Learning by exporting in Turkey: an investigation for existence and channels

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Abstract

Using a rich longitudinal database at the plant level, I shed new light on the causal nexus between exports and productivity for Turkey, a middle-income country. I find evidence for both self-selection into exporting and learning-by-exporting. My main focus is on post-entry effects. To test this hypothesis I follow recent empirical literature and I apply the Propensity Score Matching and a Difference-in-Difference estimator. I find a 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. My main contribution is to show the strict linkage between export and import activity: export starters often start also importing. Learning by exporting effects hold when I control for the role of imports and I verify larger productivity gains for firms which start exporting and importing at the same time. Finally, in order to verify if post-entry effects are not only scale effects but work through competition channel and/or technology transfers, I look for a heterogeneity according to the sectoral productivity gap between the domestic market and foreign trade partners. I verify a different timing of efficiency improvements between comparative advantage and disadvantage sectors.

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

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1 Motivation and previous literature

The nexus between trade and economic growth has always drawn the attention of economists and, traditionally, the research on this topic has been conducted at a macro level - country or industry level. The recent availability of firm and plant level datasets and the following proliferation of firm-level analysis has shown new stylized facts, especially the co-existence in the same sector of firms with heterogeneous characteristics, and has renewed the interest for the link between exports and efficiency/productivity.

Theoretical and empirical literature has verified, both for developed and developing countries, a superior performance of firms involved in international markets (Bernard and Jensen, 1999; Bernard et al., 2003; Clerides et al., 1998; Pavcnik, 2002). Since the finding of this evidence, a large number of studies have investigated, in more detail, the causal relationship between exports and firm productivity. Two main hypothesis have been suggested. First, there exist additional costs of selling goods in foreign markets: transportation costs, distribution or marketing costs, and costs in adapting domestic products to foreign consumers' tastes. These costs represent an entry barrier and one may expect more productive firms to self-select into export markets because they are more likely to cope with these sunk costs and survive in the international market. This is the first suggested hypothesis. The self-selection mechanism has also been sustained by new heterogeneous firms' models (Melitz, 2003; Bernard et al., 2003) that hypothesize the differential of productivity between firms pre-exists[1].

The second hypothesis behind the positive correlation between firm trade and efficiency concerns the role of learning-by-exporting. Previous empirical literature has suggested three main channels through which exports may increase firms' productivity: technology adoption, the exploitation of scale economies and a higher competitive pressure[2].

While there is large consensus on the self-selection hypothesis (for example, Bernard and Jensen, 1999; Clerides et al., 1998; Aw et al., 2000; Delgado et al. 2002), there is less empirical evidence supporting learning-by-exporting, results are often controversial and also channels through which

[1] Recently, some scholars have also hypothesized a conscious self-selection, supposing the existence of a forward-looking behaviour. See, for example, Alvarez and Lopez, 2005.

[2] 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.

learning could display are not clear. Wagner (2007a) review 54 micro-econometric studies with data from 34 countries, confirming that exporters are more productive than non-exporters, and the more efficient firms self-select into export markets. Post-entry effects are usually negligible or lacking, and learning-by-exporting hypothesis fails for developed and competitive countries (see for example Wagner, 2007b, who analyses West German plants). In high-income countries firms are already on the technological frontier, they are operating in an efficient and competitive context and they are using advanced technology. There could be no great learning effects in such a framework. In opposite, in a developing country, firms could take advantage of export activity through technology transfers and contacts with more efficient foreign firms, especially if they enter a developed and competitive foreign market. Kraay (1999) for China, Blalock and Jertler (2004) for Indonesia, Van Biesebroeck (2003) for Cote d'Ivoire, Fernandes and Isgut (2007) for Colombia and De Loecker (2007) for Slovenia find some positive productivity effects stemming from export entry[3].

I join this debate and present empirical evidence on the relationship between exports and firm performance for Turkey in the period 1990-2001. Turkey is an interesting country to analyse because it is a middle-low income country which underwent, during the '80s, a process of trade openness[4]. Its main trade partners are advanced countries[5], and, in opposite to less developed economies, its firms may be endowed of the human capital and capabilities to absorb positive spillovers and exploit opportunities granted by international markets. All these features make Turkey an ideal context where learning-by-exporting effects could display and be the outcome of technology/knowledge transfers and a more competitive environment, and not only caused by economies of scale.

I study both the directions of causality between exports and productivity, even if I especially focus on the learning-by-exporting hypothesis that has stronger policy implications for export promotion[6].

Previous empirical evidence for Turkey on this topic is based mainly on

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

[4]During the '80s it moved from an import substitution regime to the implementation of export-promotion policies.

[5]More than 80% of its exports are directed to OECD countries.

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

two studies. Yasar and Rejesus (2005)[7], applying Propensity Score Matching (PSM) techniques and Difference-In-Difference (DID) estimators, show that learning-by-exporting may be the reason for the positive correlation between exporting status and firm performance. They find out a productivity differential in the entry year and two years after entry[8], but their analysis concerns only a small sample of sectors. Aldan and Gunay (2008), using a different database (from Central Bank of the Republic of Turkey) and same econometric approach, highlight that both self-selection and learning-by-exporting are important. Their analysis supports positive post-entry effects on firm labour productivity and employment.

With this paper I confirm previous findings extending the analysis, compared to Yasar and Rejesus, to a large dataset, including all manufacturing sectors, and a wider time horizon. In opposite to Aldan and Gunay who analyse labour productivity, I focus on TFP and I also investigate other important firm characteristics. My contribution is also to show the link between the export entry and import activity at firm level, two forms of international involvement that are strictly related. Previous literature has disregarded this relationship[9], and I try to fill this gap.

Then, I add some evidence on the channels of learning-by-exporting, looking for an heterogeneity in post-entry effects according to the type of sector. Previous papers usually do not pay attention on the reasons and motivations behind post-entry effects. The only two exceptions are Fernandes and Isgut (2007) and De Loecker (2007) who verify a significant and larger positive advantage of participation in export market for plants selling a great share of their exports to high-income countries. This evidence sheds some light on the channels of the learning: if there are different effects according to trade partners, it is likely exporting effects work also through competition channel and technology transfers and not only through a scale effect. Behind their approach there is the idea that firms of every sector can learn when they enter advanced countries. My 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. I investigate if the

[7]They use data, like my dataset, from Turkstat but they analyse a smaller sample (three four-digit sectors) for a restricted time period 1990-96.

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

[9]Recently, Kasahara and Lapham (2007) and Castellani et al. (2008) show that firms often both export and import and Kasahara and Rodrigue (2008) have dealt with the impact of imports for firm productivity trying also to correct for export activity. Muuls and Pisu (2009) study the interactions between exports and imports for the self-selection process.

potential for learning is higher in sectors more distant to the technological frontier[10] because in these sectors spillovers may be more important.

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

2 Data and descriptive analysis

2.1 Data

In this paper I use an original Turkish plant-level database[11], from the Annual Surveys of Manufacturing Industries, collected by Turkish State Institute of Statistics (Turkstat). I have at my disposal an unbalanced panel dataset on plants with more than 25 employees for the whole manufacturing sector in the period 1990/2001[12]. The dataset consists of plant-level information on output, inputs, investments[13] and a large number of plant characteristics (foreign ownership, import activity, export activity, size, industry, region). All nominal values are deflated using 4-digit ISIC price indices (the base year is 1994) provided by Turkstat, while for capital goods I use a unique deflator for all sectors, but different deflators according to type of goods (machinery and transportation). After a cleaning procedure[14], I remain with a dataset

[10]As an indicator of distance to technological frontier I use a sectoral indicator of revealed comparative advantage. See the following analysis for an explanation of this approach.

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

[12]Turkstat collects data on plants with more than 10 employees, but before 1992 it ran two different surveys for firms with more 25 employees and firms with less than 25 employees. In order to keep a longer time horizon as possible I have decided to use data for larger firms. In addition, I am interested in export activity and only few firms with less 25 employees export, and, anyway, their export volume is very low.
Import and export data at plant-level are from Foreign Trade Statistics.

[13]I have used the Perpetual inventory method in order to obtain a capital stock measure.

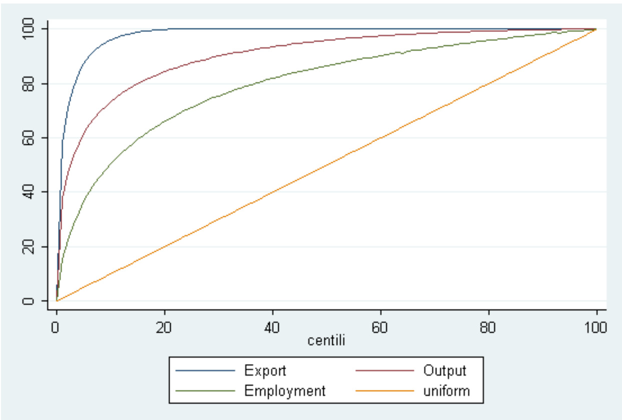
[14]I drop observations with missing data for variables of interest (output, input variables), or with implausible figures (for example, negative values). I had to delete also firms not reporting positive investment flows because I can't construct the capital stock for these firms with the perpetual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

of 5,783 firms, for a total of 46,607 observations. There are 3,072 firms exporting at least in one year in the period 1990/2001 (in opposite 2,711 firms never export). I use, as performance indicator, both labour productivity and TFP indicators. I calculate labour productivity as value added per employee. TFP measure is estimated using the semiparametric approach by Levinshon and Petrin (2003) and I have estimated the production function separately for every 2-digit (ISIC) sector (TFP). I have also applied the semiparametric approach taking into account the export status of firms (TFP^{exp})[15]. Finally, as my robustness check, I have constructed a multilateral TFP index following Good et al. (1997), TFP^{index}.

2.2 Exceptional exporters' performance

Figure 1 shows that in Turkey exports are highly concentrated, more than output and employment, in few large exporters as documented also for other European countries (Mayer and Ottaviano, 2007). This means that, if there are significant post-entry effects, export activity is positively affecting only a part of firms' population[16].

Figure 1: Export Concentration 2001



sample less than three years.

[15] I have modified the Levinshon and Petrin (2003) procedure in order to take into account the export status as an additional control in the dynamic problem (see Van Biesebroeck, 2005 and De Loecker, 2007).

[16] The beneficial impact of trade could be concerning a still smaller population if learning-by-exporting effects are also linked to the volume of exports.

Table 1 gives an overview of the firm international involvement in my database. During the analysed period (1990/2001), the share of exporters in the sample is quite constant (about 25/32%). Even if in 1996 the Customs Union agreement with the European Union (EU) went into effect, EU had already removed tariffs on imports from Turkey before 1996[17]. A large number of exporters are involved also in import activity: more than 65% of exporters are two-way traders.

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

My elaborations from firm level dataset.

Simple descriptive statistics (Table 2) confirms, also for Turkey, the "exceptional exporters' performance": exporters present a significant higher productivity (TFP and labour productivity)[18], they have a larger number of employees and a larger output, they are more capital intensive, and it is more likely they are importers and foreign-owned.

This table displays differences just in the mean value. A test for stochastic dominance, the Kolmogorov-Smirnov test, also allows to consider all moments of the productivity distribution for exporters and non-exporters[19]. The test displays, both for each year in the sample and for the whole period (pooled sample), that TFP distribution of exporters stochastically dominates

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

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

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

Table 2: Descriptive Statistics

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

All differences are statistically significant at 1%

that of non-exporters[20].

Table 3: Kolmogorov Smirnov test. TFP

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

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

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

In order to strengthen this descriptive evidence, I follow Bernard and Jensen (1999) and check for other firm characteristics: firm size, industry and regional localisation. Table 4 shows the β coefficient of the following OLS regressions[21]:

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

where y can be: TFP, labour productivity, capital stock, capital intensity (the ratio between capital stock and number of employees), number of employees (as a proxy for firm size), output and unit labour cost (calculated as total labour cost on output). The variable $export\_dummy_{it}$ indicates the export status of the firm in the period t. d_j, d_t and d_r are sectoral, time and regional dummies. All coefficients are statistically significant. Even if I check for additional controls (firm size, industry, region, year), the superior performance of exporters holds. I display an export premium of 18% for TFP

[20] I do not show the graphical analysis that is available upon request.

[21] I verified the existence of significant export premium for every year in my sample. In table I show only, as an example, export premium for the first and last year of the sample and for the pooled sample.

in the pooled sample. This evidence for Turkey is consistent to findings for other countries[22].

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)
Size	107.64	55.79	86.83
	(0.000)	(0.000)	(0.000)
Output	15.36	30.46	27.70
	(0.000)	(0.000)	(0.000)
Capital	209.92	182.93	234.16
	(0.000)	(0.000)	(0.000)
Capital Intensity	17.12	55.85	40.71
	(0.011)	(0.000)	(0.000)
ULC	-10.20	-12.21	-13.22
	(0.000)	(0.000)	(0.000)
N. observations	3,018	3,503	46,607

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

3 Self Selection

In the previous section, I have verified the positive correlation between export and some firm performance indicators. Now, being interested in shedding light on the causal relationship, I keep in my dataset firms that start exporting in the sample period and firms which never export.
I define export starter as a firm which continuously exports from t onwards (for at least two consecutive years) and which had never exported in the previous years (I request to observe at least t-1 and t-2)[23]. I end up with 8

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

[23] I allow exporters to exit the export market only one year. If starters stop exporting for two years or more, I do not consider the years following the export exit because I am interested in post-entry effects related to a continuous export activity. Anyway I have also tried to re-include in my analysis the observations after the export exit.

cohorts, one for each years between 1992-99, and 543 starters[24].

I analyse ex-ante differences between starters and never exporters in order to investigate the self-selection hypothesis. Following Bernard and Jensen (1999), I regress the productivity indicators and other firm characteristics (all in logarithm, with the exception of skill ratio and import share) in the pre-export time $t - \sigma$ ($1 \leq \sigma \leq 5$[25]) on a dummy indicating if a firm is an export starter at time t, $start_{i,t}$, and on a set of controls (number of employees, sectoral dummies, regional dummies and time dummies):

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

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

Also, I verify whether firms modify their behaviour in the pre-entry period according to the future export status analysing the growth rates. I find out that future exporters increase their size, their market share and, even if for only one year (t-2), their productivity (the relative table is available upon request), but one can not affirm that these changes are in preparation to export entry, having in mind the international market, or if these changes allow firms to enter the export market in the following period. Looking at the whole pre-entry period it is highly likely that future starters are successful firms, also before exporting, and they can enter export market because of their pre-export performance.

In the pre-entry period an interesting evidence is detected for import participation. Import and export activities are strictly linked and the Figure 2 shows an increasing import share gap between never exporters and starters[26]. In particular, one can notice a significant jump between t-1 and t (for firms that never export throughout the sample period t=0 is just the median year in the sample, so 1995): some firms entering export market also start importing materials at the same time. Different explanations for this finding

[24]The distribution of starters across the cohorts is available from author upon request.
[25]As in Serti and Tomasi (2008)
[26]This is confirmed both with relative and absolute import share. Relative import share is expressed as a deviation from the industry-year mean.

Table 5: Self-Selection: Levels

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

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

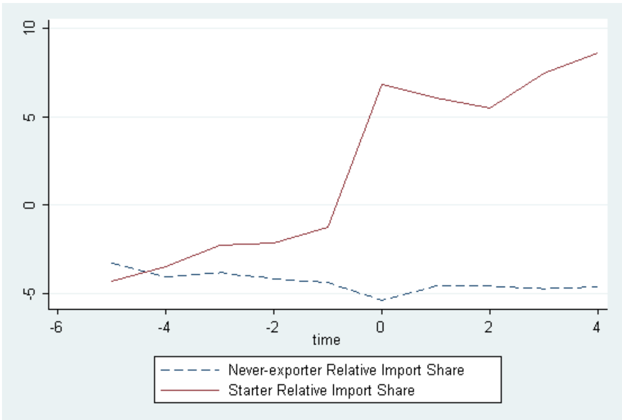
could be suggested. These two international activities may share the same sunk costs, and when firms start being involved in international markets, through imports or exports, they take part of some networks with foreign firms which may ease other internationalisation strategies. Import activity may help firms to set up relationships with local operators and understand and know the foreign markets. This experience could facilitate the export activity. In addition, the use of imported inputs may allow firms to produce and adapt goods meeting the preferences, habits and tastes of foreign consumers[27]. Finally, foreign sourcing of cheaper and/or high quality inputs could lead to productivity and efficiency improvements for firms that become able to penetrate foreign markets[28].

[27]This could especially be important for firms in developing countries exporting to advanced economies

[28]Anyway it is important to notice that no causal relationship could be at work and the

Even if it is difficult to clean the export effect from a potential import effect, it is important to have in mind in the following analysis that a great part of export starters are also involved in import activity and this foreign sourcing may start in conjunction with export entry. Previous papers, studying the link between exports and productivity, sometimes investigate the foreign/domestic ownership of starters and never exporters but they do not take into account if a firm is also an importer, and up to now literature has neglected the relationship between exports and imports at firm-level in the learning-by-exporting investigation[29].

Figure 2: Import Share Trend



4 Post-Entry Effects

According to the previous investigation, a self-selection mechanism drives the most successful, large and efficient firms in the export market. Self-selection does not exclude the potential for learning by exporting. Even if starters are already more productive when they enter foreign markets, they could further improve their performance and the differential with non exporters after the export entry. In order to test this hypothesis I consider a treatment model, where treatment is the export entry. Treated units are export starters,

positive correlation may simply mean that the same firms that can cope with sunk export entry costs are also able to set relationships with foreign suppliers.

[29]Kasahara and Rodrigue (2008) look at the opposite direction controlling for export activity in the analysis of import effects on productivity. Muuls and Pisu (2009) deal with the role of import (export) status in the self-selection process into export (import) market.

and controls are never exporting firms in the sample. Treatment does not concern only one specific year, but for every starter cohort there is a different treatment year. I am interested in the average treatment effect on the treated (ATT),

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

that is the difference for a treated firm between the outcome it obtains after exporting and the potential outcome it would have obtained if it had never exported. I am verifying if, in the hypothetical counterfactual situation of no exporting, starters would have had worse or better outcomes. I am not able to observe both outcomes for the same firm, especially $E(Y_{it}(0)|D_i = 1)$ - that is the outcome of exporters if they had not exported - is unknown. I can only calculate $E(Y_{it}(0)|D_i = 0)$, the outcome for non exporters provided that they have not exported. This means that there could be a selection bias concerning the computation of ATT that can be written as:

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

If the group of the treated is randomly selected from the population, that means the treated and the control group have the same observable and non-observable characteristics, the bias will be zero. The problem is that selection into treatment is not random and treated and non-treated firms may differ in important characteristics. I have already verified the existence of these differences in the previous self-selection analysis: self-selection bias is a real problem. Using a generic non exporter will not allow me to make causal inferences because pre-entry differences in firm characteristics may explain the difference in post-entry productivity levels of exporters and non-exporters. To solve this problem, I use both Propensity Score Matching (PSM) and Difference-In-Difference (DID) strategy[30]. With matching techniques I can construct a consistent counterfactual. In this way, if difference in productivity remains, it can be attributed to firm export activity rather than other characteristics; in opposite if there is no difference one can think that exporting does not benefit firms.

The basic idea of matching is to find, in a large group[31] of non treated units (never exporters), those firms who are similar to the starters in all

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

[31] In my sample I have at my disposal a large population of potential counterfactual units.

relevant pre-treatment (observable) characteristics to approximate the counterfactual outcome (Blundell and Costa Dias, 2000).
The PSM consists in estimating a propensity score of export entry conditional to variables at my disposal and that, in my beliefs, could affect the probability to enter export market. Then, I match treated plants with control plants using this estimated propensity score. I use the following probit to estimate the probability score of first-time exporting[32]:

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

where $START_{it}$ is a dummy variable assuming value 1 if the firm starts exporting in t. The chosen probit specification satisfies the balancing test introduced by Rosenbaum and Rubin (1983) and formalized in Becker and Ichino (2002)[33]. This probit is estimated pooling all cohorts[34]. In the regression I have kept only never exporters, for all the years they are in the sample, and starters, for the year they start exporting. I include the following variables lagged one year[35]: total factor productivity, size, the square of the size, capital stock, unit labour cost, the share of skilled production employees, foreign share[36], import status, subcontracted input and output shares, and dummies for industry, year and region. The probit specification I choose permits to correctly classify 95.58% of observations. Using the estimated scores I match plants applying the "Nearest Neighbor" (NN) matching on the "common support"[37]. The NN technique matches a starter with a never exporter

[32]As robustness checks, I have also tried to use other probit specifications, always satisfying the balancing test (Rosenbaum and Rubin, 1983). Basic results for following analysis are quite similar using these specifications.

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

[34]I have decided to use the pooled sample because, in this way, I can exploit the information contained in the largest possible dataset for modeling the export-starting decision. Estimating different probit for each cohort could lead to a loss of efficiency because the number of starters in every cohorts is low.

[35]I include lagged variables because the observable covariates I 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. Anyway it is difficult to be sure that firms do not change some important characteristics in preparation to export entry.

[36]The capital share owned by foreign shareholders.

[37]I have chosen to match the starter with a single never exporters because of the large population of never exporters at my disposal. I 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).

having the closest propensity score and I also allow that never exporters are used as a match more than once - matching "with replacement".

I have followed Girma et al. (2003) and I have applied matching cross-section by cross-section (separately for each cohort). I restrict, in this way, the matches to come from the same year. Because I do not restrict matches to come also from the same sector[38], I 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). I have also applied 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[39]. Results obtained from the matching implemented cross-section by cross-section and the matching implemented on the pooled sample are very similar.

Since I do not condition on all covariates but on the propensity score, I have to check if the matching procedure is able to balance the distribution of the relevant variables in the control and treatment group. I can use different methods to test the matching goodness. The basic idea of all approaches is to compare the situation before and after matching and test if there remain some differences between treated and control units. If significant differences are still detected, matching was not (completely) successful. At first, I show the density function of propensity score for treated, all controls and matched controls. The propensity score distribution was very different before matching, but after matching the distribution of matched controls overlap that of starters (Figure 3).

Second, I implement a standard t-test for equality of means for the covariates. Table 6 shows significant differences between starters and never-exporters in all variables for the unmatched sample. In opposite, as expected, any significant difference disappears in the matched sample[40].

Finally, I have re-estimated again, as suggested by Sianesi (2004), the propensity score on the matched sample, including only observations on

[38] I have only included sector dummies on the propensity score computation.

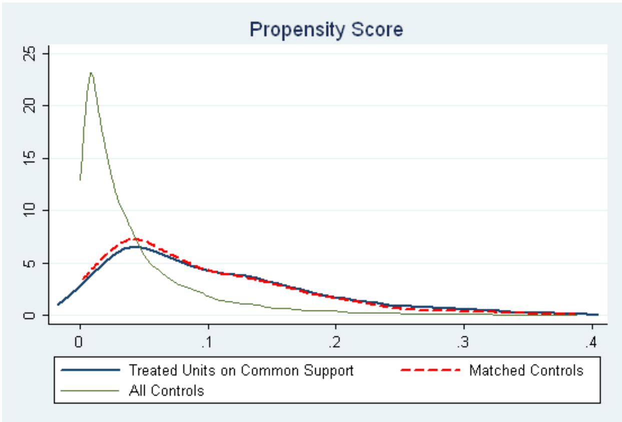
[39] I decided to implement this procedure because I have estimated the propensity score and verified the balancing property for the pooled sample. The ATT effects, in this case, are calculated on relative variables.

[40] I have rerun this check for every post-entry year of my 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. I have also implemented a t-test for the TFP growth lagged one-year and I find no statistically significant difference between starters and never matched. This is important to rule out a possible "path effect": if I find a superior productivity growth for starters after the export entry, I could be sure that this is not linked to positive productivity shocks affecting firms also previous period.

Table 6: 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

Figure 3: Propensity Scores



treated units and matched controls, and I have compared the pseudo-R^2s before and after matching. The pseudo-R^2 indicates how well the regressors explain the export probability. After matching there should be no systematic difference in the distribution of covariates between both groups and the pseudo-R^2 should be low. I find, in effect, a pseudo-R^2 not statistically different from 0 for probit on matched sample[41], this means that, according to my probit specification, treated units and their matched controls have the same probability to start exporting.

Even if matching procedure is valuable, it does not eliminate completely the self-selection bias, especially it does not eliminate the bias coming from unobservables. With DID strategy I can also take into account and correct for time-invariant unobservables. I compare the differences in outcomes after and before the treatment - in this case, before and after export entry - for the treated group, export starters, to the same differences for the untreated group, never exporters[42], on the assumption that, without the treatment, the outcomes would have been similar across the two groups of firms. The implemented DID-PSM estimator could be written as:

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

Y is the variable of my interest, for example productivity; subscripts *post*

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

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

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 $D_J^* = 0$ denotes 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 $\omega(i,j) = \frac{1}{N_i^c}$ if $j \in C$ and zero otherwise. Anyway, in my estimation $\omega(ij)$ is 1 for matched controls because every starter is matched with one control unit, the single nearest neighbor. I consider four years after the starting year and I calculate ATT effects for the entry period (t), t+1 till the period t+4. PSM may fail considering a longer time horizon because of the restriction of the matched sample. Even if I am interested mainly on productivity indicators, I investigate also ATT effects for other firm characteristics, especially size and capital endowment.

Table 7: 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%.
Bootstrapped standard errors are calculated (200 replications).

The results show that the average TFP effect of exporting is positive and statistically significant. Firms that start exporting grow more than firms that serve only the domestic market. There are also significant and positive effects on labour productivity, capital, size and output[43]. These positive effects are persistent and they last till the fourth year (third year for the capital and productivity) after the export entry[44]. Learning-by-exporting

[43]The effects on TFP and labour productivity are very similar, this means that the export activity has no significant effect on the firm capital intensity, as it is directly shown in the table. DID results on the unmatched sample bear, as expected, a stronger impact on the firm efficiency. These results are available upon request.

[44]However, it is worth mentioning that the results for t+3 and t+4 are not completely

hypothesis seems to be confirmed with every productivity indicator (LP, semiparametric TFP indicators and TFP index). When I match on the pooled sample, I obtain very similar ATT effects, only for the year t+3 the TFP effect become not significant. I 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. I have used a caliper level of 0.01 and I have obtained the same results. This robustness checks confirms the goodness of my matching procedure[45].

The sample size decreases when I focus on periods more distant from the export entry (Table 7), this drop can be attributed to different reasons: starters can stop exporting after some years; the controls or starters can exit the market; or the time dimension of the database does not allow to follow the whole history of the firms after the export entry. In order to take into account these sources of sample selection, following De Loecker (2007), I have recalculated the post-entry effects for the different firms' samples according to the number of years I can observe the starter after the export entry. Table 12 in the Appendix shows the relative results. The ATT effects are quite similar between the different samples, the only exception is for the sample of firms for which I can observe at least 5 consecutive export years after the export entry, even if this could be due to the small size of this sample.

Looking at the previous results I could hypothesize that in the entry year firms place themselves on a higher TFP path and then they stay on this "superior" path (De Loecker, 2007). This idea seems to be verified when I calculate ATT effects on yearly TFP growth rates. Table 8 shows that starters present a significant higher annual growth rate than never exporters only for the entry period. Thus, in the entry year starters go on a higher TFP path and in the following period they stay on this path and confirm their advantage compared with never exporters.

4.1 Robustness tests

The ATT calculation is a superior and flexible approach, 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, I have also tried to implement a different meth-

reliable, probably due to the small sample size, because I have experimented some changes in magnitude and significance with different probit specification for export entry.

[45]When I restrict the matching imposing a caliper=0.01 the starters I can match drop from 532 without caliper to 521 with caliper. I do not show the ATT effects for the matching on the pooled sample and the matching with caliper. These results are available upon request.

Table 8: ATT effects: Yearly Growth Rates

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

Bold values are significant at least at 10%.
Bootstrapped standard errors are calculated (200 replications).

odology. Following studies of Greenaway et al. (2003, 2004) I have pooled my observations (of starters and matched controls) concerning different post-entry periods and I have estimated the regression:

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

where TFP growth is the dependent variable. $D^{t+\sigma}$ are dummy variables assuming value 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[46]. $START_i$ is a time invariant dummy equal to 1 for starters and 0 for matched controls. The interaction $D^{t-1} * START_i$ 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 post-entry years for only exporters. I estimate this equation keeping in my dataset only starters and matched controls for the years $-1 \leq t \leq 4$: the pre-entry period, the entry year and the four years after entry [47]. In this way, TFP growth of firms is compared with one of never-exporters in the pre-entry period (t-1). I control for the lagged level of TFP and lagged size, and I always include dummies for sector, region and year. I also try to take into account firm fixed effects. The coefficient of interest is δ showing the change in the TFP growth for starters in the post-entry period. Table 9 shows the productivity growth for starters and never exporters before and after entry.

[46]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.

[47]For never-exporters these periods are set according to the related starters which they are matched with.

Table 9: Productivity Growth

	$NeverExport.$	$Starters$
Before	α	$\alpha + \gamma$
After	$\alpha + \beta$	$\alpha + \beta + \delta$

With this regression I am analysing the annual growth rates. In opposite to Table 8, here I am considering together different post-entry years and I can also control for other additional regressors that could be affecting the firm performance over the period after export entrance (lagged TFP and size). Table 8 could be compared with the column 1 and 3 of Table 13 in the Appendix. This analysis further confirms the hypothesis on learning-by-exporting. I find a higher TFP growth rate for starters in the entry period, and when I control for lagged TFP and size I obtain significant export effects also for the period t+1 and t+2. Adding firm-fixed effects, significant post-entry effects are shown for the whole post-entry period.

4.2 A comparison between continuous exporters and export stoppers

Thanks of the wide time dimension of the database I have estimated the post-entry effects for a 5-year interval after the export entry. In this interval some starters stop exporting. In the previous analysis I have calculated the productivity effects of starters till they stay in the export market, discarding the observations for starters after their exit from the export market, because my focus was on the potential gains for the firms while they are operating in the international context. Anyway, when I re-include these observations I still find positive post entry effects, even if they are a little downsized if compared with previous findings[48]. In this paragraph I also investigate if there exist some differences in post-entry effects between starters that continuously export and starters that stop exporting. I compare post-entry effects for these two starter groups and never exporters. I estimate the following

[48] These results are not shown, but are available upon request. The effects are the same for t and t+1 because of my starter definition: I request the starter exports from t onwards for at least two consecutive years.

regression:

$$\Delta TFP_{it} = \alpha + \sum_{\sigma=0}^{4} \beta D^{t+\sigma} + \gamma D^{t-1} * START_i + \delta POST_{it}^{CONT} + \eta POST_{it}^{STOP} + \\ + \varphi TFP_{i,t-1} + \theta n_{i,t-1} + \iota d_r + \mu d_j + \rho d_y + \epsilon_{ijt} \quad (8)$$

where $D^{t+\sigma}$ and $START_i$ are defined as in the equation 7; $POST_{it}^{CONT}$ and $POST_{it}^{STOP}$ are dummies capturing the post-entry effects (with no distinction according to the distance from export entry) respectively for starters which in my sample continuously export and starters which stop exporting after some years. I control for the lagged level of TFP and lagged size, and I always include dummies for sector, region and year. The analysis (Table 14 in the Appendix) confirms that there are no differences in the average yearly post-entry effects between the two types of starters. I have already verified that the jump in the productivity concerns the export entry year, then exporters stay on this superior productivity path without any great difference in the following growth rates (if compared with never exporters). In the last two columns of table 14 in the Appendix I show results of the following regression:

$$\Delta TFP_{it} = \alpha + \sum_{\sigma=0}^{4} \beta D^{t+\sigma} + \gamma D^{t-1} * START_i + \delta POST_{it}^{STAY} + \eta POST_{it}^{EXIT} + \\ + \varphi TFP_{i,t-1} + \theta n_{i,t-1} + \iota d_r + \mu d_j + \rho d_y + \epsilon_{ijt} \quad (9)$$

In this case I split the post-entry effects for starters while they are still exporting from the effects following their export exit (for starters that stop exporting after some years). Especially $POST_{it}^{STAY}$ is a dummy equal to 1 for all starters (both continuous exporters and stoppers) till they are in the export market, while $POST_{it}^{EXIT}$ captures the productivity effects for starters after they stop exporting. Results confirm that there are positive effects while starters are in the export market, but after they stop exporting no significant difference is found between stoppers and never exporters. Anyway also the significant higher productivity growth for starters while they are in the export market is likely to be driven by the effects of the first (and second) post-entry year.

5 In search of learning channels

5.1 The link between exports and imports

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, I want both to test if post-entry effects, I found previously, are driven by export entry and not import entry and I try also to verify if firms which start importing in combination with exporting obtain larger gains.

In previous sections, I have checked for the lagged import status. Including in the probit specification the lagged import dummy, I have taken into account previous import activity of matched and control units. As Table 6 has shown, there is no a significant difference in the import status between starters and never exporters after matching, so post-entry effects are cleaned for the previous firm import status[49]. Anyway, even if the matching procedure let me to control for pre-entry characteristics, it does not check for events that could happen in combination with export entry, in particular for current import entry. In this section, I 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. I split starters' sample in two groups: the first group include export starters which start also importing in t (they did not 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 import neither in t-1 nor in t[50]). In both groups I have obviously included the relative matched controls[51]. My previous results are generally confirmed (Table 10) also when I drop, from my sample, firms which start importing and exporting at the same time, even if now post-entry effects are slightly downsized and there is no significant effect in t (Group2)[52]. This finding further supports the existence of significant positive effects stemming from export activity, and I can reject the hypothesis that efficiency improvements previously found are only driven by firms' foreign sourcing. Anyway, I also verify larger productivity gains for firms which start exporting and importing at the same time. 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, and these improvements of productivity could be higher if firms turn to more complex internationalisation strategies.

[49] Even if I have not matched exactly on the lagged import status, I can see from Table 6 that the matching on this variable was quite perfect.

[50] The previous import status does not represent a problem for the interpretation of the post-entry effect I previously found because I have already controlled for the previous import activity in t-1 in the matching procedure.

[51] The matching procedure is not changed.

[52] I calculate ATT effects until t+2, because the two samples are too small for following years.

Table 10: ATT effects: Control for the current import status

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

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

5.2 Learning-by-exporting: the role of the technological gap

In this section I focus on recent studies trying to highlight the importance of domestic and foreign context in explaining the potential export effects. On one hand, Greenaway and Kneller (2007) have investigated if industry differences can explain the existence of efficiency improvements after export market entry: they find that productivity gains for exporters are lower in industries already exposed to high levels of trade and 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 has to face with, I expect that starters operating in more competitive industries benefit less from export activity if compared with starters operating in industries with a low competition level. On the other hand, De Loecker (2007) tries to investigate a different export impact according to the destination country of exporters. Behind his 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. I build on these previous studies, but my idea is that the important feature is neither the technological level or efficiency of destination country nor the domestic efficiency level in absolute terms, but the gap between the destination country and the domestic market. I suppose that there is a different scope for learning according to the productivity gap, the distance to technological frontier. Because of the difficulty in calculating an indicator of sectoral productivity gap between countries, I have decided to use, as a proxy, an indicator of comparative advantage. Turkey is a middle-income country and its main trade partners are European countries and, in general, advanced countries[53]. I 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[54].

I want to verify if learning effects are larger and significant for new exporters in comparative disadvantage industries because in these sectors the productivity gap between the domestic productive system and foreign productive systems should be higher than in comparative advantage sectors. New exporters, in comparative disadvantage industries, could be exposed to a more competitive environment than their domestic context and could be more exposed to positive spillovers, this could explain larger post-entry effects stemming from exporting. As a consequence, I could expect learning-by-exporting to be more intensive in comparative disadvantage sectors. I 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, I have used the trade flows and I have calculated the "index of revealed comparative advantage" (henceforth RCA)[55]. Com-

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

[54]This means that in comparative advantage sectors Turkish firms could be more productive in average 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. Mayer and Ottaviano (2007) report that *"The concepts of comparative advantage and comparative disadvantage are used to identify industries in which a country is stronger than its competitors and those in which it is weaker, meaning industries in which its relative costs of production are respectively low and high"*. They compare RCA (revealed comparative advantage), built on trade data, with ECA (estimated comparative advantage), built on productivity data, for Italy and UK and show a positive correlation.

[55]The RCA is defined as

$$RCA_i = \frac{X_{TUR,i}/X_{TUR}}{X_{W,i}/X_W} \tag{10}$$

where $X_{TUR,i}$ and $X_{W,i}$ are the exports of Turkey and of the comparison group of countries in the industry i, while X_{TUR} and X_W are the exports of Turkey and the comparison countries in the aggregate manufacturing sector. If this index is higher than one Turkey is more specialised in sector i than other countries so there is a comparative advantage in that sector i. In order to calculate this index I 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. These countries are the main trade partners of Turkey. Anyway I have tried to calculate RCA index with only EU countries, OECD countries and the rest of the world and I obtained the same pattern of comparative advantage. Comparative advantage sectors are: Food manufacturing (ISIC 311); Beverage Industries (ISIC 312); Textiles (ISIC 321); Wearing apparels, parative advantage index can give 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. I assume firms are more distant to frontier in comparative disadvantage sectors. After the matching procedure shown in section 4, I define postCA a vector of dummy variables for the post-entry period for starters in comparative advantage (CA) sectors, and postCD a similar vector for the post-entry period for starters in comparative disadvantage sectors (CD). I can calculate post-entry effects with the following equation:

$$\Delta TFP_{i,s} = \alpha + \beta_1 postCA_{i,s} + \beta_2 postCD_{i,s} + \epsilon_{is} \tag{11}$$

where $\Delta TFP_{i,s}$ is the productivity growth between every post-entry year and pre-entry (t-1) year[56]. The variable TFP is always expressed as a deviation from the industry-year mean, in order to capture and correct for effects that are common to all firms belonging to the same sector (especially, in order to correct for specific effects linked to comparative advantage sectors or comparative disadvantage sectors). I am analysing the change in productivity following export entry compared with pre-entry period. I consider separately post-entry effects between starters in comparative advantage sectors and starters in comparative disadvantage sectors for every year after export-entry (till the fourth year after the entry). The coefficient β_1 captures the average change in performance indicators related 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 the omitted group, that is never exporters. We run simple OLS regressions[57].

For the entry year starters in CA sectors are improving their productivity if compared with non-exporters, while there are no significant effects for starters in CD sectors (Table 11). In following years, effects in CA industries turn to be non significant, while in CD sectors exporters start having significant effects since t+1 and it seems they continuously increase their

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.

[56]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 it is calculated as $\Delta TFP_{i,1} = tfp_{i,t} - tfp_{i,t-2}$ and so on.

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

Table 11: ATT Effects: Comparative Advantage

		t	$t+1$	$t+2$	$t+3$	$t+4$
TFP	Starters CA	**0.180**	**0.187**	**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%.

efficiency. The analysis shows that 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. Thus, I verify a different timing of post-entry effects for different sectors. In CD sectors firms are not able to absorb immediately spillovers from international markets (new technologies, new production strategies), because the gap with foreign markets in these sectors could be large 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 does not face any difficulty in exploiting the potential of learning. Anyway when starters in CD industries are ready to absorb spillovers from the new context they can exploit a higher potential of learning than firms in CA industries. This hypothesis seems to be confirmed when I analyse the cumulative productivity[58] of firms (always splitting between starters in CA and CD sectors).

6 Concluding remarks

The paper analyses the link between exports and firm performance for a middle income country, Turkey. Both self-selection and post-entry effects are important drivers behind the positive correlation found between export involvement and firm productivity. The work contributes especially to sup-

[58]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

port the hypothesis of a potential for learning stemming from export activity when the analysed country is not at the technological frontier and confirms results highlighted by previous papers. Export starters show a higher performance in the post-entry period. It seems export activity places firms on a superior productivity path in the entry year and then they stay on this path in the following period.

My analysis displays also a strict linkage between export and import entry. Firms often start importing and exporting at the same time and it is important to control for this simultaneity in the analysis of post-entry effects. A deeper investigation confirms that productivity gains also hold when I take into account the current import status. In addition the benefits seem to be larger when firms are involved in both international strategies. The relationship between export and import activity at the firm level has received scarce attention, but it could become an important research field in the future.

Finally, I try to shed some light on the channels of learning-by-exporting and I look for an heterogeneity in post-entry effects according to the sectoral differential of performance between the domestic context and foreign markets. I verify a different timing of productivity improvements across sectors: new exporters in comparative disadvantage sectors take more time to reap the benefits of export entry, but, in the "long" term, the potential of learning could be larger than in comparative advantage industries because the distance to frontier is higher. This finding supports the hypothesis that competition and technology spillovers are significant channels through which exports may affect firm's productivity.

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APPENDIX

A Tables

Table 12: ATT effects on TFP: Control for Sample Selection

N. of observations	t	$t+1$	$t+2$	$t+3$	$t+4$
1-year	0.140				
2-years	0.140	0.177			
3-years	0.194	0.277	0.259		
4-years	0.204	0.241	0.188	0.218	
5-years	0.308	0.270	0.256	0.198^{+}	0.264^{+}

All values are significant at least at 10%. $^{+}$Not significant.

Table 13: Learning-by-exporting Effects

Dependent Variable: TFP growth				
	(1)	(2)	(3)	(4)
Pre-entry	-0.038	-0.016		
	(0.467)	(0.722)		
Post-entry t	**0.148**	**0.154**	**0.193**	**0.163**
	(0.005)	(0.001)	(0.015)	(0.003)
Post-entry t+1	0.052	**0.122**	0.091	**0.229**
	(0.323)	(0.008)	(0.270)	(0.000)
Post-entry t+2	-0.006	**0.091**	0.026	**0.274**
	(0.916)	(0.095)	(0.787)	(0.000)
Post-entry t+3	-0.009	0.077	0.032	**0.233**
	(0.915)	(0.305)	(0.791)	(0.005)
Post-entry t+4	0.059	0.158	0.103	**0.301**
	(0.617)	(0.119)	(0.495)	(0.004)
TFP t-1		-0.453		-1.052
		(0.000)		(0.000)
Size t-1		0.059		-0.083
		(0.000)		(0.090)
N. observations	3892	3892	3892	3892
Dummies	*YES*	*YES*	*YES*	*YES*

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

Table 14: Comparison between continuous exporters and stoppers

Dependent Variable: TFP growth				
	(1)	(2)	(3)	(4)
Pre-entry	-0.036	-0.008	-0.036	-0.008
	(0.478)	(0.859)	(0.478)	(0.859)
$POST_{it}^{CONT}$	0.045	0.106		
	(0.016)	(0.000)		
$POST_{it}^{STOP}$	0.058	0.109		
	(0.009)	(0.000)		
$POST_{it}^{STAY}$			0.056	0.114
			(0.001)	(0.000)
$POST_{it}^{EXIT}$			0.008	0.070
			(0.786)	(0.106)
TFP t-1		-0.462		-0.462
		(0.000)		(0.000)
Size t-1		0.046		0.046
		(0.000)		(0.000)
N. observations	4513	4513	4513	4513
Dummies	YES	YES	YES	YES

(1)&(2): equation 8. (3)&(4): equation 9
(1)&(3): OLS estimation without controls.
(2)&(4): OLS estimation with controls (lagged TFP and size).
P-Values are in parenthesis.