE is faster for NT than for OI. In fact, NT benefit more rapidly from LBE while OI seem to benefit only after a certain time lag.

Table 9. ATT effects: PSM-DID estimations with different import status

	t / *t*-1	*t*+1 / *t*-1	*t*+2 / *t*-1	*t*+3 / *t*-1	*t*+4 / *t*-1	*t*+5 / *t*-1	*t*+6 / *t*-1
NT – OE	0.012^{+} (0.018)	0.032^{*} (0.021)	0.052^{*} (0.021)	0.023^{+} (0.037)	0.067^{*} (0.043)	0.029^{+} (0.071)	-0.021^{+} (0.121)
OI – TWT	-0.001^{+}	0.014^{+}	0.051^{+}	0.063^{*}	0.056^{+}	0.048^{*}	-0.097^{+}

[20] Given verifications performed we argue that the use of general raw pooled sample is acceptable from now on.

[21] This group includes all export starters in each year which do not import in that year, whether or not they have imported previously.

	(0.032)	(0.034)	(0.047)	(0.039)	(0.046)	(0.029)	(0.141)

Source: Own calculations. Notes: See Table 3.

From the previous analyses we can state that imports perform two complementary roles for LBE assessment. On the one hand, we must distinguish between pure LBE (which effects are not proved in Table 8) and learning-by-importing, LBI, effects (which effects are noticed in Table 8). These LBI effects could be obtained from imported goods, the preparation for imports and imports use. On the other hand, comparing the first and the second rows of Table 9, in which any LBI effects are excluded, we can argue that previous imports may act for new exporters as a catalyser to LBE in the sense that they extend the LBE effects in time.

The link between LBE and comparative advantage sectors

We also tested the thesis that the LBE relies on sectoral features that proxy for the differences between countries regarding the development of their productive systems. Greenaway and Kneller (2007) found that LBE was weaker in firms of sectors already exposed to trade and already with high R&D intensity. Other authors argue that the potential for LBE relied on the productivity gap between domestic and foreign productive systems (e.g., De Loecker, 2007).

We also admit such hypotheses and assume that there is a different scope for learning relying on productivity and technological gap between the home and export destinations' countries or sectors. This procedure would lead us to study both: the importance of efficiency differences between Portugal and market destinations of Portuguese exports; the technological gap between Portuguese and foreign sectors. In the first case, a uniform technological gap between countries is assumed, which affects all sectors with the same intensity; in the second case, the main objective is to take care of sectoral differences given that countries are likely to have comparative advantage (CA) and comparative disadvantage (CD) sectors.

In Portuguese CD sectors, Portuguese firms are likely to be less productive than foreign firms. Thus, we want to check if learning effects are stronger for new exporters in CD sectors, which could more likely be exposed to a more competitive environment than in their domestic context. To classify sectors, we assume that trade patterns reflect this status. Using the Balassa (1965) index of revealed CA and the sectoral classification produced by Amador et al. (2007), we assume that Portugal has a CA in sectors in which it is more specialized than the world average;[22] in these cases, this would imply a Balassa index higher than 1 (Appendix A).

Hence, we tested the argument that LBE is more effective in CD sectors. Thus, after the PSM-DID for the whole sample, we defined Post_CA a vector of dummy variables for the post-entry period for starters in CA sectors, and Post_CD a similar vector for the post-entry period for starters in CD sectors. Finally, we computed ATT effects running an OLS of:

$$\Delta TFP_{i,s} = \alpha + \beta_1 Post\_CA_{i,s} + \beta_2 post\_CD_{i,s} + \varepsilon_{i,s} \text{, where} \quad (5)$$

$\Delta TFP_{i,s}$ is the productivity growth between the post- and pre-entry (t-1) period. To correct for specific effects linked to CA or CD sectors, we use relative $TFP_{i,s}$ expressed as a deviation from the sector-year mean, to capture and correct for effects that are common to firms in the same sector. Results in Table 10 confirm our argument: in CD sectors, new exporters present significant effects of LBE since the first year of exporting and they increase their productivity substantially more than never exporters and somewhat more than starters in CA sectors. In a different argument, Maggioni (2009) in a study for Turkish manufacturing firms had remarked that firms belonging to CA sectors could immediately take advantage of the export activity when they enter foreign markets; our study does not prove that claim.

Table 10. PSM-DID estimations of TFP according to starters comparative advantage

	t / t-1	t+1 / t-1	t+2 / t-1	t+3 / t-1	t+4 / t-1	t+5 / t-1	t+6 / t-1
Starter in CA sectors	-0.006 (0.018)	0.030* (0.017)	0.034* (0.022)	0.034^{+} (0.031)	0.045^{+} (0.039)	-0.077^{+} (0.054)	0.016^{+} (0.091)
Starter in CD sectors	0.045* (0.031)	0.039* (0.027)	0.072* (0.049)	0.002^{+} (0.057)	0.024^{+} (0.063)	-0.035^{+} (0.083)	-0.162^{+} (0.191)

Source: Own calculations. Notes: See Table 3.

LBE at industry level

[22] The ideal index should be computed in a bilateral basis given that the CA is affected by bilateral trade policy.

Table 11 shows the differences on LBE effects depending on the sectors starters belong to. We notice that wearing apparel (CAE 18) and non-metallic products (CAE 26) show hints of negative effects on TFP from their new exporting activity. On the contrary, starters from leather, leather products (CAE 19) and electrical machinery (CAE 31) are the ones that present more obvious LBE positive effects. Some other sectors present only partial hints of LBE: textiles (CAE 18), wood (CAE 20) and metal products (CAE 28). Finally, for some sectors we do not obtain any evidence of LBE effects (e.g., machinery, CAE 29). However, considering the limitations of data for some sectors several computations were not possible.

Table 11. PSM-DID estimations of TFP according to CAE sectors

	t / *t*-1	*t*+1 / *t*-1	*t*+2 / *t*-1	*t*+3 / *t*-1	*t*+4 / *t*-1	*t*+5 / *t*-1	*t*+6 / *t*-1
CAE 15	0.060* (0.33)	0.031^{+} (0.047)	0.035^{+} (0.065)	0.013^{+} (0.061)	-0.039^{+} (0.081)	-0.092^{+} (0.131)	-0.351* (0.188)
CAE 17	-0.016^{+} (0.031)	-0.021^{+} (0.055)	0.043^{+} (0.064)	0.179* (0.102)	0.086^{+} (0.142)	-0.108^{+} (0.241)	-
CAE 18	0.044^{+} (0.045)	0.149^{+} (0.113)	0.046^{+} (0.211)	-0.188^{+} (0.312)	-0.131* (0.104)	-	-
CAE 19	0.015 (0.011)	0.542* (0.292)	0.095* (0.065)	-	-	-	-
CAE 20	-0.043^{+} (0.065)	0.113* (0.059)	-0.049^{+} (0.164)	-0.053^{+} (0.173)	-	-	-
CAE 26	-0.122^{+} (0.122)	-0.159* (0.093)	0.018^{+} (0.093)	-0.089^{+} (0.112)	0.049^{+} (0.163)	0.035^{+} (0.175)	-
CAE 28	0.011^{+} (0.038)	0.004^{+} (0.073)	-0.079^{+} (0.088)	-0.012^{+} (0.142)	0.339* (0.242)	0.094^{+} (0.231)	-
CAE 29	0.028^{+} (0.043)	-0.004^{+} (0.064)	0.027^{+} (0.074)	0.045^{+} (0.102)	0.044^{+} (0.123)	-0.141^{+} (0.195)	
CAE 31	0.002^{+} (0.091)	0.019^{+} (0.086)	0.141* (0.092)	0.137* (0.091)	-	-	-
CAE 36	0.037^{+} (0.082)	0.011* (0.061)	0.023^{+} (0.187)	-0.055^{+} (0.171)	-0.094^{+}		

Source: Own calculations. Notes: See Table 3;We only report cases with at least one year of significant ATT effect. Complete data is available at Table 15b in Silva et al. (2010b)

The link between LBE, foreign capital and R&D workforce

Since affiliates or subsidiaries of multinational firms are in a certain sense internationalized, it is not clear whether the LBE argument could be applied to such firms. They may have already benefited from knowledge flows of their international investors. Thus, we expect to be less room for learning effects in starters that share capital with foreign multinationals. Moreover, according to Helpman et al. (2004), the most productive firms choose to engage in foreign direct investment and most probably share their technology and expertise with their affiliates or subsidiaries. Since in our database there was a low share of starters that report to have foreign capital, we could not perform an appropriate PSM-DID for the sub-sample of such firms; thus, we decided to pool this group with the one composed by firms that report having workers assigned to R&D activities. Hence, we split our database into two mutually exclusive groups: (i) firms that, in the first year of exporting, report to have a share of foreign capital or a share of specialized workers; (ii) firms that do not report any of these two features. Then, we applied the usual PSM-DID estimator to each group and checked for the matching quality.

Results in Table 12 show that LBE effects in starters with foreign capital or skilled workers are limited to the year of entry while firms domestically owned and without a R&D workforce experience a persistent higher growth of efficiency compared with non-starters.

Table 12. ATT effects estimations according to starters foreign capital or skilled labour

	t / *t*-1	*t*+1 / *t*-1	*t*+2 / *t*-1	*t*+3 / *t*-1	*t*+4 / *t*-1	*t*+5 / *t*-1	*t*+6 / *t*-1
Starter with Skill or Forcap	0.174^{*} (0.098)	-0.044^{+} (0.065)	-0.054^{+} (0.054)	-0.033^{+} (0.087)	-	-	-
Starter without Skill or Forcap	0.016^{+} (0.023)	0.051^{*} (0.036)	0.082^{*} (0.053)	0.054^{+} (0.076)	0.122^{*} (0.087)	0.146^{+} (0.187)	-

Source: Own calculations. Notes: See Table 3. Given the low numbers of starters with foreign capital or specialized employees it is not possible to compute ATT effects for years *t*+4, *t*+5 and *t*+6.

The link between LBE and firms' characteristics: size, TFP and wage

We also tested the firms' size importance in explaining the LBE effects. Using the dummy covariate "small", equal to one for firms with less than 50 workers and zero otherwise, we split our database of starters and of controls into two mutually exclusive sub-groups. Then, we applied the usual PSM-DID estimator. Results (in Silva et al., 2010b, Table 17) reveal that, in contrast with "small" firms, "big" ones have significant LBE effects, suggesting firms may need a certain dimension to benefit from external learning – the so called absorptive capacity.

We also argue that starters with lower TFP levels can better benefit from LBE effects. To test this idea, we again split our database into two mutually exclusive groups: (i) firms with a TFP lower than the average level for all firms, in the year before export entry; (ii) firms with a TFP higher than the average level for all firms, in the year before export entry. Results (in Silva et al., 2010b, Table 19) show that starters with: lower TFP levels can benefit more rapidly from the LBE positive effects; higher TFP levels only benefit from LBE three years after starting to export but this positive effect lasts for two years.

Since wages may reflect the labour skill and firms' technological capacity, starters with lower wages may have a greater potential to benefit from the LBE effects due to the distance between their knowledge level and that of their trader partners. However, as lower wage firms more likely have lower absorptive capacity may not have the requirements for benefiting from LBE potential effects. Thus, we split our database into quartiles. Results (in Silva et al., 2010b, Table 20) show that starters with the lowest wage levels benefit immediately and during three successive years from positive LBE effects,[23] whereas starters with an initial higher wage level do not benefit from exports. Thus, wage levels seem to proxy correctly for firms' technological level and this also means that firms with low technological levels seem to learn when trading abroad with more developed knowledge environments.

The link between LBE and export intensity of starters

Following several studies (e.g., Castellani, 2002; Andersson and Lööf, 2009), one can argue that starters are able to overcome the sunk costs of entering foreign markets when they achieve a certain export-intensity threshold. Moreover, if we assume that higher-export intensity firms may have a higher degree of commitment to foreign operations and also a higher frequency of foreign sales, this would justify the existence of a more sophisticated structure and of a superior organisational capability.

[23] Following Table 10 analysis, we also uncover for firms of group 2 that no significant effect is observed in the wage level for such starters until the fifth year; then a decrease is observed.

These facts would explain the higher capacity for learning for more intensive exporters. Besides, low-export intensity firms may rely on occasional exports, without a clear exporting strategy that limits the option to profit from a higher productivity growth. In a study for Singapore, Chongvilaivan (2008) also stated that LBE success relies mainly on intensity of exports. Fernandes and Isgut (2007) for Colombian firms also noticed that the LBE effects were negligible for firms that only participate marginally in foreign markets.

In line with these studies, we tested the importance of export intensity (% of exports in turnover) in Portuguese new exporters. Now, we split our sample of starters in three mutually exclusive groups: (i) starters with an average export intensity inferior to 5%, in the starting year and in the next two years; (ii) starters that reach an average export intensity higher than 5% but always inferior to 35%, in that period; (iii) starters with an average export intensity higher than 35% in the three years span. We kept all controls for each group.

Table 13. ATT effects estimations of TFP according to starters export intensity

	t / *t*-1	*t*+1 / *t*-1	*t*+2 / *t*-1	*t*+3 / *t*-1	*t*+4 / *t*-1	*t*+5 / *t*-1	*t*+6 / *t*-1
High export intensity	0.016^{+} (0.041)	0.064^{*} (0.035)	0.109^{*} (0.062)	-0.075^{+} (0.065)	0.179^{*} (0.231)	0.111^{+} (0.121)	
Medium export intensity	0.065^{+} (0.100)	0.107^{+} (0.058)	0.085^{+} (0.141)	0.071^{+} (0.059)	0.152^{+} (0.241)	-	
Low export intensity	0.031^{+} (0.046)	0.040^{+} (0.040)	0.060^{+} (0.06)	0.056^{+} (0.053)	0.114^{*} (0.077)	0.063^{+} (0.111)	

Source: Own calculations. Notes: See Table 3. Given the narrowness of each subsample it is unfeasible to compute ATT for the 6th year after export entry.

Results in Table 13 seem to confirm previous hypotheses.[24] Starters with lower export intensity take more time to benefit from their exporting activity since positive and significant effects on their efficiency occur just four years after starting to export. In contrast, starters with high export intensity take advantage of their exports faster, in a longer period and with a higher level. Moreover, results of medium export intensity group suggest the relationship between export intensity and LBE is not a linear one, in line with Fryges and Wagner (2008).

[24] Given the fact that we do not control for export intensity after three years of entry the results for *t*+4 and *t*+5 must be read with particular caution.

The link between LBE and exports destinations

In line with De Loecker (2007), we analysed LBE according to exports' market destination. In this case, we split our database of starters into several groups, according to the countries they export to in the year of entry and in the next year,[25] and then we computed ATT separately for each cohort. Our division into groups comprised the following cases: (i) firms that export only to the European Union (EU); (ii) firms that export only to Portuguese Language countries (PL); (iii) firms that export only to other Developed countries outside the EU (ODev); (iv) firms that export only to non-developed countries (NDev); (v) firms that export only to EU+PL; (vi) firms that export only to EU+ODev; (vii) firms that export to more than one of the groups of countries mentioned before (Multiple). Bearing in mind the importance of Spain as our main trade partner, we were also able to study the LBE effects, in the first four years, for firms that only export to Spain. Moreover, since few observations existed for groups (v) and (vi), it was not possible to obtain estimates of ATT for those cases.

Table 14. ATT effects: PSM-DID (TFP) according to exports' destinations

	t / *t*-1	*t*+1 / *t*-1	*t*+2 / *t*-1	*t*+3 / *t*-1	*t*+4 / *t*-1	*t*+5 / *t*-1	*t*+6 / *t*-1
Firms that export to multiple destinations	-0.022^{+} (0.035)	0.053^{+} (0.051)	0.021^{+} (0.071)	0.117^{*} (0.075)	0.091^{+} (0.192)	0.091^{+} (0.221)	-
Firms that export only to EU	0.050^{*} (0.031)	0.152^{**} (0.061)	0.097^{*} (0.061)	0.122^{*} (0.021)	0.089^{+} (0.012)	0.055^{+} (0.042)	-
Firms that export only to Spain	0.003^{+} (0.012)	0.032^{+} (0.030)	-0.106^{+} (0.111)	0.064^{+} (0.108)	-	-	-
Firms that export only to PL	-0.022^{+} (0.059)	0.079^{*} (0.047)	0.064^{+} (0.050)	0.063^{+} (0.056)	0.141^{**} (0.067)	0.116^{+} (0.099)	0.098^{+} (0.261)
Firms that export only to NDev	-0.079^{+} (0.098)	-0.025^{+} (0.171)	-0.061^{+} (0.199)	-0.074^{+} (0.089)	0.007^{+} (0.081)	-0.147^{+} (0.126)	-
Firms that export only to ODev	-0.028^{+} (0.030)	0.036^{+} (0.171)	-0.111^{*} (0.061)	0.098^{*} (0.061)	0.188^{*} (0.121)	-	-

Source: Own calculations. Notes: see Table 3.

[25] For some starters (about 20% of the total) it was not possible to identify the group of countries to which they had exported in two years period, due to two different factors: firms that did not present a constant pattern of export destinations along the two years and the mismatch between the two main datasets used.

Results in Table 14 present some important features: (i) for firms that export exclusively to NDev markets we cannot confirm LBE effects; (ii) firms that export to the EU seem to obtain fast LBE; moreover, those effects last for 4 consecutive years; (iii) firms that export to PL seem to obtain positive LBE effects but not so consistently as for exports to EU; (iv) firms that export only to ODev countries only obtain positive LBE effects from the third and fourth complete years after beginning to export; (v) for firms that only export to Spain we cannot confirm the existence of positive LBE effects; (vi) firms that mix several types of destinations seem to get moderately positive LBE effects. Thus, these results show that LBE depends on the teaching potential of the exports destination markets and on the absorptive capacity of exporters to make suitable use of such benefits.[26]

The link between LBE and the specific year of entry (economic cycle)

Assuming that LBE effects may depend on the cycle of world trade and also on the economic cycle of the countries that buy Portuguese exports, we perform estimations of the ATT effects for TFP, splitting firms by their entry year in export markets.

Results of Table 15 show that LBE is present for every cohort of starters whatever the year they initiate exports; nevertheless, we noticed distinct LBE "strengths" across years. Although comparisons are difficult given the different time spans involved in each cohort of starters, we can observe strong LBE effects for starters in 1999 relative to other years. In order to uncover such fact, we performed a non-exhaustive study on the relative performances of each year starters. Results in Appendix B show that 1999 starters achieved the highest levels in factors that enhance LBE, namely: (i) import share; (ii) export intensity; (iii) weight of exports to EU and ODev; (iv) weight of Group 5 firms', with higher technological level.

Table 15. ATT effects: PSM-DID for TFP according to the entry year of starters

	t / *t*-1	*t*+1 / *t*-1	*t*+2 / *t*-1	*t*+3 / *t*-1	*t*+4 / *t*-1	*t*+5 / *t*-1	*t*+6 / *t*-1

[26] In this line it would be recommended a mixed study combining both export destination and firms´ level of initial TFP. Given the narrowness of our database such test was not possible.

1997	-0.008^{+} (0.026)	-0.015^{+} (0.035)	0.061* (0.033)	0.006^{+} (0.048)	0.047+ (0.061)	-0.041 (0.069)	-0.067^{+} (0.071)
1998	-0.008^{+} (0.033)	0.077** (0.047)	0.012^{+} (0.051)	0.047^{+} (0.064)	0.046^{+} (0.061)	0.094* (0.049)	-
1999	0.018^{+} (0.051)	0.012^{+} (0.041)	0.069* (0.047)	0.107* (0.057)	0.126* (0.081)	-	-
2000	0.062^{+} (0.071)	0.094* (0.052)	0.051^{+} (0.071)	0.061^{+} (0.053)	-	-	-
2001	-0.011^{+} (0.049)	0.039^{+} (0.054)	0.082* (0.056)	-	-	-	-
2002	0.008 (0.071)	0.023 (0.017)	-	-	-	-	-

Source: Own calculations. Notes: See Table 3.

4. Concluding remarks

In this first study on Learning-by-Exporting effects in Portuguese firms, for 1996-2003 period, we observe that export starters present, relative to non-starters, a higher growth rate in some crucial variables, after exports begin. This conclusion is robust to the use of a FE model or a PSM-DID estimator. PSM-DID estimations were subject to several robustness checks: we tested the LBE effects using three different concepts of export starters and export controls, and, in addition, we used complementary methodologies to assure that when pooling several cohorts of sectoral groups and years the quality of the PSM was not compromised.

We found that new exporters present (in relation to non-starters) a higher growth rate on the majority of performance variables: efficiency, turnover, employees and capital intensity. Sales seem to be the only variable that presents immediate higher growth rate, while the others take some time to display that superiority. Moreover, it seems that exports do not place Portuguese starters on a higher productivity path from the entry year but only after a two year period. Results also confirm a strict linkage between export and import entry as strongest LBE effects are obtained by firms that also start importing at the same time.

The "heterogeneity" analysis allowed us to understand that the "treatment effects" are not homogeneous, but rather that they vary with firms' features (size, sector, future export intensity, foreign-capital share, specialized-workers share, initial wage and productivity levels, destination of exports and comparative-advantage level). In fact, we shed some light on the LBE channels; new exporters in comparative disadvantage sectors benefit more from export participation, which could support the thesis that competition and technology spillovers are significant channels through which exports may affect productivity. We also found that LBE effects are not noticed for firms that export only to Non-Developed countries; it seems to exist a hierarchy of LBE effects as Portuguese firms move their exports to countries of high development levels or as they obtain superior export intensity.

In future research it would be important to clarify some issues. In line with Fryges and Wagner (2008), it would be interesting to apply the generalised propensity score methodology (which allows for continuous treatment of different export intensity) for Portuguese firms to test if LBE is (or not) a linear relationship. By joining our data to data on innovative performance of firms, it would be possible to test the links between LBE and firms' innovation ability. A final question arises: is LBE the result of active learning that firms perform accordingly to their learning capacities or does the very fact of being in international markets generate passive learning that always occurs in those competitive environments even if the firm is unable to enhance it? Can we find merit on firms that achieve LBE?

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APPENDIX A. Relative specialization of Portuguese exports (1995-2004);

Balassa Index for Portuguese industries (average for 1995-1999 and 2000-2004)

Sector code	Sector Description	Balassa index	Technological level
15, 16	Food, beverages and Tobacco	1.0	Low
17, 18, 19	Textiles, wearing apparel and leather	3.4	Low
20, 21, 22, 36	Wood, pulp and paper; printing; furniture	2.2	Low
24	Chemicals	0.5	Medium
25	Rubber, plastic	0.9	Medium
26	Non-metalic mineral product	2.6	Medium
27	Basic metals	0.3	Medium
28	Fabricated metal products	1.1	Medium
29	Machinery	1.3	Medium-High
30	Office machinery and computers	0.3	High
31	Electrical machinery	1.3	Medium-High
32	TV and communication equipment	0.6	High
33	Medical, precision and optical instruments	0.3	High
34	Motor vehicles	1.3	Medium-High

35	Other transport equipment	0.7	Medium-High
37	Recycling	0.8	Low

Source: Adapted from Amador et al. (2007).

APPENDIX B. Comparative level of Starters in each year

	Weight of firms of Group 5	Export intensity	Weight of EU+Dev export destination	Import share	Initial average TFP level	Initial size (number of employees)
1997	65	93	81	58	79	94
1998	91	94	90	93	85	91
1999	100	100	100	100	90	84
2000	97	60	91	96	89	85
2001	79	76	90	93	83	100
2002	85	83	100	95	100	92

Source: Own calculations.
Note: In each column, values in percentage relative to the year of highest performance (100).