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

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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. Only more productive and larger firms succeed in entering the export market, especially size is a crucial explanatory variable for the export decision. 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 take into account various firms' characteristics and, in particular, we

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control for other forms of firm international involvement (foreign ownership and import status). 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. There are also large and persistent post-entry effects on firm's size and market share.

Empirical evidence shows also a strict linkage between export and import activity: export starters often start also importing in the entry year. Focusing on this firm group, we verify larger productivity gains for firms which start exporting and importing at the same time.

In addition we try to test the role of the productivity gap between domestic market and foreign countries. We use a sectoral indicator of comparative advantage in order to capture this differential of productivity. We hypothesize that learning effects could be large for new exporters in comparative disadvantage industries because in these sectors the domestic productive system should be (relatively) less productive than foreign productive systems if compared with what happens in comparative advantage sectors, and firms could be more distant to technological frontier. So new exporters could obtain higher spillovers from export activity in comparative disadvantage industries because they are entering a more competitive and productive environment with respect to domestic context. We verify a difference in learning potential across sectors according comparative advantage and we find also a different timing in learning-by-exporting.

1 Introduction

Economists have always been interested in the nexus between trade and economic growth. Traditionally, the research on the impact of trade on growth have been conducted at a macro level (country or industry level). However, neither the existing theoretical models nor empirical analyses have led to a definitive and clear conclusion for this issue. The recent 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. A new strand of literature has built on firm heterogeneity and has focused on the specific channels by which trade may affect economic growth. When the attention is turned to the firm, international trade could contribute to the producvity level of a sector mainly through two channels. First, because of the co-existence of heterogeneous firms, trade may yield productivity improvements by reshuffling the resources among plants within the same industry, trade (trade liberalisation) may lead to intra-industry resource reallocation from low- to high-productivity firms, and from non-exporting firms to exporters. In addition to the reallocation effects, intra-firm productivity growth could also be at work. New heterogeneous firm models have dealt with the reallocation mechanism (see for example Melitz (2003); Bernard et al. (2003)). In opposite, the learning potential of firm export participation has not been theoretically examined, even if some empirical works have tried recently to shed some light on this important topic. The scarce analysis for the impact of export entry on firm efficiency is strange if we take into account that, from a policy standpoint, the motivation of export subsidies, granted by many governments, should be learning and efficiency effects running through export.

With this paper we turn our attention on firm behaviour and we try to individuate the drivers behind the positive correlation between export involvement and performance for Turkey. We study both directions of causality between export and productivity, even if the main aim is to investigate the learning-by-exporting hypothesis that has also policy implications of export promotion.

We verify the superior performance of Turkish exporters compared with non-exporters. However, this significant difference between exporters and nonexporters can not shed some light on the direction of causality. Many papers support self-selection hypothesis, but there is no definitive consensus on the importance of learning-by-exporting. The potential of learning linked to export activity remains a controversial topic, and also channels through which learning could display are not clear. When studies verify the existence of some learning effects, they usually don't investigate the channels of these efficiency improvements. These scant evidence could be related with the characteristics of countries analysed in previous papers. It is usually the case of developed and high-technology countries where exporting could have few effects. If firms operate in a country where competition and efficiency level are high and where high technologies are available, benefits from export activity could reduce. In opposite we may expect that in a low-middle income economy, like Turkey, firms can take advantage of export activity through technology transfer and contacts with more efficient foreign firms, especially if they enter a developed and competitive foreign market. Some previous papers have verified the existence of effects following the export entry for Turkey (Yasar and Rejesus, (2005); Aldan and Gunay, (2008)). In addition Turkey is also an interesting country for this topic because it started to implement export-promotion policies since 1980 after abandoning the import substitution regime.

We join this debate using Turkish plant-level data in the period 1990-2001. In particular, following recent literature, we shed light on these issues applying propensity score matching approach and difference in difference estimators. The next section gives a brief literature review. In Section 3 the data are described and summarized. Section 4 verifies for Turkey the existence of the "Exceptional exporters' performance". Sections 5 and 6 present results on self-selection and learning-by-exporting hypothesis. In Section 7 we try to characterise sectoral post-entry effects according to comparative advantage. A final Section gives concluding remarks.

2 Review of previous literature

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 productivity.

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. Because of this barrier we may expect more productive firms self-select into export markets because they are more likely to cope with these sunk costs of entry and survive in the international market. Differences between exporters and non-exporters may be explained by an ex ante productivity gap between firms. This is the first suggested hypothesis in order to explain the positive link between exports and firm performance. This self-selection mechanism has also been sustained by the new heterogeneous firm models (Melitz, 2003; Bernard et al., 2003).

The second hypothesis behind the positive correlation between firm trade and efficiency concerns the role of learning-by-exporting. Previous (empirical) literature has identified three main channels through which exports may affect firm's productivity. 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. Even if channels for potential learning seem to be clear, new theoretical models, based on heterogeneity hypotesis, don't explore whether and how export might affect the firm efficiency. Heterogeneous firm models hypothesize the differential of productivity between firms pre-exists (it is an exogenous fact) and they don't allow the possibility for post-entry effects, that is the don't allow exporters could become more productive than non exporters after export entry, or they could, at least, increase the productvity gap (if a self-selection mechanism is already at work). Recently some scholars have also suggested the hypothesis of a conscious self-selection (Alvarez and Lopez (2005)): firms in the pre-exporting time change their behaviour, they start investing in technology and human capital in order to get ready for the entry in the export market. The behaviour of firms might be forward-looking. Export activity (or better, the expectation of exporting) would cause some investments and a change in productivity, even if, empirically you could first notice the investment and performance change and later export entry. Few papers have examined this firm forward-looking behaviour (due to problems in studying the effects of expectations). Anyway, even if firms accomplish some changes in their activity in preparation to export entry, a potential for learning (following export entry) is always allowed.

In recent years a large number of studies have examined the relationship between exports and productivity exploiting the availability of firm-level datasets. While there is large consensus on self-selection hypothesis (for example, Bernard and Jensen (1999), Clerides et al. (1998), Aw et al. (2000) and Delgado et al. (2002)), there is little empirical evidence supporting learning-by-exporting and results are often controversial. Few papers find a significant export effect: Kraay (1999) for China, Castellani (2002) and Serti and Tomasi (2008) for Italy, Blalock and Jertler (2004) for Indonesia, Van Biesebroeck (2003) for Cote d'Ivoire, and De Loecker (2007) for Slovenia find some potential for learning stemming from export entry. Wagner (2007a) review 54 micro-econometric studies with data from 34 countries, confirming that exporters are more productive than non-exporters, and the more productive firms self-select into export markets, but there is little evidence supporting learning-by-exporting hypothesis. Especially, when developed and competitive countries are analysed, learning-by exporting hypothesis fails, see for example Wagner (2007b) who analyses West German plants. Firms are already productive and efficient, 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 evidence supporting benefits from export activity is found for developing countries or, countries, even if developed, could learn from more competitive partners because they are not on the technological frontier (like Italy[1]). Also Fernandes and Isgut (2007), in a study finding post-entry effects for Colombia, affirm that developing countries are more likely to benefit from learning by exporting. They also find evidence that learning by exporting in Colombia concerns mainly young manufacturing plants, which present an higher propensity and need to learn, but there is no a strong evidence of productivity effects for established exporters. They also show a larger positive advantage of participation in export market for young manufacturing plants selling a great share of their exports to high-income countries. This hypothesis is also tested and verified by De Loecker (2007). He tries to estimate productivity gains from export entry separately for high and low income regions and he finds significant higher productivity premia for firms exporting their products to high income regions. 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.

We focus now our attention on country we analyse. Empirical evidence for Turkey is based mainly on two studies. Yasar and Rejesus (2005) [2], using propensity score matching (PSM) techniques and difference-in-difference (DID) estimators, find that learning-by-exporting may be the reason for the positive correlation between exporting status and firm performance. They examine effects of both the entrance and exit behavior of plants. They find a pro-

[1]For Italy, Castellani (2002) and Serti and Tomasi (2008) have found a potential for learning by exporting. Even if Italy is a developed country its productive system is less competitive than other European countries (their main trade partners). This could explain the positive effects from export activity

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

ductivity differential in the entry year and two years after entry. In addition productivity of firms that exit the export market is statistically lower than the matched continuous exporters during the year of exit and two years after exit. Aldan and Gunay (2008), using a different database (from Central Bank of the Republic of Turkey) and same econometric approach (PSM and difference-in-difference estimator), show that both self-selection and learning-by-exporting are important. Their analysis supports positive effects on firm labor productivity and employment.

Previous studies usually concentrate on relationship between productivity and export activity in order to verify the learning-by-exporting hypothesis. They don't generally investigate in more detail channels of learning. In a recent work, Bratti and Felice (2008), seek to identify the existence of a causal effect of export status on the introduction of product innovations, a potential channel of learning-by-exporting. In our paper we try also to add some evidence on the channels of post-entry effects using an indirect approach, and looking for heterogeneity in post-entry effects according the type of sector.

3 Data

In this paper we use an original Turkish plant-level database[3], 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[4].

[3]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

[4]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. In addition 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 firm-level are from Foreign Trade Statistics.

All nominal values are deflated using sectoral price indices (1994=100) provided by Turkstat. In opposite 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[5], we remain with a dataset of 5,783 firms [6]. There are 3,072 firms exporting at least one year in the period 1990/2001 (in opposite 2,711 firms never export). 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,..). We use, as our performance indicator, both a labour productivity indicator and TFP 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)[7] (see Appendix B for a description of TFP estimation).

We start giving an overview of the firm export activity in Turkey. With this paper we try to individuate the drivers behind the positive correlation between firm export involvement and performance for Turkey, with a particular focus on learning-by-exporting. As in the report of Mayer and Ottaviano (2007) on the internationalisation of European countries, we verify that, also in Turkey, "internationalisation is for the few" and exports are highly concentrated (more than output and employment) in few large exporters.

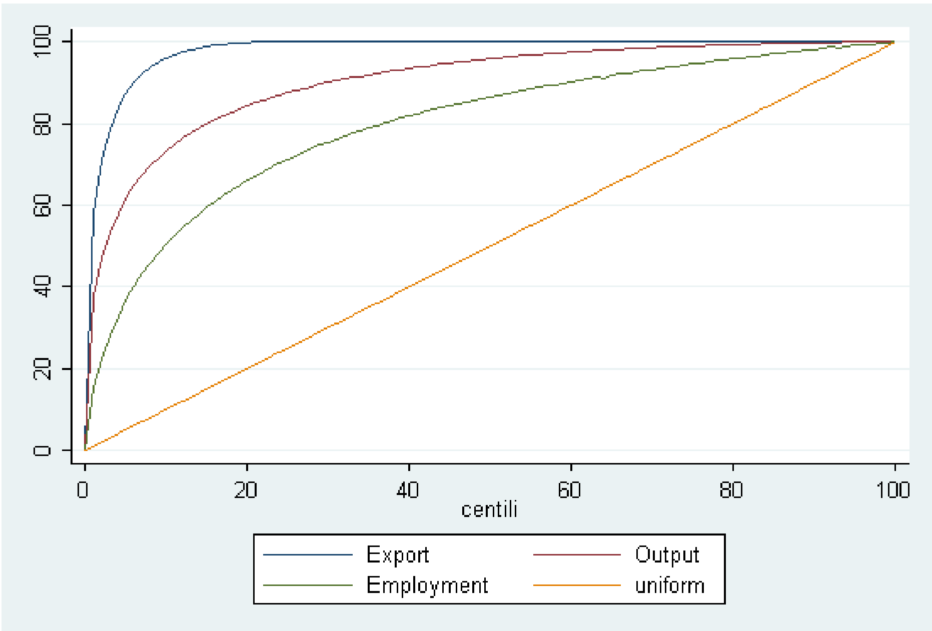
[5]We drop firms with missing data for variables of interest (output, input variables), or with implausible figures (for example, negative values). We had to delete also firms not reporting positive investment flows because we can't construct the capital stock for these firms, as shown in Appendix A. 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 rates: output/labour, material/output, capital/output, energy/output. We have also deleted firms that are in the sample only one or two years.

[6]For a total of 46,607 observations

[7]Results are in general confirmed when we use this TFP index.

This means that export activity, if there are significant post-entry effects, is positively affecting only a part of firm population[8]. We rank firms (from left to right along the horizontal axis) in terms of their individual exports, starting with firm with the biggest export volume. 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).

Figure 1: Export Concentration 2001



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"[9] with more than 25 employees. As we can see from

[8]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

[9]That is, 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.

the figure 1 few large firms contribute to a large amount of exports[10]. Table 1 gives an overview of the firm international involvement in our database (after the cleaning). We can see that a large number of exporters are also involved in import activity. We should take into account this feature when we analyse export entry effects. 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[11].

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

[10]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.

[11]Customs Union had more effects on the tariffs on Turkish imports, so we can see the impact of this agreement mainly on Turkish imports.

4 Exceptional exporters' performance

4.1 Descriptive analysis

Before investigating in more detail the learning by exporting hypothesis we start 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 want to test, also for Turkey, this stylized fact in literature. From simple descriptive statistics (Table 2), we can see exporters present a significant higher productivity (TFP and labour productivity)[12], 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. In opposite there is only a little advantage in skill ratio. This is only a preliminary analysis and we don't check for any firm characteristics.

Table 2: Descriptive Statistics

	TFP	LP	K/L	$Size$	$SkillRatio$	FDI	$Import$
$Exporter$	40.11	719.74	588.57	246	21.22	8.85	65.83
$NonExporter$	29.97	483.86	370.11	114	19.70	3.82	16.46

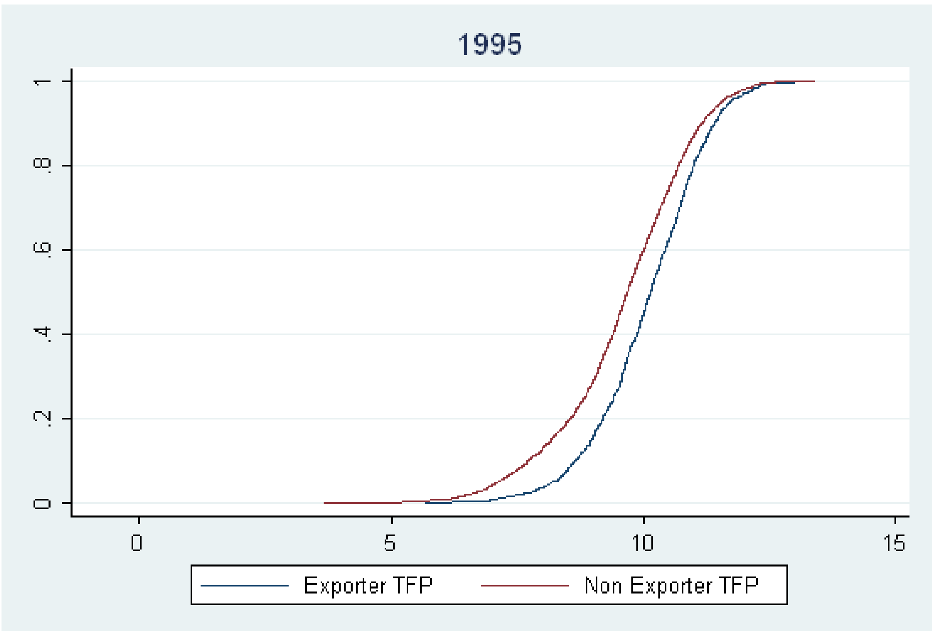
All differences are statistically significant at 1%

In table 2 we look at differences just in the mean value, we focus on one moment of the productivity distribution. A stricter test that considers all moments is a test for stochastic dominance of the productivity distribution for exporters over the productivity distribution for non-exporters. We follow Delgado, Farinas and Ruano (2002) who implemented first time that test in order to investigate the issue of exports and productivity. Let F and G denote the cumulative distribution functions of productivity for exporters and nonexporters. Then first order stochastic dominance of F relative to G

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

means that F(z)G(z) must be less or equal zero for all values of z, with strict inequality for some z. We show the Kolmogorov-Smirnov test for every year in our sample and the graphical analysis of productivity distribution for 1995 (as an example). We compare the TFP (and LP) distribution for exporters and non-exporters for the whole period (pooled sample) and for each year of sample. Looking at the Kolmogorov-Smirnov test[13] (table 3), and the graph we can affirm that productivity distribution of exporters dominates the distribution of non-exporters (this evidence is confirmed for every years even if graphs are not showed).

Figure 2: TFP Distribution



4.2 Export Premium

In previous subsection we have investigated differences according export status without taking into account any other firm characteristics. Following

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

Table 3: Kolmogorov Smirnov test

	TFP		LP	
	D	$pValue$	D	$pValue$
1990	0.166	0.000	0.176	0.000
1991	0.169	0.000	0.177	0.000
1992	0.175	0.000	0.215	0.000
1993	0.180	0.000	0.185	0.000
1994	0.195	0.000	0.223	0.000
1995	0.175	0.000	0.214	0.000
1996	0.181	0.000	0.238	0.000
1997	0.168	0.000	0.273	0.000
1998	0.154	0.000	0.219	0.000
1999	0.130	0.000	0.155	0.000
2000	0.090	0.000	0.110	0.000
2001	0.115	0.000	0.196	0.000
Pooled	0.149	0.000	0.193	0.000

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 regression of the following equation:

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

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 4 shows the β coefficient of regressions with different dependent variables[14]. We transform coefficients in exact percentage values[15]. All coefficients are statistically significant. Even

[14]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.

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

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.

Table 4: 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)
Number Employees	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.

5 Self Selection

We have verified the positive correlation between export and some firm performance indicators. But, as we told before, we are interested in shed light on causal relationship. In order to obtain this aim, we keep in our dataset data concerning firms starting to export in the sample period and firms never export.

We need to give a definition of starter. We consider a firm as an export starter if it doesn't export in previous years, especially in the period t-1 and t-2 (we consider as export entry year the first year in our sample the firm exports, but we also require that it doesn't export in the two previous years, so we want to observe at least a two-year pre-entry period) then it starts to export in t and continue to export in t+1. Our starter is a firm who starts to export the first time (in my sample) in t, it exports also in t+1, and we are sure it doesn't export in t-1 and t-2. For following years we keep the starter in our dataset if it continues exporting (we permit it stops exporting for only one year in the period following export entry, but if it stops exporting two years or more we delete it from dataset[16]). We construct 8 starter cohorts (for each cohort the entry period is 1992/1999). After the initial data cleaning we remain with 543 starters. Table 5 shows the distribution of starters across the 8 cohorts.

Table 5: Starters

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

We start analysing ex-ante differences between starters and never exporters in order to investigate the self-selection hypothesis. In our analysis 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) and Serti and Tomasi (2008), we regress our performance variables (all in logarithm, with the exception of skill ratio and import share) in period t on

[16]We want to catch the effect of a continuous export activity and not an occasional activity

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 $y_{i,t}$ can be our variables in levels or growth rates.

When we investigate variables in levels (Table 6) 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 exporting starters are more productive, larger, present higher capital intensity, higher output. These differences are persistent and are at work for the whole pre-entry period. We can especially notice a huge advantage for starters in capital and output. Starters usually are importers and anyway they present an higher import_share. In opposite we can't notice a significant differential in the skill ratio at least till the period t-1.

We want to verify also if firms modify their behaviour in the pre-entry period. We try to investigate if there are some changes in the path of the main firm characteristics according to the future export status. Analysing growth rates in the pre-export period (table 7), we can notice that since two years before exporting, the productivity growth of future starters is higher than never-exporters. 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 their productivity, but we can't be sure that these changes are in preparation to export entry (that is, if firms spend some efforts in order to be ready for the participation to export market and make some decisions with in mind the international market) or if it's also because of these changes that

Table 6: Self-Selection: Levels

	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$
TFP	22.62	18.02	17.37	24.59	30.42
	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)
TFP^{exp}	21.08	17.38	16.02	22.95	28.57
	(0.002)	(0.003)	(0.002)	(0.000)	(0.000)
TFP^{index}	24.01	18.85	15.33	25.41	30.57
	(0.001)	(0.002)	(0.005)	(0.000)	(0.000)
LP	41.77	42.12	44.14	51.06	61.25
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number Employees	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	70.46	95.54	109.05	89.51	99.77
	(0.)	(0.000)	(0.000)	(0.000)	(0.000)
Output	82.82	101.00	119.76	121.71	157.70
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ULC	-8.53	-8.60	-12.71	-12.39	-15.25
	(0.120)	(0.069)	(0.000)	(0.000)	(0.000)
Skill ratio	53.16	-23.71	-26.78	67.62	144.80
	(0.553)	(0.757)	(0.666)	(0.245)	(0.021)
Import share	79.81	180.62	309.34	313.94	421.00
	(0.421)	(0.052)	(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}. See appendix for a more detailed description.

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. Anyway, in our following analysis, we have taken into account the productivity growth we found out in the pre-entry period, because it could be also that starters are placed on a path of growth and it is interesting to control for this feature.

Table 7: 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	2.73	13.91	1.59	0.58	8.49	6.48
	(0.700)	(0.005)	(0.805)	(0.918)	(0.055)	(0.079)
TFP^{exp}	2.58	13.77	1.72	0.67	8.50	6.53
	(0.714)	(0.006)	(0.790)	(0.906)	(0.055)	(0.076)
TFP^{index}	0.83	13.28	1.56	-2.25	8.12	5.63
	(0.908)	(0.007)	(0.812)	(0.695)	(0.065)	(0.128)
LP	5.31	14.87	1.98	2.60	8.87	7.29
	(0.459)	(0.003)	(0.759)	(0.648)	(0.044)	(0.049)
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	15.21	7.49	3.16	11.77	3.92	6.16
	(0.004)	(0.021)	(0.259)	(0.001)	(0.076)	(0.001)
Capital Intensity	4.31	-2.84	-2.96	5.89	-2.18	-.028
	(0.405)	(0.393)	(0.309)	(0.095)	(0.350)	(0.988)
Output	21.97	21.35	14.35	10.22	8.46	15.38
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ULC	-4.83	-4.99	-2.72	-4.45	0.73	-6.18
	(0.224)	(0.080)	(0.472)	(0.121)	(0.763)	(0.004)
N. observations	6,411	9,453	6,864	8,395	10,128	12,111

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

When we control for size, as done by Bellone et al. (2007), some results in the self-selection analysis change (table 8 and 9). In particular, for productivity we find a positive differential since t-2 (even if also in t-5 there is a positive premium for starters) and this gap is significantly reduced if compared with the gap found previously when we don't check for size. For growth rates, our results are generally confirmed (even if for TFP now only between t-3 and t-2 starters are growing more than never exporters). So when we take into account the differences in size, the ex-ante changes are in part downsized. This analysis put 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 8: Self-Selection: Levels. Control for size

	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$
TFP	15.13	9.15	7.85	14.52	18.32
	(0.026)	(0.107)	(0.129)	(0.001)	(0.000)
LP	24.75	21.44	20.81	26.27	30.92
	(0.001)	(0.001)	(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 dummies, and size.

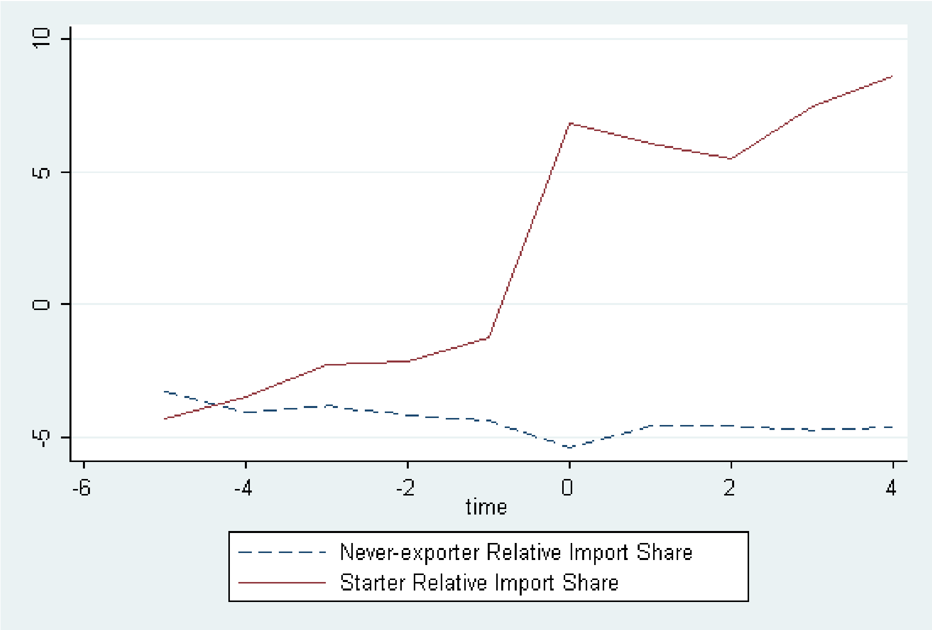
Table 9: Self-Selection: Growth Rates. Control for size

	$t-5/t-3$	$t-3/t-1$	$t-5/t-4$	$t-4/t-3$	$t-3/t-2$	$t-2/t-1$
TFP	1.02	6.44	0.99	0.54	8.42	5.98
	(0.771)	(0.007)	(0.877)	(0.923)	(0.054)	(0.102)
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)
N. observations	6,411	9,453	6,864	8,395	10,128	12,111

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

In the pre-entry period we find also a specific evidence about import activity. Import and export activity seem strictly linked. Import involvement of starters presents a jump between t-1 and t both when we take into account the import share and the import status (dummy).

Figure 3: Import Share Trend



This evidence is shown in the graph 3, we can see a continuous increase in the import share gap between never exporters and starters[17]; 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 being involved in international market, they create some network with foreign firms which allow them both export and import. Or firms, that want to export, need to improve the quality of their good or adapt them to the requests and tastes of foreign customers and, in order to fullfil this need, imported 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 follo-

[17]This is confirmed both with relative and absolute import share

wing analysis that a great part of export starters are also involved in import activity and that this import activity sometimes starts in conjunction with export entry. Previous papers, when they study the link between exports and productivity, investigate sometimes the foreign/domestic ownership of the firm but they 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.

6 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. As we noticed, 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. We analyse the characteristics in level for the post-entry period. We apply the same strategy used for self-selection, but now the regression we run is:

$$y_{i,t} = \alpha + \beta start_{i,t-\gamma} + \delta size_{i,t} + \eta d_j + \omega d_t + \mu d_r + \epsilon_{it} \tag{3}$$

where $start_{i,t-\gamma}$ is, this time, a dummy variable equal to 1 if the firm has starterd exporting in $t - \gamma$ and $0 \leq -\gamma \leq 4$; and $y_{i,t}$ are our variables in levels.

Table 10 shows that starters in post-entry period continue to present superior characteristics compared with never-exporters, and this differential seems to increase during the time. This evidence is common to every variable (productivity, capital, capital intensity, size). Starters have a positive productivity (TFP) gap in t-1 of 30% and after four years following the export entry this gap increase to 40%. Anyway this analysis can not say anything about the real effects from participation into export market.

Table 10: Post-Entry Effects: Levels

	t	$t+1$	$t+2$	$t+3$	$t+4$
TFP	35.40	38.59	34.72	38.45	40.54
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TFP^{exp}	33.41	36.58	32.05	34.32	35.73
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TFP^{index}	37.46	41.42	35.12	39.03	39.62
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LP	68.62	74.77	72.92	84.70	93.65
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number Employees	89.27	97.02	102.86	128.81	154.60
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital	275.55	304.13	353.27	480.77	599.70
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital Intensity	98.42	105.12	123.44	153.82	174.83
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Output	196.33	203.90	219.57	261.10	305.83
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ULC	-17.48	-15.15	5 -13.7	-8.49	-2.36
	(0.000)	(0.000)	(0.000)	(0.044)	(0.642)
Skill Ratio	171.50	236.51	298,20	271.29	451.80
	(0.004)	(0.000)	(0.000)	(0.001)	(0.000)
N. observations	14,619	14,539	14,080	12,320	10,542

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

6.1 Learning-by-exporting: Matched sample

In order to shed some light on post-entry effects, we need to take into account the ex-ante different characteristics between starters and never exporters. If we find out, for example, a significant productivity increase we want to be sure that this effect is coming from export entry and not from previous characteristics of firms starting to export. There is a problem of selection we have to solve. In order to deal with this problem we use Propensity score Matching and difference-in-difference estimator.

We are considering a treatment model, where our treatment is the export entry. Our treated units are export starters, and our controls are firms never export in our sample. A particular aspect of this treatment is that it does not concern only one specific period, one specific year, but for every starter cohort we have a different treatment year.

We are interested in the average treatment effect on treated (ATT), that is the difference for a treated firm between the outcome it obtain after exporting and the potential outcome it would have obtained if it didn't export. I want to find out if, in the hypothetical counterfactual situation of no exporting, starters would have had worse or better outcomes.

$$\begin{aligned} ATT &= E(Y_{it}(1) - Y_{it}(0)|D_i = 1) = \\ &= E(Y_{it}(1)|D_i = 1) - E(Y_{it}(0)|D_i = 1) \end{aligned} \tag{4}$$

We are not able to observe both outcomes for the same individual. 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 didn't export) is unkown. This means that there could be a bias concerning the computation of ATT. The selection bias is:

$$B(ATT_t) = E(Y_{it}(0)|D_i = 1) - E(Y_{it}(0)|D_i = 0) \tag{5}$$

If the group of the treated is randomly selected from the population, that means the treated and the group of the control 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 individuals may differ in important characteristics. We have really already verified the existence of these differences in the previous analysis (self-selection): this means that self-selection bias is a real problem. To solve this problem we use both difference-in-difference strategy and PSM. In the DID strategy we compares 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[18]), on the assumption that, without the treatment, the outcomes would have been similar across the two groups of firms. So the ATT effect is calculated on this difference (before/after):

$$\begin{aligned} ATT &= E(Y_{i1}(1) - Y_{i1}(0)|D_i = 1) = \\ &= E(Y_{i1}(1) - Y_{i0}(1)|D_i = 1) - E(Y_{i1}(0) - Y_{i0}(0)|D_i = 0) \end{aligned} \tag{6}$$

But difference-in-difference estimator doesn't eliminate completely the self-selection bias. In order to construct a consistent counterfactual, we use also matching techniques. Using a generic non-exporters 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 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[19] of non treated unites (never exporters), those firms who are similar to the starters in all relevant pre-treatment characteristics X to approximate the counterfactual outcome

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

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

(Blundell and Costa Dias, 2000). The use of matching to construct a valid control group is based on the hypothesis of conditional independence: conditional on all relevant observable variables, the potential outcomes are independent of treatment, that is treatment status is random. We are assuming that the set of observable variables at our disposal are enough to eliminate the bias stemming from the non-random selection of the firms into the exporters and non-exporters group. Our hypothesis is that, given the set of variables at our disposal, firms with the same characteristics are randomly exposed to the export activity. This method assume that there is no selection bias that stems from "selection on unobservables"[20].

Since conditioning on all significant covariates is difficult when the dimension of the vector X is high, Rosenbaum and Rubin (1983) have suggested the use of balancing scores b(X), that is a function of the observed covariates X. One possible balancing score is the propensity score, the conditional probability of receiving treatment (start to export) given pre-treatment (before exporting) characteristics (X). The Propensity score matching consists in estimating a propensity score of export entry conditional to variables at our disposal and that we think they could affect the probability to enter export market. Then we match plants (treated plants with control plants) using this estimated propensity score. PSM requires to take some decisions concerning the probit specification and matching criteria; so results could be affected by these choices[21]. We can choose between different probit specifications according our belief in which variables affect the export entry. We choose our variables taking into account the empirical works on export decision. In addition we want a probit specification satisfying the balancing test introduced

[20] This is a strong assumption, but we think that it could be satisfied provided our large and rich dataset. Anyway, in addition, we use also a difference-in-difference estimator which explicitly allow selection on unobservables. 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".

[21] For this reason, we have tried to implement some robusteness analysis changing both probit specification and matching criteria.

by Rosenbaum and Rubin. According the balancing property, formalized in Becker and Ichino (2002), 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. With this test we split the sample in ranges in order to have the same average propensity score for the treated and the control in each interval. Then, within each interval, we test that the means of every covariate do not differ between treated and controls. This test tells that the decision to export is random, treated and control units are identical on average.
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.
We use the following probit to estimate the probability score of first-time exporting[22]:

$$Pr(START_{it} = 1) = f\{TFP_{t-1}, n_{t-1}, k_{t-1}, ulc_{t-1}, SkillProd_{t-1}, Import_{t-1}, ForeignShare_{t-1}, SubInp_{t-1}, SubOut_{t-1}, dummies\} \tag{7}$$

where $START_{it}$ is a dummy variable assuming value 1 if the firm starts exporting in t. This probit is estimated pooling all cohorts (matching procedure is then applied both cross-section by cross-section, that is separately for each cohort, and on the pooled sample). In the regression we have kept only never exporters, for every years they are in the sample, and starters, for the year they start exporting. I have decided to use the pooled sample because, in this way, I can exploit the information contained in the largest possible dataset for modelling the export-starting decision. Estimating different probit

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

for each cohort could be a loss of efficiency because the number of starters in every cohort is low (as already shown in table 5). We include the following explanatory variables: total factor productivity, size (number od employees), capital stock, unit labour cost, the share of skilled production employees, foreign share, import dummy, subcontracted input and output shares, and dummies for industry, year and region. We include also the square term of size. Every variable is lagged for one period[23]. 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[24]. The nearest neighbor technique matchs 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[25], 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. We decided to implement this procedure

[23]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. Anyway from previous analysis it seems that pre-entry changes in some characteristcs of future starters are mainly linked to their larger size and not to a specific plan in preparation for export entry.

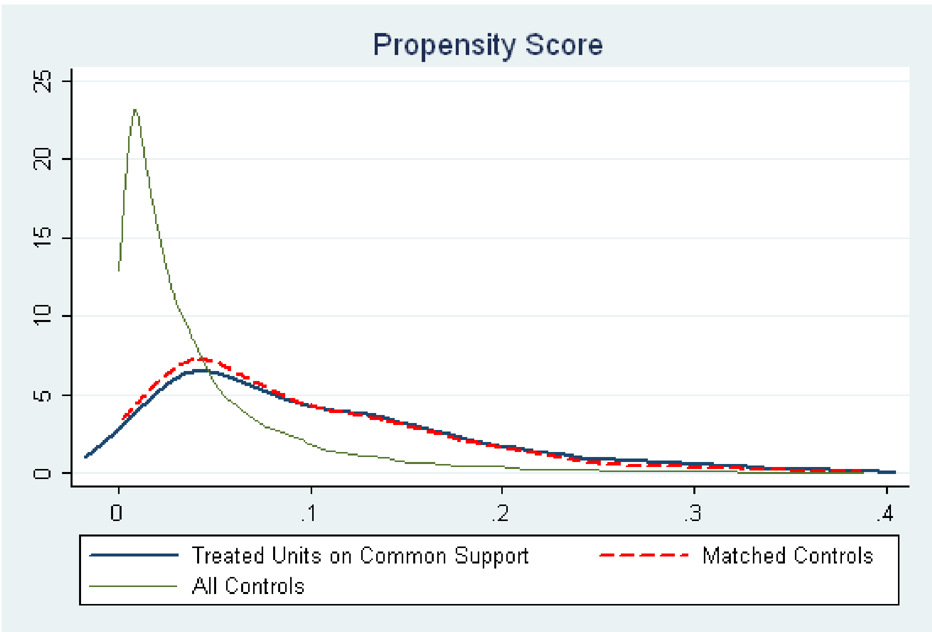
[24]We have chosen to match the starter with a single never exporters because of the large population of never exporters at our disposal.

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

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. The results obtained using these two different matching criteria 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 do this check. 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, in order to verify the quality of matching we show the density function of pscore for treated, all controls and matched control. We can see 4) that the propensity score distribution was very different before matching for all controls and treated units, 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 11 shows significant differences betweeen starters and never-exporters in all variables analysed for the unmatched sample. In opposite, for the matched sample, there are no significant differences in the characteristics of the plants entering the export market and the matched non-exporters (as expected). This means that the matching procedure is effective: the statistically significant differences in means between exporters and non-exporters before matching become insignificant after matching. We have made this check for every following 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. Results confirm the quality of matching.
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 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[26], this means that, according our probit specification, treated units and their matched controls have the same probability to start exporting.

After matching procedure, we calculate ATT effects. The implemented DID-PSM estimator could be written as:

$$M^{DID-PSM} = \frac{1}{n_i} \sum_{i \in D_i^*=1} [(Y_{i,post} - Y_{i,pre}) - \sum_{j \in D_j^*=0} \omega(i,j)(Y_{j,post} - Y_{j,pre})] \quad (8)$$

Y is the variable of our interest (for example productivity). Subscripts *post*

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

Table 11: 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

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 12: 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%

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 fourth year (third year for the capital) after the export entry. We have to notice that when we consider years farer from the entry the sample is reduced, especially for t+3 and t+4 the results are not completely reliable[27].

Learning-by-exporting hypothesis seems 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 singificant. 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[28].

In order to accounting for productivity trends prior export entry, we also construct a new control group based on a new probit specification including the productivity change in the period preceding the export entry in addition to previous covariates in order to take into account some potential "path effects", starters could be on a path of growth. We have done this check because future starters could be affected by positive shocks to their productivity in the pre-export period that allow them to self-select into the export market, these positive shocks could also continue over time in the post-entry period. Taking into account the produtctivity growth before export entry could help us to capture this productivity shocks. Results are confirmed even if in t+2 and t+3 ATT effects become not significant, but we can continue observing a significant growth in productivity for the entry year and the following year (and also for t+4). This robustness check supports our conclusion that new exporters outperform plants remaining in domestic market[29].

[27]Using different probit specifications we have found different results for this two periods for their significance, especially for productivity indicators

[28]When we restrict the matching imposing a caliper=0.01 the starters we can match drop from 532 (without caliper) to 521 (with caliper).

[29]We don't show the ATT effects for the matching on the pooled sample, the matching with caliper and the matching accounting for productivity trends prior to export entry. These results are available on request. We have to notice that when we include lagged productivity growth in the probit specification, the balancing property is not balanced.

From these results we can't infer which channels are behind the productivity increase, in effect the performance improvement could be caused by a competition and technology effect of international markets (so, a real learning effect) or could be the effect of the exploitation of scale economies.
If exporters become more productive with respect to their pre-export level of productivity compared to never exporters doesn't mean that they are growing faster every year over the whole post-entry period, as also noticed in De Loecker (2007). We could, for example, hypothesize that in the entry year firms place themselves on a higher TFP path and then they stay on this "superior" path. 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:

$$ATT_s = \frac{1}{n_i} \sum_{i \in D_i = 1} [(TFPGrowth_{i,s}) - \sum_{j \in D_j = 0} \omega(i,j)(TFPGrowth_{j,s})] \quad (9)$$

where $TFPGrowth_{i,s} = tfp_s - tfp_{s-1}$.
Table 13 show the ATT effects concerning growth rates. We can see 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 folowing period they stay on this path and confirm their advantage compared with never exporters.

Robusteness check The ATT calculation is a superior method, 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. Anyway, as robustness check, we have also tried to implement a different methodology. Following studies of Greenaway, Girma and

Table 13: ATT effects: Yearly Growth Rates

	t	$t+1$	$t+2$	$t+3$	$t+4$
TFP	**0.140**	0.047	0.003	0.037	0.065
	(0.011)	(0.382)	(0.959)	(0.698)	(0.576)
LP	**0.138**	0.055	0.028	0.046	0.082
	(0.012)	(0.301)	(0.638)	(0.631)	(0.482)

Bold values are significant at least at 10%

Kneller (2003, 2004) we have pooled our observations (of starters and matched controls) concerning different post-entry periods and we have estimated the regression:

$$\begin{aligned}\Delta TFP_{it} &= \alpha + \sum_{\sigma=0}^{4} \beta D^{t+\sigma} + \gamma D^{t-1} * START_i + \sum_{\sigma=0}^{4} \delta D^{t+\sigma} * START_i + \\ &+ \varphi TFP_{i,t-1} + \theta n_{i,t-1} + \iota d_r + \mu d_j + \rho d_y + \epsilon_{ijt} \qquad (10)\end{aligned}$$

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[30]. $START_i$ 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 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[31]. We estimate this equation keeping in our dataset only starters and matched controls for the years $-1 \leq t \leq 4$ (where t=0 is the entry period), so we consider the pre-entry period, the entry year and the

[30]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.

[31]For example $D^{t+3} * START_i$ is 1 in period t for starters if they started to export 3 years before, in t-3.

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. Then 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 growth of TFP specific to starters in the post-entry period.
With this regression we are analysing the annual growth rates. In addition, in opposite to Table 12, 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).

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 effects are shown for the whole post-entry period. The conclusions of this startegy are very similar with our previous analisys. When we take into account the annual growth rates, we find a jump for starter TFP especially in the entry-period.

7 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.

Table 14: 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 control
(4)Fixed Effects estimation with controls (lagged TFP and size)
P-Values are in brackets.

In previous sections, we could check for the previous import status, that is since we include in the probit specification the lagged import dummy, we could take into account previous import activity of matched and control units, as Table 11 has shown, there is no a significant difference in the import status between starters and never exporters after matching[32]. Anyway, even if matching procedure let us to control for pre-entry characteristics, it doesn't check for events could happen in combination with export entry, that is 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 in t-1 nor in t[33]). In both group we have obviously included the relative matched controls[34]. As shown in table 11, there is no a statistical difference in import status between starters and matched controls, so we can see that 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 effects are slightly downsized and there is not a significant effect in t[35]. This finding further support the goodness of significant positive effects stemming from export activity.

We verify also (Table 15) larger productivity gains for firms which start exporting and importing at the same time, for example we found a post-entry

[32] Even if we have not matched exactly on the lagged import status, we can see from Table 11 that the matching was quite perfect.

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

[34] The matching procedure is not changed.

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

TFP effect of 14% for the total sample, 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.

Table 15: ATT effects: Control for the current import status

	TFP		
	t	$t+1$	$t+2$
Group1	**0.206**	**0.239**	**0.210**
	(0.008)	(0.005)	(0.064)
Group2	0.109	**0.156**	**0.229**
	(0.110)	(0.039)	(0.015)

Group1 = New Importers
Group2 = Old Importers, Non Importers
Bold values are significant at least at 10%

8 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, to high levels 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 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 only 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[36]. 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[37].

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

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

[37]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

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

$$RCA = \frac{X_{TUR,i}/X_{TUR}}{X_{W,i}/X_W} \tag{11}$$

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) sectoral trade data from CEPII (Research Center in International Economics) and the comparison group of countries are the European Union countries, Russian Federation and Usa[38]. 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 previous section, we define postCA

[38]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.

a vector of dummy variables for the post-entry period for starters in comparative advantage (CA) sectors and postCD a vector of dummy variables for the post-entry period for starters in comparative disadvantage sectors CD. We can calculate ATT effects with the following equation:

$$\Delta TFP_{i,s} = \alpha + \beta_1 postCA_{i,s} + \beta_2 postCD_{i,s} + \epsilon_{is} \tag{12}$$

where $\Delta TFP_{i,s}$ is the productivity growth between the post-entry and pre-entry (t-1) period[39]. The variable tfp is always expressed as a deviation from the industry-year mean. 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 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[40].

We can verify (Table 16) that 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). 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

[39]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.

[40]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.

Table 16: 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%

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 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[41] of firms (always

[41] 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

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.

9 Concluding remarks

This paper analyzes the link between exports and firm performance for a middle income country, Turkey. We find evidence for both self-selection and post-entry effects. This 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. 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.

Our analysis displayes also a strict linkage between export and import entry. The positive 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 will be 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 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. 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:

$$K_{t+1} = (1-\delta)K_t + I_t{}^{42} \tag{13}$$

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[43] can be obtained by solving:

$$K_0 = \tfrac{I_0}{(g+\delta)} \tag{14}$$

where δ is the depreciation rate and g is the growth rate of capital that we assume equal to energy growth[44]. We construct separatly two measures of capital stock for: machinery; and equipment, transportation, veichles. For these two stocks we use two different depreciation rates following literature: 10% and 20%[45]. 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:

$$K_{\tau-1} = \tfrac{K_\tau}{1-\delta} \tag{15}$$

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

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

[44]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.

[45]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.

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 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.

$$Y = Af\{KL\} \tag{16}$$

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[46].

$$y_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + \omega_t + \eta_{it} = \alpha_l l_{it} + \phi_t(k_{it}; e_{it}) + \eta_{it} \tag{17}$$

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 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:

$$y_{it} = \delta_0 + \alpha_l l_{it} + \sum_{i=0}^{3} \sum_{j=0}^{3-i} \delta_{ij} k_t^i e_t^j + \eta_{it} \tag{18}$$

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):

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

$$min_{\alpha_k^*} \sum (y_{it} - \widehat{\alpha}_l l_{it} - \alpha_k^* k_{it} - E[\widehat{\omega_t | \omega_{t-1}}])^2 \quad (19)$$

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

$$\hat{\omega_t} = \gamma_0 + \gamma_1 \omega_{t-1} + \gamma_2 \omega_{t-1}^2 + \gamma_3 \omega_{t-1}^3 + \upsilon_{it} \quad (20)$$

We include also time dummies to capture congiuntural events and trends over time.

Our productivity measure is the residual of the production function:

$$tfp = y - \widehat{\alpha}_l * l - \widehat{\alpha}_k * k \quad (21)$$

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:

$$export_t = g(k_t, \omega_t) \quad (22)$$

In addition electricity consumption depends now also on export status:

$$e_t = e(k_t, \omega_t, export_t) \quad (23)$$

So when we invert the energy consumption function we have:

$$\omega_t = \omega(k_t, e_t, export_t) \quad (24)$$

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.

$$\mathrm{TFP}_{it}^{index} = (y_{it} - \overline{y}_t) + \sum_{\tau=2}^{t}(\overline{y}_\tau - \overline{y}_{\tau-1}) - \sum_{n=1}^{N} 0.5(s_{nit} + \overline{s}_{nt})(x_{it} - \overline{x}_{nt}) + \\ - \sum_{\tau=2}^{t}\sum_{n=1}^{N} 0.5(\overline{s}_{n,\tau} + \overline{s}_{n,\tau-1})(\overline{x}_{n,\tau} - \overline{x}_{n,\tau-1}) \quad (25)$$

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[47], 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[48]. 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 (25) 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

[47] 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

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

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}.