Learning by exporting: which channels? An empirical analysis for Turkey

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Very very preliminary and incomplete. Not for quotation and circulation

Abstract

Using a rich longitudinal database at the plant level, this paper tries to shed light on the causal nexus between exports and productivity for Turkey, a middle-income country. We find evidence for both self-selection into exporting and learning-by-exporting. Our main focus is on post-entry effects. To test this hypothesis we follow recent empirical literature and we apply the Propensity score matching approach and a difference-in-difference estimator. We find an higher labour productivity and TFP growth for exporting firms in the entry year and some years following the entry. Exports seem to place firms on a superior productivity path. Empirical evidence shows a strict linkage between export and import activity: export starters often start also importing. Focusing on this firm group, we verify larger productivity gains for firms which start exporting and importing at the same time. Finally, we try to investigate the potential channels of learning-by-exporting. Post-entry effects could be more important in sectors where the productivity gap between domestic market and foreign countries is larger. The finding of heterogeneous effects, according to sectoral comparative advantage, could confirm the theoretical hypothesis that exporting effects are not only scale effects but they works also through competition channel and/or technology transfers.

Keywords: Exports, Self selection, Learning-by-exporting, Matching
JEL codes: F14, D24

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1 Motivation and previous literature

Economists have always been interested in the nexus between trade and economic growth. Traditionally, the research on the growth effects of trade has been conducted at a macro level (country or industry level). The recent availability of firm and plant level dataset and the following proliferation of firm-level analysis has shown new stylized facts, especially the co-existence in the same sector of firms with heterogeneous characteristics, and has renewed the interest for the link between exports and efficiency/productivity at a micro level.

Theoretical and empirical literature has verified, both for developed and developing countries, a superior performance of firms involved in international markets (Bernard and Jensen, 1999; Bernard et al., 2003; Clerides et al., 1998; Pavcnik, 2002). Since the finding of this evidence, a large number of studies have investigated, in more detail, the causal relationship between exports and firm productivity. Two main hypothesis have been suggested. There exist additional costs of selling goods in foreign markets: transportation costs, distribution or marketing costs, and costs in adapting domestic products to foreign consumers tastes. These costs represent an entry barrier and we may expect more productive firms to self-select into export markets because they are more likely to cope with these sunk costs of entry and survive in the international market. This is the first hypothesis suggested: differences between exporters and non-exporters may be explained by an ex ante productivity gap between firms. The self-selection mechanism has also been sustained by new heterogeneous firm models (Melitz, 2003; Bernard et al., 2003) that hypothesize the differential of productivity between firms pre-exists (it is an exogenous fact).

The second hypothesis behind the positive correlation between firm trade and efficiency concerns the role of learning-by-exporting. The learning potential of firm export participation has not been theoretically examined, neither by new theoretical models based on heterogeneity hypotesis. Anyway previous (empirical) literature has suggested three main channels through which ex-

ports may increase firm's productivity: technology adoption, the exploitation of scale economies and an higher competitive pressure[1].
Recently some scholars have also suggested the hypothesis of a conscious self-selection (Alvarez and Lopez, 2005): firms in the pre-exporting time prepare themselves in order to get ready for the entry in the export market. The behaviour of firms might be forward-looking. Anyway, even if firms accomplish some changes in preparation to export entry, a potential for learning (following export entry) is always allowed.
While there is large consensus on self-selection hypothesis (for example, Bernard and Jensen, 1999; Clerides et al., 1998; Aw et al., 2000; Delgado et al. 2002), there is little empirical evidence supporting learning-by-exporting, results are often controversial and also channels through which learning could display are not clear[2]. Wagner (2007a) review 54 micro-econometric studies with data from 34 countries, confirming that exporters are more productive than non-exporters, and the more efficient firms self-select into export markets. Post-entry effects are usually negligible or lacking, and learning-by exporting hypothesis fails for developed and competitive countries (see for example Wagner, 2007b, who analyses West German plants). In high-income countries firms are already on the technological frontier, they are operating in an efficient and competitive context, they are using advanced technology, and they are in an environment not constrained. There could be no great learning effects in a such framework. In opposite, in a developing country, firms could take advantage of export activity through technology transfers and contacts with more efficient foreign firms, especially if they enter a developed and competitive foreign market. Kraay (1999) for China, Blalock and Jertler (2004) for Indonesia, Van Biesebroeck (2003) for Cote d'Ivoire,

[1]First, exporting firms may increase their knowledge through the access to new production techniques, new technologies or new management methods. In addition, firms entering the export market can take advantage of economies of scale, as exporting increases the relevant market size. Finally it could also be at work a competition effect: the more competitive international context could force exporters to become more efficient and could also stimulate innovation.

[2]When studies verify the existence of some learning effects, they usually don't investigate the channels of these efficiency improvements.

Fernandes and Isgut (2007) for Colombia and De Loecker (2007) for Slovenia find some positive productivity effects stemming from export entry[3].

We join this debate and present empirical evidence on the relationship between export and firm performance for Turkey in the period 1990-2001. Turkey is an interesting country to analyse because it is a middle-low income country which underwent, during the '80s, a process of trade openness[4]. It has important trade flows with developed countries, especially more than 80% of its exports are directed to OECD countries, and this feature makes Turkey a context where learning-by-exporting effects could display. We study both directions of causality between export and productivity, even if we focus especially on the learning-by-exporting hypothesis that has also policy implications for export promotion[5].

Previous empirical evidence for Turkey on this topic is based mainly on two studies. Yasar and Rejesus (2005) [6], applying propensity score matching (PSM) techniques and difference-in-difference (DID) estimators, show that learning-by-exporting may be the reason for the positive correlation between exporting status and firm performance. They find a productivity differential in the entry year and two years after entry[7], but their analysis concern only a small sample of sectors. Aldan and Gunay (2008), using a different database (from Central Bank of the Republic of Turkey) and same econometric approach (PSM and DID estimator), show that both self-selection and learning-by-exporting are important. Their analysis supports positive post-entry effects on firm labor productivity and employment. With this pa-

[3]Castellani (2002) and Serti and Tomasi (2008) have recently found a potential for learning by exporting for Italy. Even if Italy is a developed country, it is not on the technological frontier, its productive system is less competitive than other European countries (their main trade partners) and there could be some scope for positive effects from export activity.

[4]During the '80s it started to implement export-promotion policies after abandoning the import substitution regime.

[5]From a policy standpoint, the motivation of export subsidies, granted by many governments, should be learning and efficiency effects running through export.

[6]They use data, like our dataset, from Turkstat but they analyse a smaller sample (three four-digit sectors) for a restricted period 1990-1996.

[7]Yasar and Rejesus (2005) examine effects of both the entrance and exit behavior of plants.

per we confirm previous findings extending the analysis, compared to Yasar and Rejesus, to a large dataset, including all manufacturing sectors, and a wider time horizon. In opposite to Aldan and Gunay who analyse labour productivity, we focus on TFP and we also investigate other important firm characteristics[8]. Our original contribution is to show the link between the export entry and import activity, two forms of international involvement that we find strictly related. We also try to add some evidence on the channels of learning-by-exporting, looking for heterogeneity in post-entry effects according to the type of sector. Previous papers usually don't pay attention on the reasons and motivations behind post-entry effects. The only two exceptions are Fernandes and Isgut (2007) and De Loecker (2007) who verify a significant and larger positive advantage of participation in export market for plants selling a great share of their exports to high-income countries. This evidence sheds some light on the channels of the learning: if there are different effects according to trade partners, it is likely exporting effects works also through competition channel and technology transfer and not only through a scale effect. Behind their approach there is the idea that firms of every sector can learn when they enter advanced countries. Our idea is that the important feature is not only the technological level or efficiency of destination country, but the gap between the destination country and the domestic market. We show that the potential for learning is higher in sectors more distant to technological frontier[9] because in these sectors spillovers may be more important.

The next section gives a brief description of data and shows a preliminary statistical analysis. Section 3 verifies for Turkey the existence of the "Exceptional exporters' performance". Sections 4 and 5 present results on self-selection and learning-by-exporting hypothesis. In Section 6 we go in search of learning channels, we analyse the link between export entry and import activity and we try to characterise sectoral post-entry effects according to

[8]Firm shares, unit labour cost and capital.

[9]As an indicator of distance to technological frontier we use a sectoral indicator of revealed comparative advantage.

comparative advantage. A final Section gives concluding remarks.

2 Data and descriptive analysis

2.1 Data

In this paper we use an original Turkish plant-level database[10], from the Annual Surveys of Manufacturing Industries, collected by Turkstat. We have at our disposal an unbalanced panel dataset on plants with more than 25 employees for the whole manufacturing sector in the period 1990/2001[11]. The dataset consists of plant-level information on output, inputs and a large number of plant characteristics (foreign ownership, import activity, export activity, size, industry, region,..).

All nominal values are deflated using sectoral price indices (1994=100) provided by Turkstat, while for capital goods we use a unique deflator for all sectors, but different deflators according to type of goods (machinery and transportation).

After a cleaning procedure[12], we remain with a dataset of 5,783 firms, for a total of 46,607 observations. There are 3,072 firms exporting at least in one year in the period 1990/2001 (in opposite 2,711 firms never export). We use, as our performance indicator, both a labour productivity indicator and TFP

[10] The observation unit is a plant that has its own accounts. We use the terms firm and plant as synonym because most of the firms are single plant firms.

[11] Turkish State Institute of Statistics (TURKSTAT) collects data on plants with more than 10 employees, but before 1992 it runs two different survey for firms with more 25 employees and firms with less than 25 employees. We have decided to use data for larger firms because we are interested in export activity and only few firms with less 25 employees export, and, anyway, their export volume is very low.
Import and export data at plant-level are from Foreign Trade Statistics.

[12] We drop observations with missing data for variables of interest (output, input variables), or with implausible figures (for example, negative values). We had to delete also firms not reporting positive investment flows because we can't construct the capital stock for these firms, as shown in Appendix A. Finally we drop firms which are considered as outliers for at least one year in the sample period. We consider as outliers observations from the bottom and top 0.5 percent of distribution of some main ratio: output/labour, material/output, capital/output, energy/output. We have also deleted firms that are in the sample less than three years.

indicators. We calculate labour productivity as value added per employee. TFP measure is estimated using the semiparametric approach by Levinshon and Petrin (2003) and we have estimated the production function separately for every 2-digit (ISIC) sector. As our robustness check, we have also constructed a multilateral TFP index following Good et al. (1997)[13] (see Appendix B for a description of TFP estimation).

2.2 Preliminary analysis

Figure 1 shows that also for Turkey (Mayer and Ottaviano, 2007) exports are highly concentrated (more than output and employment) in few large exporters. This means that, if there are significant post-entry effects, export activity is positively affecting only a part of firm population[14]. We rank firms in the graph in terms of their individual exports[15], starting with firm with the biggest export volume, and we put on horizontal axis the percentiles of firm population. Along the vertical axis we measure their cumulative contribution to aggregate exports. We compare export concentration with output and labour concentration and with an hypothetical situation in which all firms export the same value (uniform distribution).

We can see that few large firms contribute to a large amount of exports and exports are more concentrated than output and employment[16].
Table 1 gives an overview of the firm international involvement in our database (after the cleaning). A large number of exporters are also involved in

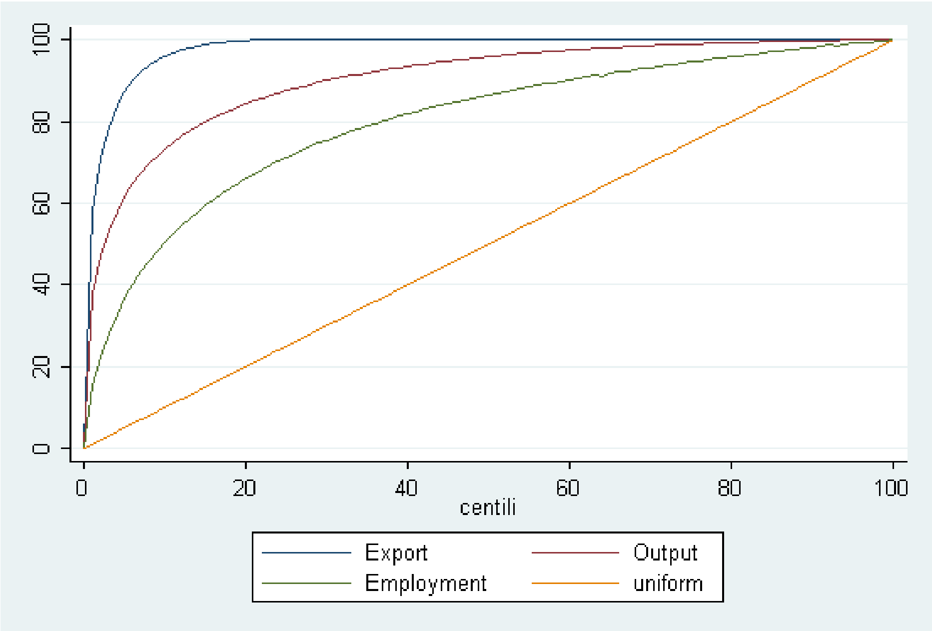
[13] Results are confirmed when we use this TFP index.

[14] If learning-by-exporting effects are also linked to the volume of exports, the beneficial impact of trade could be concerning a still smaller population

[15] The concentration rates (for export, output and employment) are calculated taking into account all the population of firms of the "Annual Surveys of Manufacturing Industries" with more than 25 employees. We are using the database before the cleaning procedure; only we have deleted from this dataset firms with missing and negative values for output and/or employment.

[16] We have also repeated the same exercise for aggregate imports, and we found that imports are more concentrated than output and employment, and they are also slightly more concentrated than exports.

Figure 1: Export Concentration 2001



import activity. During the period analysed (1990/2001), the share of exporters in the sample is quite constant (between 25/32%). Even if in 1996 the Customs Union agreement with the European Union (EU) went into effect, in the following period Turkish exports did not increase substantially. EU had already removed tariffs on imports from Turkey before 1996[17].

3 Exceptional exporters' performance

We start, now, comparing exporters and non-exporters and verifying the existence of export premia in different performance indicators. As already documented, there are a lot of works supporting the "exceptional exporters' performance" for both developed and developing countries. We test, also for Turkey, this stylized fact in literature. Simple descriptive statistics (Table

[17]Customs Union had more effects on the tariffs on Turkish imports, so the impact of this agreement was mainly on Turkish imports.

Table 1: Firms in international trade

Year	*Exporters* (%)	*Only Exporters* (%)	*Only Importers* (%)	*TwoWay Traders* (%)
1990	25.35	8.68	10.74	16.67
1991	29.80	11.22	12.06	18.58
1992	28.63	11.45	11.74	17.18
1993	28.42	10.23	11.21	18.19
1994	30.55	11.48	10.05	19.08
1995	32.20	11.99	10.39	20.21
1996	26.34	8.36	11.49	17.98
1997	25.51	6.80	11.40	18.71
1998	28.84	8.83	12.50	20.01
1999	27.93	8.48	12.92	19.45
2000	30.13	10.54	13.16	19.59
2001	31.17	10.56	13.22	20.61

2), show exporters present a significant higher productivity (TFP and labour productivity)[18], they have a larger number of employees and a larger output, they are more capital intensive, and it is more likely they are importers and foreign-owned.

Table 2: Descriptive Statistics

	TFP	*LP*	*K/L*	*Size*	*FDI*	*Import*
Exporter	40.11	719.74	588.57	246	8.85	65.83
NonExporter	29.97	483.86	370.11	114	3.82	16.46

All differences are statistically significant at 1%

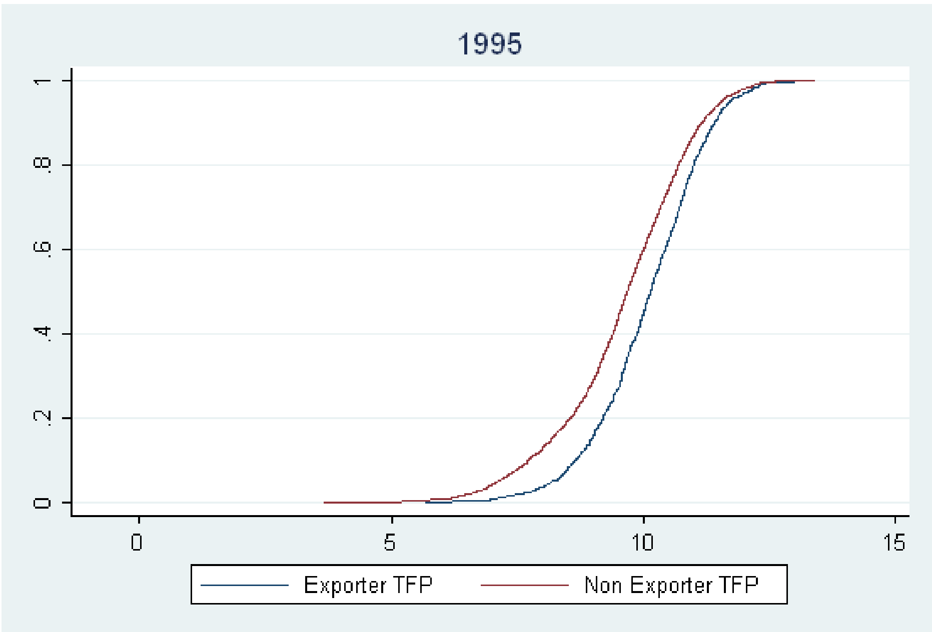
In table 2 we look at differences just in the mean value. In order to consider all moments of the productivity distribution for exporters and non-exporters we apply also a test for stochastic dominance, the Kolmogorov-Smirnov test[19]. We have calculated the test and we have compared, graphically, the TFP distribution for exporters and non-exporters for every year in

[18]The export advantage in productivity concerns all industries and all dimensional classes. Relative data are available on request.

[19]Delgado et al. (2002) have implemented for the first time this test in order to investigate the issue of exports and productivity.

our sample and for the whole period (pooled sample). We show only the graphical analysis of productivity distribution for 1995 as an example. Both test and graphical analysis confirm that productivity distribution of exporters dominates the distribution of non-exporters. Results of Kolmogorov-Smirnov test are displayed in the appendix.

Figure 2: TFP Distribution



In order to strenghten this descriptive evidence, we check now for other firm characteristics. Following Bernard and Jensen (1999), we apply the standard approach in literature to show that the positive productivity differential of exporters compared to non-exporters is statistically significant, and substantial, even if we control for firm size, industry and regional localisation. We present simple OLS regressions of the following equation:

$$y_{it} = \alpha + \beta export\_dummy_{it} + \delta size_{it} + d_j + d_t + d_r + \epsilon_{it} \tag{1}$$

where y can be: TFP, labour productvity, capital stock, capital intensity (the ratio between capital stock and number of employees), number of employees (our proxy for firm size), output and unit labour cost (calculated as total labor cost on output). The variable $export\_dummy_{it}$ indicates the export status of the firm in the period t. Table 3 shows the β coefficient of regressions with different dependent variables[20]. We transform coefficients in exact percentage values[21]. All coefficients are statistically significant. Even if we check for controls (firm size, industry, region, year), the superior performance of exporters remains. We can see an export premium of 18% for TFP in the pooled sample. This evidence for Turkey is consistent to findings for other countries[22].

Table 3: Export Premium

	1990	2001	*Pooled*
TFP	11.20	21.06	17.93
	(0.004)	(0.000)	(0.000)
LP	15.81	32.90	27.64
	(0.000)	(0.000)	(0.000)
Size	107.64	55.79	86.83
	(0.000)	(0.000)	(0.000)
Output	15.36	30.46	27.70
	(0.000)	(0.000)	(0.000)
Capital	209.92	182.93	234.16
	(0.000)	(0.000)	(0.000)
Capital Intensity	17.12	55.85	40.71
	(0.011)	(0.000)	(0.000)
ULC	-10.20	-12.21	-13.22
	(0.000)	(0.000)	(0.000)
N. observations	3,018	3,503	46,607

Robust standard errors are calculated. P-Values are in brackets.
Coefficients shown have been calculated as $(exp^{\beta} - 1) * 100$.
Coefficients are from regressions controlling for sector, region and time dummies and for the firm size.

[20] We verified the existence of significant export premium for every year in our sample. In table we show only, as an example, export premium for the first and last year of the sample and for the pooled sample.

[21] The coefficient shown in table is calculated as $(exp^{\beta} - 1) * 100$.

[22] For example De Loecker (2007) find out a labour productivity premium of 30%; Serti and Tomasi (2008), for Italy, show a TFP premium between 7.5% and 15% according the year of analysis.

4 Self Selection

In the previous section, we have verified the positive correlation between export and some firm performance indicators. Now, being interested in shedding light on the causal relationship, we keep in our dataset the firms starting to export in the sample period and firms which never export.
We define export starter as a firm which continously exports from t onwards (for at least two consecutive years) and which had never exported in the two previous years (t-1 and t-2)[23]. We end up with 8 cohorts, one for each years between 1992-1999, and 543 starters. Table 4 shows the distribution of starters across the 8 cohorts.

Table 4: Starters

Years	1992	1993	1994	1995	1996	1997	1998	1999	Total
Starters	78	62	99	76	69	30	75	54	543

We analyse ex-ante differences between starters and never exporters in order to investigate the self-selection hypothesis. We are interested both in productivity indicators, TFP and labour productivity (measured as value added per unit of labor input) and other firm characteristics, as size and capital intensity. Following Bernard and Jensen (1999), we regress our performance variables (all in logarithm, with the exception of skill ratio and import share) in period t on dummies indicating if a firm is an export starter at time t+1 (t+2,...,t+5) and on a set of controls (number of employees, sectoral dummies, regional dummies and time dummies).

$$y_{i,t} = \alpha + \beta start\_dummy_{i,t+\sigma} + \delta size_{i,t} + \eta d_j + \omega d_t + \mu d_r + \epsilon_{it} \tag{2}$$

where $start\_dummy_{i,t+\sigma}$ is a dummy variable equal to 1 if the firm starts exporting in $t + \sigma$ and $0 \leq \sigma \leq 5$; and, following Serti and Tomasi (2008),

[23]We allow exporters to exit the export market only one year.

$y_{i,t}$ is our variable in level or growth rate.
When we investigate variables in levels (Table 5) we find out support to self-selection hypothesis: more productive firms become exporters. This evidence is confirmed both when we use labour productivty and total factor productivty (TFP index or TFP from Levinshon and Petrin estimation). Before entering export market starters are more productive, larger and present higher capital intensity and higher output than never exporters. These differences are persistent and are at work for the whole pre-entry period, with the exception of TFP, for which we have significant pre-entry premia in t-1, t-2 and also t-5. We can especially notice a huge advantage for starters in capital and size.

We want to verify also if firms modify their behaviour in the pre-entry period according to the future export status. From the analysis of growth rates in the pre-export period (table 6), we can notice that the productivity growth of future starters is higher than never-exporters only two years before the entry. There are also significant differences in growth rates of capital, output and size lasting the whole period analysed. In opposite there is no a significant difference in growth rate of capital intensity. It seems that future exporters in the pre-export period increase their size, their market share and, even if also for only one year, their productivity, but we can't be sure that these changes are in preparation to export entry (that is, if firms spend some efforts and make some decisions with in mind the international market) or if it's also because of these changes that firms can enter and decide to enter the export market in the following period (because their previous success in business permits them to cope with sunk costs of entry). Looking at the whole pre-entry period it is highly likely future starters are successfull firms, also before exporting, and they can enter export market because of their pre-export performance[24].

[24]When we have tried to investigate growth rates without controlling for firm size, we found wider growth differential, especially for productivity. This puts in evidence the importance of size in determining the export entry. It is likely that only larger firms succeed in facing with additional costs and barriers related to export participation.

Table 5: Self-Selection: Levels

	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$
TFP	15.13	9.15	7.85	14.52	18.32
	(0.022)	(0.094)	(0.111)	(0.000)	(0.000)
TFP^{exp}	13.58	8.45	6.54	12.93	16.57
	(0.038)	(0.122)	(0.182)	(0.001)	(0.000)
TFP^{index}	12.05	5.16	0.77	9.55	12.15
	(0.071)	(0.353)	(0.879)	(0.020)	(0.004)
LP	24.75	21.44	20.81	26.27	30.92
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Size	39.54	49.32	59.11	62.29	75.88
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital	137.86	191.98	232.61	207.56	251.35
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Intensity	54.99	73.21	80.87	63.58	67.85
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ULC	-11.80	-12.44	-16.62	-16.44	-19.45
	(0.028)	(0.006)	(0.000)	(0.000)	(0.000)
Output	20.87	22.05	23.48	22.08	28.31
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
N. observations	7,734	9,483	11,430	13,635	14,265

Robust standard errors are calculated. P-Values are in brackets. Coefficients are from regressions controlling for sector, region and time dummies.
Note: TFP is the total factor productivity calculted from Levinshon and Petrin (LP) approach. TFP^{exp} is productivity indicator from LP approach and taking into account the export status. TFP^{index} is the multilateral TFP index following Good et al. (1997). See appendix for a more detailed description.
The employment and capital regressions don't include the size as control variable.

In the pre-entry period we find also a specific evidence about import activity. Import and export activity are strictly linked.

This evidence is shown in the graph 3. There is a continuous increase in the import share gap between never exporters and starters[25]; especially we can notice a significant jump between t-1 and t (for firms that never export throughout the sample period the period t=0 is just the median year in our sample period, so 1995). Some firms, entering export market, also start importing materials. One possible explanation is that, when firms start

[25]This is confirmed both with relative and absolute import share. Relative import share is expressed as a deviation from the industry-year mean.

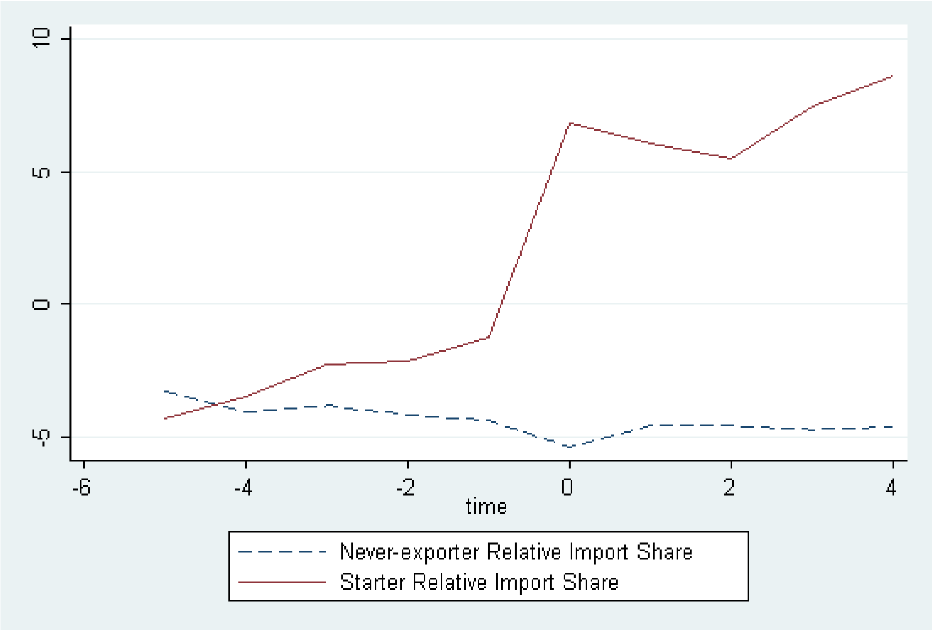
Table 6: Self-Selection: Growth Rates

	$t-5/t-3$	$t-3/t-1$	$t-5/t-4$	$t-4/t-3$	$t-3/t-2$	$t-2/t-1$
TFP	2.07	13.31	0.98	0.54	8.42	5.97
	(0.770)	(0.008)	(0.879)	(0.924)	(0.059)	(0.110)
TFP^{exp}	2.00	13.25	1.17	0.69	8.48	6.07
	(0.777)	(0.008)	(0.856)	(0.904)	(0.057)	(0.104)
TFP^{index}	1.48	14.85	1.82	-1.48	9.17	6.26
	(0.837)	(0.003)	(0.782)	(0.798)	(0.039)	(0.097)
LP	4.08	13.74	0.96	2.23	8.46	6.52
	(0.569)	(0.006)	(0.881)	(0.697)	(0.056)	(0.082)
Number Employees	10.45	10.63	6.30	5.55	6.24	6.19
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Capital	13.93	7.10	2.15	11.15	3.54	6.10
	(0.008)	(0.030)	(0.441)	(0.003)	(0.113)	(0.001)
Capital Intensity	-0.04	-6.92	-5.90	3.03	-4.78	-2.48
	(0.994)	(0.034)	(0.036)	(0.389)	(0.039)	(0.200)
Output	23.26	23.83	14.93	11.05	9.45	16.72
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
ULC	-3.66	-3.52	-2.05	-3.60	1.78	-5.41
	(0.364)	(0.225)	(0.590)	(0.216)	(0.468)	(0.012)
N. observations	6,411	9,453	6,864	8,395	10,128	12,111

Robust standard errors are calculated. P-Values are in parenthesis.
Coefficients are from regressions controlling for sector, region and time dummies.

being involved in international market, they create some networks with foreign firms which allow them both export and import. Or, as an alternative, firms, that want to export, need to improve the quality of their goods or adapt them to the requests and tastes of foreign customers. In order to fullfil these needs, foreign materials could be more suitable.
Even if it's difficult to clean the export effect from a potential import effect, it is important to have in mind in the following analysis that a great part of export starters are also involved in import activity and that this import activity may start in conjunction with export entry. Previous papers, studying the link between exports and productivity, investigate sometimes the foreign/domestic ownership of the starters and never exporters but they

Figure 3: Import Share Trend



don't take into account if a firm is also importer, and up to now literature has neglected the relationship between export and import at firm-level.

5 Post-Entry Effects

We have confirmed the presence of a self-selection mechanism that drives the most successfull, large and efficient firms in the export market. Self-selection doesn't exclude the potential for learning by exporting. Even if starters are already more productive, they could further improve their performance and the differential with non exporters after the export entry.

We are considering a treatment model, where treatment is the export entry. Treated units are export starters, and controls are never exporting firms in the sample. Treatment does not concern only one specific year, but for every starter cohort we have a different treatment year.

We are interested in the average treatment effect on the treated (ATT), that is the difference for a treated firm between the outcome it obtains after exporting and the potential outcome it would have obtained if it had never exported. We are verifying if, in the hypothetical counterfactual situation of no exporting, starters would have had worse or better outcomes.

$$\begin{aligned} ATT &= E(Y_{it}(1) - Y_{it}(0)|D_i = 1) = \\ &= E(Y_{it}(1)|D_i = 1) - E(Y_{it}(0)|D_i = 1) \end{aligned} \tag{3}$$

We are not able to observe both outcomes for the same firm. We can only calculate $E(Y_{it}(0)|D_i = 0)$, the outcome for nonexporters provided that they have not exported, but $E(Y_{it}(0)|D_i = 1)$ (that is the outcome of exporters if they had not exported) is unkown. This means that there could be a bias concerning the computation of ATT. The selection bias can be written as:

$$B(ATT_t) = E(Y_{it}(0)|D_i = 1) - E(Y_{it}(0)|D_i = 0) \tag{4}$$

If the group of the treated is randomly selected from the population, that means the treated and the control group have the same observable and non-observable characteristics, then the bias will be zero. The problem is that selection into treatment is not random and treated and non-treated firms may differ in important characteristics. We have really already verified the existence of these differences in the previous analysis (self-selection): self-selection bias is a real problem. To solve this problem, we use both difference-in-difference strategy and PSM[26]. With matching techniques we can construct a consistent counterfactual. Using a generic non-exporter will not allow us to make causal inferences because there could be differences in firm characteristics in pre-export period that may explain the difference in productivity levels of exporters and non-exporters. We want that treatment is random. Only in this way, if difference in productivity remains, it can be attributed to firms export activity rather than other characteristics; in

[26] As affirmed by Blundell and Costa Dias (2000) the use of matching estimator in combination with difference-in-differences approach can "improve the quality of non-experimental evaluation results significantly".

opposite if there is no difference we can think that exporting doesn't benefit firms. The basic idea of matching is to find, in a large group[27] of non treated unites (never exporters), those firms who are similar to the starters in all relevant pre-treatment (observable) characteristics X to approximate the counterfactual outcome (Blundell and Costa Dias, 2000).

The Propensity score matching consists in estimating a propensity score of export entry conditional to variables at our disposal and that, we think, could affect the probability to enter export market. Then we match plants (treated plants with control plants) using this estimated propensity score. We use the following probit to estimate the probability score of first-time exporting[28]:

$$\begin{aligned} &Pr(START_{it} = 1) = f\{TFP_{t-1}, n_{t-1}, k_{t-1}, ulc_{t-1}, SkillProd_{t-1}, Import_{t-1}, \\ &ForeignShare_{t-1}, SubInp_{t-1}, SubOut_{t-1}, dummies\} \end{aligned} \tag{5}$$

where $START_{it}$ is a dummy variable assuming value 1 if the firm starts exporting in t. The chosen probit specification satisfyes the balancing test introduced by Rosenbaum and Rubin and formalized in Becker and Ichino (2002)[29].

This probit is estimated pooling all cohorts[30]. In the regression we have kept only never exporters, for all the years they are in the sample, and starters, for the year they start exporting. We include the following variables

[27]In our sample we have at our disposal a large population of potential counterfactual unites.

[28]As robustness checks, we have also tried to use other probit specifications, always satisfying the balancing test. Results for following analysis are quite similar using these specifications.

[29]The matching of plants is "balanced" if observations with the same propensity score have the same distribution of observable (and unobservable) characteristics regardless of treatment status. This test tells that the decision to export is random, treated and control units are identical on average.

[30]We have decided to use the pooled sample because, in this way, we can exploit the information contained in the largest possible dataset for modelling the export-starting decision. Estimating different probit for each cohort could be a loss of efficiency because the number of starters in every cohorts is low (as already shown in table 4).

lagged one year[31]: total factor productivity, size, the square of the size, capital stock, unit labour cost, the share of skilled production employees, foreign share[32], import status, subcontracted input and output shares, and dummies for industry, year and region. The probit specification we choose permits to correctly classify 95.58% of observations.

Using scores from previous probit specification, we match plants using nearest neighbor matching on the "common support"[33]. The nearest neighbor technique matches a starter with a never exporter having the closest propensity score (we also permit that never exporters are used as a match more than once, matching "with replacement").

We have followed Girma et al. (2003) and we have applyed matching cross-section by cross-section (separately for each cohort). We restrict, in this way, the matches to come from the same year. Because we don't restrict matches to come also from the same sector[34], we have calculated ATT effects both on absolute and relative variables (in the latter case, variables are expressed as a deviation from the industry-year mean, in order to take into account the sectoral and time evolution). We have also tried to apply the matching to the pooled sample, that means a starter could be matched with a never exporter who has the most similar propensity score, but it could be from a different year and a different sector[35]. Results obtained from the matching implemented cross-section by cross-section and the matching implemented

[31]We use lagged variables because the observable covariates we use to estimate the propensity score should not be affected by treatment. This means that also variables that are affected by the anticipation of the export entry should not be included in the model. It's difficult to be sure firms don't change some important characteristics in preparation to export entry.

[32]The capital share owned by foreign shareholders.

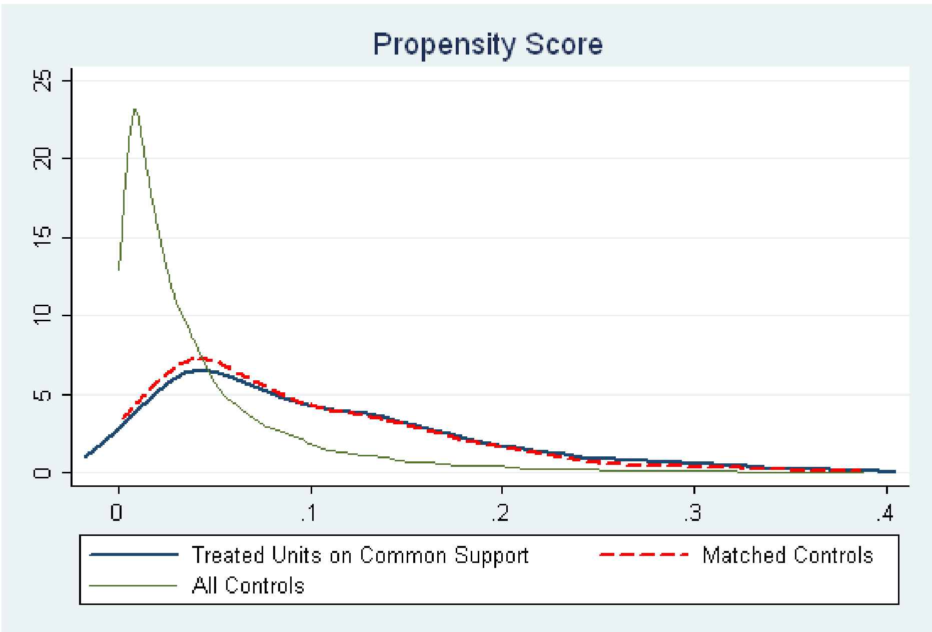
[33]We have chosen to match the starter with a single never exporters because of the large population of never exporters at our disposal. We restrict matching to plants in the "common support", that is the observations whose "propensity score belongs to the intersection of the supports of the propensity score of treated and controls" (Becker and Ichino, 2002). We drop treated units who have a pscore higher than the maximum pscore of the controls or less than the minimum pscore of the controls.

[34]We have only included sector dummies on the propensity score computation.

[35]We decided to implement this procedure because we have estimated the propensity score and verified the balancing property for the pooled sample. The ATT effects, in this case, are calculated on relative variables.

on the pooled sample are very similar.
Since we do not condition on all covariates but on the propensity score, we have to check if the matching procedure is able to balance the distribution of the relevant variables in the control and treatment group. We can use different methods to test the matching goodness. The basic idea of all approaches is to compare the situation before and after matching and test if there remain any differences between treated and control units. If there are differences, matching was not (completely) successful. At first, we show the density function of pscore for treated, all controls and matched controls. We can see (Figure 4) that the propensity score distribution was very different before matching, but after matching the distribution of matched controls overlap that of starters.

Figure 4: Pscore



Second, we implement a standard t-test for equality of means for the covariates to check if significant differences remain between starters and matched controls after the matching. Table 7 shows significant differences betweeen starters and never-exporters in all variables analysed for the unmatched sample. In opposite, any significant difference disappears in the matched sample (as expected)[36].

Finally, we have reestimated again, as suggested by Sianesi (2004), the propensity score on the matched sample, including only odservations on treated units and matched controls, and we have compared the pseudo-R^2s before and after matching. The pseudo-R^2 indicates how well the regressors X explain the export probability. After matching there should be no systematic differences in the distribution of covariates between both groups and the pseudo-R_2 should be low. We find, in effect, a pseudo-R^2 not statistically different from 0 for probit on matched sample[37], this means that, according to our probit specification, treated units and their matched controls have the same probability to start exporting.

Even if matching procedure is valuable, it doesn't eliminate completely the self-selection bias, especially it doesn't eliminate the bias coming from unobservables. With DID strategy we can also take into account and correct for time-invariant unobservables. We compare the differences in outcomes after and before the treatment (in our case, before and after export entry) for the treated group (export starters) to the same differences for the untreated group (never exporters[38]), on the assumption that, without the treatment, the outcomes would have been similar across the two groups of firms. The implemented DID-PSM estimator could be written as:

[36] We have rerun this check for every post-entry year of our analysis (for the times t+1, t+2, t+3, t+4), because the sample in every period is different due to the exit of starters and/or controls. We have also implemented a t-test for the TFP growth lagged one-year and we find no statistically significant differences between starters and never matched. This is important to rule out a possible "path effects", if we will find a superior productivity growth for starters after the export entry, we could be sure that this is not linked to positive productivity shocks affecting firms also previous period.

[37] Pseudo R^2=0.0078 and p-value of joint not-significance of all coefficients is: $Prob > chi2 = 0.9985$

[38] For never exporters t=0, that is the potential entry year, is the export entry year of the treated firms it is matched with

Table 7: Comparison of treated and control

	$N.Obs$	TFP	LP	K	K/L	ULC	$Size$	$SkillProd$	$ForShare$	$Importer$	$SubInp$	$SubOut$
Unmatched Sample												
Starters	543	9.87	12.86	16.75	12.21	-2.60	4.55	16.19	1.38	0.28	5.08	4.72
Never exporters	13,576	9.41	12.40	15.56	11.58	-2.47	3.98	15.97	3.40	0.11	3.62	8.00
T-Test		-7.91	-10.57	-15.60	-9.47	3.50	-18.83	-0.32	-4.48	-12.20	-3.27	3.05
Matched Sample												
Starters	532	9.86	12.85	16.62	12.17	-2.60	4.52	16.35	3.47	0.27	5.17	4.81
Never exporters	532	9.87	12.82	16.69	12.11	-2.61	4.50	15.27	3.57	0.28	5.98	3.62
T-Test		0.14	-0.46	-0.71	-0.74	-0.30	-0.24	-1.24	0.10	0.41	1.14	-1.18

$$M^{DID-PSM} = \frac{1}{n_i} \sum_{i \in D_i^*=1} [(Y_{i,post} - Y_{i,pre}) - \sum_{j \in D_j^*=0} \omega(i,j)(Y_{j,post} - Y_{j,pre})] (6)$$

Y is the variable of our interest (for example productivity). Subscripts *post* and *pre* denote that variable concerns the period pre or post-entry. $D_i^* = 1$ denotes the group of starters in the region of common support, while $D_J^* = 0$ denote the group of never exporters (always in the region of common support). n_i is the number of treated units on the common support. The number of control firms that are matched with a starter i is N_i^c and the weight $w_{ij} = \frac{1}{N_i^c}$ if $j \in C$ and zero otherwise. Anyway, in our estimation $\omega(j)$ is 1 for matched controls because every starter is matched with only one control unit (with a single nearest neighbor). We consider four years after the starting year and we calculate ATT effects for the entry period t, t+1 till the period t+4, because when we consider a longer time horizon the matched sample is restricted and PSM may fail.

Even if we are interested mainly on productivity indicators (both labour productivity and TFP), we investigate also ATT effects for other firm characteristics, especially size and capital endowment.

Table 8: ATT Effects: PSM-DID estimates

	t	$t+1$	$t+2$	$t+3$	$t+4$
TFP	**0.140**	**0.177**	**0.259**	**0.218**	0.264
TFP^{exp}	**0.141**	**0.180**	**0.265**	**0.223**	0.267
TFP^{index}	**0.158**	**0.184**	**0.266**	**0.221**	**0.312**
LP	**0.137**	**0.184**	**0.279**	**0.254**	**0.311**
Number Employees	**0.072**	**0.107**	**0.125**	**0.112**	**0.146**
Capital	0.021	**0.080**	**0.155**	**0.229**	0.243
Capital Intensity	-0.042	-0.013	0.043	0.155	0.127
Output	**0.164**	**0.237**	**0.370**	**0.398**	**0.364**
ULC	**-0.077**	**-0.140**	**-0.163**	**-0.229**	-0.056
N. observations	1064	948	588	324	186

Bold values are significant at least at 10%.

Boostrapped standard errors are calculated (200 replications).

The results show that the average TFP effect of exporting is positive and statistically significant. Firms that start exporting grow more than firms that serve only the domestic market. There are also significant and positive effects on labour productivity, capital, size (number of employees) and output. These positive effetcs are persistent and they last until the fourth year (third year for the capital and productivity) after the export entry[39].
Learning-by-exporting hypothesis seems to be confirmed with every productivity indicator (LP, semiparametric TFP indicators and TFP index). When we match on the pooled sample, we obtain very similar ATT effects, only for the year t+3 the effect become not significant. We have also tried to impose a tolerance level on the maximum propensity score distance (caliper) in order to face with the risk of bad matches if the closest neighbour is far away. We have used a caliper level of 0.01 and we have obtained the same results. This robustness checks confirms the goodness of our matching procedure[40].
However, we could hypothesize that in the entry year firms place themselves on a higher TFP path and then they stay on this "superior" path (De Loecker, 2007). In this case, annual growth rates are higher for starters only for the entry period, but not for the following period. This idea seems to be verified when we calculate ATT effects on yearly TFP growth rates. Table 9 shows that starters present a significant higher annual growth rate than never exporters only for entry period. If we consider together this table with previous table on DID-PSM estimates we can conclude that, even if export activity has effects on firm performance lasting for some years following the export entry, it's in the entry year that starters go on a higher TFP path and in the following period they stay on this path and confirm their advantage compared with never exporters.

[39]However, it is worth mentioning that the results for t+3 and t+4 are not completely reliable, probably due to the small sample size.

[40]When we restrict the matching imposing a caliper=0.01 the starters we can match drop from 532 (without caliper) to 521 (with caliper).
We don't show the ATT effects for the matching on the pooled sample and the matching with caliper. These results are available on request.

Table 9: ATT effects: Yearly Growth Rates

	t	$t+1$	$t+2$	$t+3$	$t+4$
TFP	**0.140**	0.034	-0.050	0.068	0.020
	(0.017)	(0.537)	(0.409)	(0.259)	(0.772)
LP	**0.138**	0.043	-0.026	0.079	0.032
	(0.018)	(0.433)	(0.670)	(0.195)	(0.632)

Bold values are significant at least at 10%.
Boostrapped standard errors are calculated. P-vales are in parenthesis

Robusteness check The ATT calculation is a superior and flexible approach, in our opinion, if compared with OLS regression in estimating the conditional expectation of the outcome variable, because it does not impose linear functional form restrictions. Coupling the PSM with a DID estimator we can handle the selection bias with the problem of time-invariant unobserved heterogeneity. Anyway, as robustness check, we have also tried to implement a different methodology. Following studies of Greenaway, Girma and Kneller (2003, 2004) we have pooled our observations (of starters and matched controls) concerning different post-entry periods and we have estimated the regression:

$$\begin{aligned} \Delta TFP_{it} &= \alpha + \sum_{\sigma=0}^{4} \beta D^{t+\sigma} + \gamma D^{t-1} * START_i + \sum_{\sigma=0}^{4} \delta D^{t+\sigma} * START_i + \\ &\quad + \varphi TFP_{i,t-1} + \theta n_{i,t-1} + \iota d_r + \mu d_j + \rho d_y + \epsilon_{ijt} \end{aligned} \tag{7}$$

where TFP growth is our dependent variable. $D^{t+\sigma}$ are dummy variables assuming 1 in the event time for never-exporters and exporters. These dummies capture the effect of events that occur in $t+\sigma$ but are common to all firms[41]. $START_i$ is a time invariant dummy equal 1 for starters and 0 for matched controls. The interaction $D^{t+\sigma} * START_i$ is 1 only for starters in

[41]For example, D_{t+3} is equal to 1 in period t for starters if in t-3 they started exporting, and it is equal to 1 also for never-exporters if in t-3 the related starters (which never-exporters is matched with) started exporting.

the period before export entry; this variable captures different pre-entry characteristics between starters and never exporters (if the matching was good it should not be significant). $D^{t+\sigma} * START_i$ is equal to 1 in the event time for only exporters. We estimate this equation keeping in our dataset only starters and matched controls for the years $-1 \leq t \leq 4$: the pre-entry period, the entry year and the four years after entry (for never-exporters these periods are set according to the related starters which they are matched with). In this way, TFP growth is compared with TFP growth of never-exporters in the pre-entry period (t-1) because all dummies (both $D^{t+\sigma}$ and the interaction $D^{t+\sigma} * START_i$) are always 0 for non-exporters in the pre-entry period. We control for the lagged level of TFP and lagged size, and we always include dummies for sector, region and year. We also try to take into account firm fixed effects. Our coefficient of interest is δ showing the change in the TFP growth for starters in the post-entry period. Table 10 shows the productivity growth for starters and never exporters before and after entry.

Table 10: Productivity Growth

	Never Exporters
Before	α
After	$\alpha + \beta$
	Starters
Before	$\alpha + \gamma$
After	$\alpha + \beta + \delta$

With this regression we are analysing the annual growth rates. In opposite to Table 9, here we are considering together different post-entry years and also we can control for other additional regressors that could be affecting and determining the firm performance over the period after export entrance (lagged TFP and size). Table 9 could be compared with the column 3 of

Table 11.

Table 11: Learning-by-exporting Effects: OLS

Dependent Variable: TFP growth				
	(1)	(2)	(3)	(4)
Year t	-0.207	-0.169	-0.201	-0.0708
	(0.001)	(0.001)	(0.001)	(0.089)
Year t+1	-0.088	-0.096	-0.070	-0.035
	(0.121)	(0.042)	(0.285)	(0.440)
Year t+2	-0.108	-0.109	-0.071	-0.052
	(0.089)	(0.061)	(0.336)	(0.309)
Year t+3	-0.105	-0.121	-0.068	-0.017
	(0.119)	(0.045)	(0.463)	(0.791)
Year t+4	-0.163	-0.192	-0.120	-0.044
	(0.097)	(0.030)	(0.309)	(0.583)
Pre-entry	-0.038	-0.016		
	(0.467)	(0.722)		
Post-entry t	**0.148**	**0.154**	**0.193**	**0.163**
	(0.005)	(0.001)	(0.015)	(0.003)
Post-entry t+1	0.052	**0.122**	0.091	**0.229**
	(0.323)	(0.008)	(0.270)	(0.000)
Post-entry t+2	-0.006	**0.091**	0.026	**0.274**
	(0.916)	(0.095)	(0.787)	(0.000)
Post-entry t+3	-0.009	0.077	0.032	**0.233**
	(0.915)	(0.305)	(0.791)	(0.005)
Post-entry t+4	0.059	0.158	0.103	**0.301**
	(0.617)	(0.119)	(0.495)	(0.004)
TFP t-1		-0.453		-1.052
		(0.000)		(0.000)
Size t-1		0.059		-0.083
		(0.000)		(0.090)
N. observations	3892	3892	3892	3892
Dummies	*YES*	*YES*	*YES*	*YES*

(1) OLS estimation without controls. (2) OLS estimation with controls (lagged TFP and size). (3) Fixed Effects estimation without controls. (4)Fixed Effects estimation with controls (lagged TFP and size). P-Values are in parenthesis. Bold values are significant at least at 10%.

This analysis further confirms our hypothesis on learning-by exporting. We find an higher TFP growth rate for starters in the entry period as we found when we calculated ATT effects on growth rates. When we control for lagged TFP and size we obtain significant export effects on growth also for the period t+1 and t+2. Adding firm-fixed effects, significant post-entry effects are shown for the whole post-entry period. The conclusions of this strategy are very similar with our previous analisys, even if here we are controlling also for other variables in the post-entry period (lagged productivity and lagged size). When we take into account the annual growth rates, we find a jump for starter's TFP, especially in the entry year.

6 In search of learning channels

6.1 The link between export and import

Empirical evidence shows, as already noticed, a strict linkage between export and import activity: export starters often start also importing in the entry year. In this section, we want both to test if post-entry effects, we found previously, are not due to import entry instead of export entry and we try also to verify if firms which start importing in combination with exporting obtain larger gains.

In previous sections, we could check for the previous import status. Including in the probit specification the lagged import dummy, we could take into account previous import activity of matched and control units. As Table 7 has shown, there is no a significant difference in the import status between starters and never exporters after matching[42]. Anyway, even if matching procedure let us to control for pre-entry characteristics, it doesn't check for events that could happen in combination with export entry, that is for current import entry.

We split our starters' sample in two groups: the first group include export starters which start also importing in t (they didn't import in t-1, but import in t); the second firm group includes the other firms (firms that already imported in t-1 and continue importing, and firms that don't import neither

[42]Even if we have not matched exactly on the lagged import status, we can see from Table 7 that the matching on this variable was quite perfect.

in t-1 nor in t[43]). In both group we have obviously included the relative matched controls[44]. As shown in table 7, there is no statistical difference in import status between starters and matched controls, so our post-entry effects is cleaned for the previous firm import status. In opposite, in this section, we want to test if the current import status (in t) could affect, in combination with exporting, post-entry effects, and could contribute to explain them.

Our previous results are generally confirmed also when we drop, from our sample, firms which start importing and exporting at the same time, even if now post-entry effects are slightly downsized and there is no significant effect in t[45]. This finding further supports significant positive effects stemming from export activity.

We verify also (Table 12) larger productivity gains for firms which start exporting and importing at the same time. The post-entry TFP effect for the total sample is 14%, the same effect for new-importers and new-exporters is equal to 20.6%. This analysis represents a robustness check of previous results, but also shed some light on the nexus between exports and imports: participation in export market increase the firm performance, but these improvements of productivity could be higher if firms start also using importerd materials.

6.2 Learning-by-exporting: Which channels?

In this section we follow, in part, a recent study of Greenaway and Kneller (2007). Greenaway and Kneller (2007) have investigated if industry differences can explain whether learning effects boost productivity after export market entry: they find that export effects on productivity growth are lower in industries already exposed to high levels of trade and to high levels

[43]We have already controlled for the previous import activity in t-1 in the matching procedure.

[44]The matching procedure is not changed.

[45]We calculate ATT effects until t+2, because the sample is too small for following years.

Table 12: ATT effects: Control for the current import status

	TFP		
	t	$t+1$	$t+2$
Group1	**0.206**	**0.239**	**0.210**
	(0.010)	(0.016)	(0.093)
Group2	0.109	**0.156**	**0.229**
	(0.172)	(0.084)	(0.042)

Group1 = New Importers. Group2 = Old Importers and Non Importers.
Boostrapped standard errors are calculated. Bold values are significant at least at 10%.

of *R&D* intensity and in sectors where the presence of foreign firms in the domestic market is important. If post-entry effects are also due to competition the firm need to face with, we expect that starters operating in more competitive industries benefit less from export activity if compared with starters operating in less competitive industries. If learning-by-exporting works through the competition channel (competition effect), these effects will be present only if firms in domestic market face with low competition.

We follow this approach but we affirm that the potential for learning depend upon the (productivity) gap between the domestic productive system and the foreign productive systems (that exporters enter). We suppose that there is a different scope for learning according to the productivity gap, the distance to technological frontier.

De Loecker (2007) try to investigate a different export impact according to the destination country of exporters. Behind this approach there is the idea that advanced countries are more productive in every sector and firms of every sector can learn when they enter advanced countries. Our idea is that the important feature is not the technological level or efficiency of destination country, but the gap between the destination country and the domestic market.

Because of the difficulty in calculating an indicator of sectoral productivity gap between countries, we have decided to use, as a proxy, an indicator of comparative advantage. Turkey is a middle-income country and its main

trade partners are European countries and, in general, advanced countries[46]. We can suppose that, in sectors where Turkey has no a comparative advantage, Turkish firms are less productive, in average, than foreign firms; in opposite in comparative advantage sectors Turkish productive system is more efficient (in absolute or relative terms) than foreign productive systems[47].
We want to verify if learning effects are larger and significant for new exporters in comparative disadvantage industries because in these sectors the productivity gap between the domestic productive system and foreign productive systems should be higher than in comparative advantage sectors. New exporters, in comparative disadvantage industries, could be exposed to a more competitive environment than their domestic context and could be more exposed to positive spillovers, this could explain larger post-entry effects stemming from exporting. We expect learning-by-exporting to be more intensive in comparative disadvantage sectors.
We have split sectors according to the comparative advantage. In order to take into account the Turkey's pattern of comparative advantage (and disadvantage) across industries, we have used the observed pattern of trade and we have calculated the "index of revealed comparative advantage" (henceforth RCA) defined as

$$RCA = \frac{X_{TUR,i}/X_{TUR}}{X_{W,i}/X_W} \tag{8}$$

where $X_{TUR,i}$ and $X_{W,i}$ are the exports of Turkey and of the comparison group of countries in the industry i, X_{TUR} and X_W are the aggregate exports of Turkey and the comparison countries in the aggregate manufacturing sector. If this index is higher than one the country exhibit a comparative advantage in that sector i, because Turkey is more specialised in sector i than other countries. In order to calculate this index we have used 3digit (ISIC) sec-

[46]Turkish exports to OECD countries in manufacturing sector represent 80% of total exports.

[47]This means that in comparative advantage sectors Turkish firms could be more productive than firms of trade partner countries or, even if they could be less efficient than foreign firms, the differential of productivity should be lower than in comparative disadvantage sectors

toral trade data from CEPII (Research Center in International Economics) and the comparison group of countries are the European Union countries, Russian Federation and Usa[48]. Comparative advantage index can give us an idea about the comparison between domestic market and foreign markets in every sector, and it can show the technological gap of Turkish industries to frontier. We assume firms are more distant to frontier in comparative disadvantage sectors.

After the matching procedure shown in section 5, we define postCA a vector of dummy variables for the post-entry period for starters in comparative advantage (CA) sectors, and postCD a similar vector for the post-entry period for starters in comparative disadvantage sectors CD. We can calculate ATT effects with the following equation:

$$\Delta TFP_{i,s} = \alpha + \beta_1 postCA_{i,s} + \beta_2 postCD_{i,s} + \epsilon_{is} \tag{9}$$

where $\Delta TFP_{i,s}$ is the productivity growth between the post-entry and pre-entry (t-1) period[49]. The variable tfp is always expressed as a deviation from the industry-year mean, in order to capture and correct for effects that are common to all firms belonging to the same sector (especially, in order to correct for specific effects linked to comparative advantage sectors or comparative disadvantage sectors). We are analysing the change happened to our variable following export entry compared with pre-entry period. We consider separately post-entry effects between starters in comparative advantage sectors and starters in disadvantage sectors for every year after export-entry (until the fourth year after the entry). The coefficient β_1 can be interpreted

[48]These countries are the main trade partners of Turkey. Anyway we have tried to calculate RCA index with only EU contries, OECD countries and the rest of the world and we obtained the same pattern of camparative advantage. Comparative advantage sectors are: Food manufacturing (ISIC 311); Beverage Industries (ISIC 312); Textiles (ISIC 321); Wearing apparels, except footwear (ISIC 322); Rubber products (ISIC 355); Manufacture of Non-Metallic Mineral product, except product of petroleum and coal (ISIC 361; ISIC 362; ISIC 369). The pattern of comparative advantage is quite constant during the sample period.

[49]For the entry period it is calculated as $\Delta TFP_{i,0} = tfp_{i,t} - tfp_{i,t-1}$, where tfp is in logarithms. For the first year following the entry is calculated as $\Delta TFP_{i,1} = tfp_{i,t} - tfp_{i,t-2}$ and so on.

as the average change in performance indicators attributable to the entrance in the export market for starters in comparative advantage sectors, while the coefficient β_2 can be interpreted as the same effect for starters in comparative disadvantage sectors. Estimated coefficients on dummy variables $postCA_{i,s}$ and $postCD_{i,s}$ have to be interpreted as efficiency differentials with respect to omitted group, that is never exporters. We run simple ols regressions[50].

Table 13: ATT Effects: Comparative Advantage

		t	$t+1$	$t+2$	$t+3$	$t+4$
TFP	Starters CA	**0.180**	**0.129**	**0.264**	0.059	0.086
	Starter CD	0.104	**0.157**	**0.254**	**0.352**	**0.399**
CumTFP	Starters CA	**0.180**	**0.307**	**0.476**	0.378	0.715
	Starter CD	0.104	**0.341**	**0.609**	**0.818**	**1.467**

Bold values are significant at least at 10%.

For the entry year starters in CA sectors are improving their productivity more than starters in CD sectors, especially there are no significant effects for starters in CD sectors for the entry year (Table 13). In t+3 and t+4 starters in CA industries don't present any significant difference with never exporters. In comparative disadvantage sectors, exporters start having significant effects since t+1 and it seems they increase their productivity more than never exporters and more than starters in comparative advantage. Firms in CA sectors can take advantage from the export activity immediately when they enter foreign markets, in opposite it seems that firms in CD sectors need some time in order to exploit the opportunities offered by foreign markets. We verify a difference in the magnitude of post-entry effects according the comparative advantage, but we can see also a different timing for different sectors. This evidence could mean that firms in CD sectors need more time

[50] We add some weights in the regression, because the same never-exporters could be matched with different starters. We put a weight equal to 1 for all starters, and for never-exporters we consider the number of starters they are matched with.

in order to exploit the potential of learning offered by export activity. They, for example, need more time in order to absorb spillovers from international markets (new technologies, new production strategies), because the gap with foreign markets in these sectors is larger and they have to accomplish some efforts in order to prepare themselves to take advantage from the new context. In opposite, in CA sectors firms could be able immediatly to take advantage from new technology, new production methods and from a more competitive context. But when starters in CD industries are ready to absorp spillovers from the new context they can exploit an higher potential of learning-by-exporting than firms in CA industries. This hypothesis seems to be confirmed when we analyse the cumulative productivity[51] of firms (always splitting between starters in CA and CD sectors). We can see the superior benefit for starters in CA sectors in the entry year, but since t+1 starters in CD sectors increase their cumulative performance more than other starters.

7 Concluding remarks

The paper analyzes the link between exports and firm performance for a middle income country, Turkey. Both self-selection and post-entry effects are important drivers behind the positive correlation found between export involvement and firm productivity. The work contributes especially to support the hypothesis of a potential for learning stemming from export activity when the country analysed is not at the technological frontier and confirms results highlighted by previous papers. Export starters show an higher performance in the post-entry period. It seems export activity places firms on a superior productivity path in the entry year and they continue staying on this path in the following period.

[51]The cumulative productivity is calculated as

$$CumTFP_{i,s} = \sum_{\delta=0}^{s} tfp_{i,t+\delta} - tfp_{i,t-1}$$

, where t is the entry year

Our analysis displayes also a strict linkage between export and import entry. The benefits of the involvement in international markets are larger when firms start exporting and importing at the same time. The relationship between export and import activity at the firm level has received scarce attention, but it could become an important research field in the future.
In addition, we try to shed some light on the channels of learning-by-exporting and we investigate an heterogeneity in post-entry effects according to the sectoral differential of performance between domestic context and foreign markets. We verify a different timing and magnitude of productivity improvements across sectors: new exporters in comparative disadvantage sectors take more time to benefit from export participation, but, in the "long" term, the potential of learning seems larger than in comparative advantage industries because the distance to frontier is higher. This finding supports the hypothesis that competition and technology spillovers are significant channels through which exports may affect firm's productivity.

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A Appendix: Measuring the capital stock

Because of the lack of book value information on capital, we need to construct a reliable estimation for capital stock. We use gross investment data in order to apply the perpetual inventory method (PIM). In each period the capital stock is calculated following the equation:

$$K_{t+1} = (1-\delta)K_t + I_t{}^{52} \tag{10}$$

Even if our analysis is about the period 1990/2001, we have investment data starting 1983, so we construct capital series using data for the period 1983/2001. The initial capital stock[53] can be obtained by solving:

$$K_0 = \frac{I_0}{(g+\delta)} \tag{11}$$

where δ is the depreciation rate and g is the growth rate of capital that we assume equal to energy growth[54]. We construct separatly two measures of capital stock for: machinery; and equipment, transportation, veichles. For

[53] It is the capital stock for the first year we can observe the firm and we have data to calculate capital series

[54] We use growth in electricity as a proxy for growth in capital. We construct the average energy growth for the first four years since a firm has a non-zero investment flow. We suppose that if a firm increases his capital stock it will need to increase also the energy consumption because a larger stock of machinery and transportation requires more electricity and fuel. In addition previous research both at firm-level and industry-level has sometimes used electricity consumption as a proxy for capital. As an alternative, we have also tried to construct the initial capital stock using the growth rate of output, and we have calculated growth rates for different time periods. Finally we have constructed the initial capital stock using the average of investment flows in the first three years as Yasar and Rejesus (2005). Results are very similar, and there is an high correlation (more than 90%) between capital stocks constructed with different methods.

these two stocks we use two different depreciation rates following literature: 10% and 20%[55]. Our total capital stock is the sum of these two stocks. For any firms where investment in the first year is zero, we re-apply the previus equation using the first observation with investment different from zero (year τ) and we calculate the capital stock for previous years as:

$$K_{\tau-1} = \frac{K_{\tau}}{1-\delta} \tag{12}$$

because $I_{\tau-1}$ is zero.

B Appendix: TFP Estimation

B.1 Semiparametric Estimation

In order to investigate the effects of export activity we need an indicator of firm performance. In recent years great attention has been paid on the TFP measure. TFP estimation involves some problems to solve. Since productivity and input choices are likely to be correlated, OLS estimation (that requires inputs are exogenous) of firm-level production functions introduces a simultaneity or endogeneity problem. Semiparametric estimation methods have been proposed in order to solve the endogeneity question. Both Olley and Pakes (1996) and Levinsohn and Petrin (2003, LP) have developed a semiparametric estimator that takes into account the simultaneity bias (and the selection bias in the case of the OP estimator). Olley and Pakes suggest to use investment flows as a proxy for unobserved productivity shocks. As a consequence, only non-negative values of investment can be used in the analysis. But for developing countries and also for a medium-income country like Turkey this is a problem because we have a large number of zero investment observations, firms don't invest every year and we should delete a great amount of observations, with a loss of information and efficiency. In

[55]These depreciation rates are in line with rates suggested in OECD research papers and in previous literature. These depreciation rates were for example used in Taymaz and Yilmaz (2007) for Turkey; and in Arnold and Javorcik (2005) for Indonesia.

opposite LP suggest to use intermadiate inputs (material, electricity) as a proxy variable and we have only few zeros for these variables, so this estimation is more reliable. We begin assuming that production is described by a Cobb-Douglas function using labor and capital.

$$Y = Af\{KL\} \tag{13}$$

We use a value added specification, so our regressor is value added (Y); K and L are inputs of capital and labour respectively and A is unobservable productivity term (the Hicksian neutral efficiency level), which differs across firms and time periods. Taking natural logs we have a linear production function. Labour input is the number of employee and capital has been calculated as shown in Appendix A. We estimates production function for every 2-digit (ISIC Rev.2) industry separately.
LP approach rely on the assumption that intermediate inputs are a proxy of productivity and they assume a strict positive monotonic relationship between intermediate input and productivity, conditional to capital[56].

$$y_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + \omega_t + \eta_{it} = \alpha_l l_{it} + \phi_t(k_{it}; e_{it}) + \eta_{it} \tag{14}$$

We assume that productivity, our state variable, follow a Markov process unaffected by the firm's control variables. The LP approach consists of two steps. In a first step, coefficients on the variable inputs in the production function and the joint effect of all state variables on output are estimated. In our case, the former is just labor and the joint effect of capital and productivity. We assume intermediate input to be a monotonically increasing function of productivity: we have tested this and we found that this property is in general satisfied for 2-digit estimates with electricity as proxy variable. Also we have decided to use electricity as our proxy instead of material, because, as suggested by Arnold and Javorcik (2005), electricity cannot be stored, so its consumption is likely to follow changes in production activity

[56]We have tested this hypothesis and we found that it is in general satisfied for 2-digit estimates

more closely than material consumption.
We can in this way invert this equation and we obtain an observable expression for productivity. So we use a third-order polynomial approximation in k_t and e_t in place of productivity shock, and we estimate parameters of the value-added equation using OLS:

$$y_{it} = \delta_0 + \alpha_l l_{it} + \sum_{i=0}^{3} \sum_{j=0}^{3-i} \delta_{ij} k_t^i e_t^j + \eta_{it} \tag{15}$$

After estimating this expression, we obtain an estimate of labour elasticity (α_l) and an estimate of the term $\phi_t(k_{it}; e_{it})$.
The second step consists in minimize the following equation (using a golden section search algorithm) in order to estimating the capital elasticity (α_k):

$$min_{\alpha_k^*} \sum (y_{it} - \widehat{\alpha}_l l_{it} - \alpha_k^* k_{it} - E[\widehat{\omega_t | \omega_{t-1}}])^2 \tag{16}$$

where $\omega_t = \hat{\phi}_t - \alpha_k^* k_{it}$ and $E[\widehat{\omega_t | \omega_{t-1}}]$ is the predicted values from the regression

$$\hat{\omega_t} = \gamma_0 + \gamma_1 \omega_{t-1} + \gamma_2 \omega_{t-1}^2 + \gamma_3 \omega_{t-1}^3 + \upsilon_{it} \tag{17}$$

We include also time dummies to capture congiuntural events and trends over time.
Our productivity measure is the residual of the production function:

$$tfp = y - \widehat{\alpha}_l * l - \widehat{\alpha}_k * k \tag{18}$$

This indicator is in logarithm. In the text this productivity is indicated as TFP.

We have also modified this procedure in order to take into account the export status as an additional control in the dynamic problem. Following Van Biesebroeck (2005) and De Loecker (2007), we suppose that the firm has to decide which markets (only domestic, or domestic and foreign) it will operate in and this decision is affected by capital stock and productivity:

$$export_t = g(k_t, \omega_t) \tag{19}$$

In addition electricity consumption depends now also on export status:

$$e_t = e(k_t, \omega_t, export_t) \tag{20}$$

So when we invert the energy consumption function we have:

$$\omega_t = \omega(k_t, e_t, export_t) \tag{21}$$

Now we proceed as before, the only difference is that we add the export status (and its interaction with other variables) in the third-order polynomial of the first step. This productivity taking into account the export status is indicated in the text as TFP^{exp}.

B.2 TFP Index

As our robustness check, we have calculated a multilateral TFP index following Good et al. (1997). This indicator assumes constant returns of scale.

$$\mathrm{TFP}_{it}^{index} = (y_{it} - \overline{y}_t) + \textstyle\sum_{\tau=2}^{t}(\overline{y}_\tau - \overline{y}_{\tau-1}) - \sum_{n=1}^{N} 0.5(s_{nit} + \overline{s}_{nt})(x_{it} - \overline{x}_{nt}) + \\ - \textstyle\sum_{\tau=2}^{t}\sum_{n=1}^{N} 0.5(\overline{s}_{n,\tau} + \overline{s}_{n,\tau-1})(\overline{x}_{n,\tau} - \overline{x}_{n,\tau-1})$$
(22)

y is value added, x is a vector of inputs (labor and capital) and s is a vector of input share of every input in the production function. The bar over the variables denotes their mean, that is arithmetic mean for the share and geometric means for the input and output variables, while the index i indicates the variables concerning the single firm i. We have calculated the input shares both as cost share, the weight of a single input in the total cost

of firms[57], and also as revenue share, that means the weight of an input on total output (value added in our case), in this case we have assumed the capital share as our residual.
The productivity index for a given firm and year is expressed in relation to a hypothetical firm in the same industry[58]. This hypothetical firm has, as shown, outputs and inputs equal to the geometric means of outputs and inputs over all observations (in the same sector) and input share equal to the arithmetic mean of input shares.
The first and second term of the right-side in the equation (22) is the deviation of the firm output and inputs from those of the reference firm in the industry (2-digit) in year t. The other two terms are the cumulative change in the output and inputs of the reference firm between t and the initial year. The logarithm of TFP is zero for the (hypothetical) firm in 1990 (the first year of our sample that we assume as base year); firms with lower productivity will show negative values and those with higher productivity will have positive values. This productivity index is indicated in the text as TFP^{index}.

C Kolmogorov-Smirnov test

[57]The cost of labor input is the real wage bill plus employees' social contribution and premium; while the cost of capital is calculated as user cost of capital multiplied by the stock of capital. The user cost of capital is done by $c_k = p_t^k * (i_t + \delta - \pi_t)$, where p_t^k is the price of capital, δ is the depreciation rate (10% for machinery and 20% for equipment and veichles), i_t is the interest rate (we have used interest rates for 12-months time deposits), and π_t is the variation rate in the price of capital

[58]The hypothetical firm varies across 2-digit industries.

Table 14: Kolmogorov Smirnov test. TFP

	1990	1991	1992	1993	1994	1995	1996
D	0.166	0.169	0.175	0.180	0.195	0.175	0.181
$pValue$	0.000	0.000	0.000	0.000	0.000	0.000	0.000

	1997	1998	1999	2000	2001	Pooled
D	0.168	0.154	0.130	0.090	0.115	0.149
$pValue$	0.000	0.000	0.000	0.000	0.000	0.000

HA: Exporters stochastically dominate Non Exporters. Test on logarithmic TFP and LP.