Self Selection and Post-Entry effects of Exports. Evidence from Italian Manufacturing firms*

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Abstract

A large body of empirical research suggests the superior performance of exporting firms relative to non exporters. Specifically, firms involved in foreign markets are found to be larger, more productive, more capital and skilled-intensive. This paper provides empirical evidence of the relationship between firm's performances and export behavior in Italian manufacturing firms. Similarly to other empirical studies, we find that exporters are more productive relative to non exporters. Our empirical analysis support the idea that the superior performance of the former is due to a market selection mechanism according to which only the most productive firms are capable of entering international markets. Moreover, we provide empirical evidence on the causal effects of exporting on productivity (and other interesting firm characteristics) by using an econometric approach that combines propensity score matching and Differences in Differences techniques.

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1 Introduction

The issue of heterogeneity across firms has been widely discussed in the evolutionary literature (Nelson and Winter, 1982, Dosi,1988). According to this literature the presence of heterogeneous firms within industries imposes to go beyond the representative agent framework and requires a further investigation about the determinants of such heterogeneity. The growing availability of longitudinal micro-level datasets has recently allowed researchers to better investigate the differential in firm performances, measuring intra industry dynamics and variance in productivity, wages and profitability (Baily et al., 1992, Bartelsman and Doms, 2000). A large body of empirical research documented the high and persistent level of heterogeneity across firms and establishments, emphasised the relative contribution of entry, exit to aggregate productivity growth, and showed the reallocation mechanism of output and input from less to more productive firms (Foster, et al. 1998, Baily, et al. 1996, Barteslman and Dhrymes, 1998). A mixture of economic factors seems to be relevant: from the managerial ability, to the level of firms technology and the exposure to international markets (Bartelsman and Doms, 2000; Tybout, 1998).

Concerning the link between productivity and the exposure to foreign markets, several analyses have documented the better performances of exporting firms and plants relative to non exporters: the former tend to be larger, to have higher level of productivity, and to be more capital intensive and technologically more sophisticated. Two different interpretations have been proposed to explain such a productivity "export premium": (i) self-selection; (ii) post-entry mechanisms.

The self-selection hypothesis argues that export markets select the most efficient firms among the set of potential entrants into foreign trade. This may be due to the fact that either (1) participating in international markets implies being exposed to more intensive product competition (see Aw and Hwang, 1995), or (2) entering the international markets entails comparatively higher sunk costs of entry than operating in domestic markets (Jovanovic 1982, Roberts and Tybout 1997, Melitz 2003).

The post-entry hypothesis, instead, is based on the idea that firms become more efficient after they begin exporting. One often cited reason for this post-entry increase in productivity is the so-called learning by exporting mechanism according to which exports work as a conduit of technological transfer which, in turn, allows a change in firm's productivity trajectory (Clerides et al, 1998). More precisely, exporting firms may increase their technological knowledge through the access of new production methods or new products design from their buyers. Moreover, the more competitive international environment could force them to become more efficient and it could stimulate innovation. In addition to the learning mechanisms, firms that become exporters may improve their productivity simply by increasing their capacity utilization and by taking advantages of economies of scale, as exporting increases the relevant market size. Indeed, the higher international demand may raise firms' volume of production, allowing them to exploit static economies of scale.

Clearly, the self-selection and the post-entry hypotheses are not mutually exclusive. The superior performance of exporters compared to non-exporters can be due to both effects: to evaluate the relative contributions of the two explanations is an empirical question. Indeed, although both mechanisms are plausible, sectoral heterogeneity and countries specificities could alter the way in which the two operate. Most of the studies found substantial evidence in favour of the self-selection mechanism, showing that only the more productive firms find it profitable to compete in international market[1].

However, less widespread evidence has been found in favour of the post-entry mechanisms. Kraay (1999) finds evidence of an increase in productivity as a result of firms' exposure to exporting from a panel of Chinese industrial enterprises. Aw, Chung and Roberts (1998) find similar results for a subset of sectors using firm-level data from the Taiwanese manufacturing industry. Delgado et al. (2002) implement a non parametric method on a panel of Spanish firms finding evidence of an improvement in firms' productivity after they become exporters, but only when limiting their analysis to young firms. Castellani (2001) found that only exporters with a high share of export intensity, measured in terms of the share of foreign sales on total turnover, exhibit a significant productivity growth as a result of their exposure to international markets.

Using a large panel for Italian manufacturing, which covers the universe of firms with more than 20 employees over the period 1989-1997, our paper tests these two possibly complementary explanations. Although other empirical research for Italian manufacturing firms have documented the differences between exporters and non exporters (Castellani 2001, Ferragina and Quintieri, 2000, Sterlacchini, 2001; Basile 2001), the possibility to use a longitudinal micro-level dataset allow us to apply, for the first time, panel data and matching techniques on Italian data, adding evidence on the relationship between international involvement and firm performances. In particular, we want: (1) to confirm whether there exist export premia characterizing exporting firms as compared to non exporters; (2) to verify if there is a self-selection mechanism at work by comparing the productivity (and other relevant firm characteristics) of new exporters with that of never exporters in the period prior to the entry; (3) to assess the post-entry effects by comparing the performances of entering firms with that of never exporters in the post entry period.

The contribution of the paper is to empirically test the self-selection and the post-entry effects hypotheses not only with respect to productivity and size, as usually done in the literature, but also taking into consideration other interesting firm characteristics as capital endowment, workforce composition and labor cost competitiveness. Besides, to sort out the post-entry explanation, i.e. to estimate the effect of the export activity on exporters' performances, we use matching and difference in differences techniques. The aim of implementing these econometric methodologies is to evaluate the causal effect of export activities on firms' performances. Indeed, if self-selection of better firms into exporting is at work, a simple comparison between the characteristics of export starters and never exporters cannot reveal any causal impact of export activity on exporters' performances. A credible test of the post-entry explanation should try to take into account possible biases stemming from self-selection. In order to reduce this bias (that is due to the observational nature of this study), we will combine the "selection on observables" with the "selection on time constant unobservables" hypotheses by employing the propensity score matching jointly with the Differences in Differences estimator (PSM-DID) introduced by Heckman et al. (1998, 1997) [2]. In other words, we will assume that conditional on observables the

[1] Bernard and Jensen (1999) for the US, Bernard e Wagner (1997) for Germany, Aw, Chung and Roberts (1998) for Taiwan and South Korea, Clerides, Lach and Tybout (1998) for Colombia, Mexico and Morocco, Alvarez and Lopez (2005) for Chile, Delgado et al (2002) for Spain, De Loecker (2004) for Slovenia, Castellani (2002) for Italy, van Biesebroeck (2003) for Sub-Saharan Africa, documented that more productive firms ex ante self select into the export markets. See Wagner 2005 and Greenaway and Kneller 2005 for a review of the literature.

[2] Also Girma et al. (2004) and Greenaway at al. (2005) implement a PSM-DID approach, however the

bias stemming from unobservables is the same in different time periods before and after the decision to export. Similar assumptions, with the exception of the linear functional form, are also maintained by the parametric conditional Differences in Differences estimator. The main virtues of the PSM-DID technique, with respect to the traditional DID, is reducing the bias component due to non-overlapping support of observables between the exporters and the non-exporters and the bias component due to misweighting on the common support of observables.

The various methodologies implemented yield qualitatively the same and quantitatively very similar results. We find that future exporters have from the beginning comparatively "better" characteristics with respect to never exporters and they already benefit from these characteristics before going international by increasing their scale of production and their sales. Moreover, the results of all the different econometric strategies we employ point to the presence of some post entry effects, according to which exporters increase their performances after they start exporting.

The reminder of the paper is organized as follows. In Section 2 we discuss our data presenting some preliminary evidence on the better performance of exporting firms with respect to non-exporters and we present our estimation results of the export premia with respect to different firms' characteristics. In Section 3 we investigate econometrically whether ex ante firms' characteristics influence the decision to enter into export markets and validate the self-selection hypothesis. In Section 4 we focus on the post-entry effects. Implementing a matching approach we analyze whether export participation can be considered as a source of performances improvement. Finally, in the last section the main findings are summarized.

2 Descriptive Statistics and Export Premia

The research we present draws upon the MICRO 1 databank developed by the Italian Statistical Office (ISTAT)[3] MICRO 1 contains longitudinal data on a panel of 38.771 Italian manufacturing firms with employment of 20 units or more and it covers the years 1989-97. Due to entry, exit and missing values, we obtain an unbalanced panel data containing information for an average of around 20.000 firms per year. Firms are classified according to the Ateco codes of principal activity, the Italy's National Statistical Office (ISTAT) codes for sectoral classification of business, which corresponds, to a large extent, to the European NACE 1.1 taxonomy. All the nominal variables have been deflated at 2 digit level and are measured in millions of 1995 Italian lira.

The database contains information on many variables appearing in a firm balance sheet. For the purpose of this work we utilize the following available information: export activity, number of employees, type of occupation of employees (blue/white collars), sales, value added, capital, labor cost, intermediate inputs cost, industry and geographical location (Italian regions). Capital is proxied by tangible fixed assets at historical cost.

propensity score matching is simply a sample selection device and the actual computation of the treatment effects is done by using a standard parametric DID. Arnold and Hussinger (2005), who also employ a PSM-DID methodology, instead compare exporters with non exporters (not starters with never exporters) and includes lagged export status as a regressor in their "pooled" propensity score estimation.

[3]The database has been made available under the mandatory condition of censorship of any individual information.

Using the export variable information, we group the Italian manufacturing firms into two categories: exporters (*Exp*) and non exporters (*Non Exp*). The former are defined as firm that export in the year under analysis and, similarly, the latter as firms that serve only the domestic market for that year. This can be considered reasonable as far as the comparison between exporters and non exporters' performances is carried on year by year, without taking into account the time dimension of our database. However, in order to disentangle the causality from export to productivity and to determine whether more productive firms self select into exporting or whether exporting improves firms performance, one need to differentiate between firms that begin to export during the time frame of observation, i.e. *Export Starters*, and firms that sell exclusively to the domestic market for the entire period, i.e. *Never Exporters*.

As a preliminary step we compare exporters versus non exporters, looking at a wide range of performance characteristics. In particular, we evaluate the differences between the two groups of firms taking into account various measures, such as productivity, scale of operation, capital inputs, workforce composition and cost competitiveness.

To measure firm-level productivity we use two indicators: Labour Productivity (LP), i.e. value added per employee, and Total Factor Productivity (TFP). We compute the latter employing the semi-parametric estimation technique implemented by Levinshon and Petrin (2003). This estimation procedure allows deriving factor coefficients by controlling for possible simultaneity and selection bias which arise when using ordinary least square methods (see the Appendix 1 for a brief outlines of our estimation procedure)[4]. The scale of operation is measured by total shipments (sales) and by total employment. With respect to capital endowments we observe both the absolute value and the value of capital per employee (the so called capital intensity, CI). We built up an index for the composition of the workforce, the skilled labor intensity (SLI), conventionally defined as the percentage of white collars over the total number of employees. As a measure of cost competitiveness we calculate the unit labor costs (ULC), obtained by dividing the total labor compensation by real output[5].

Table 1 presents the number of active firms within the Manufacturing sector in each of the nine years, together with the percentage of exporting firms, and their export intensity. The number of active firms remains substantially stable over time, with a minor reduction in the period between 1993 and 1997. The participation rate in foreign markets increases: while in the 1989 about 64% of firms were exporting, by 1996 the percentage increased to 71%. Overall, along the nine years covered by the sample, exporters represents on average 67% of the firms, a figure that reveal the importance of exports in Italian Manufacturing[6]. The last column displays the average export intensity (EI), computed taking the arithmetic average of the ratio of export over sales for every exporting firms. The value of EI has increased over time, rising from 28% in 1989 to 33% by the end of the sample period.

The increase in the participation rate in export activities and in the export intensity

[4] We aggregate the manufacturing industries according to the Pavitt's taxonomy and we estimate the TFP with respect to the four groups: traditional, scale intensive, specialized suppliers and science based.

[5] Unit labor costs are affected both by wages per employee, the number of employees and labor productivity: an increase in labor compensation or a decrease in labor productivity will raise ULC.

[6] Of course, there is a great heterogeneity in the participation rate of Italian manufacturing firms among size classes, sector and geographical location. As previous empirical analyses (Ferragina e Quintieri, 2000; Sterlacchini, 2001; Castellani 2002), we have found that large firms, belonging to the specialized supplier sectors (according to the Pavitt's taxonomy, 1984) and located in the Northern regions are among the more active in foreign markets.

Table 1: Number of Active firms, of Exporting firms and Export Intensity

Year	Number of Firms	Exporting firms (%)	Average Export Intensity (%)
1989	19922	64.2	28.4
1990	21208	63.5	27.9
1991	19740	64.5	28.2
1992	21301	66.6	27.0
1993	22076	67.7	30.0
1994	21720	68.5	30.8
1995	20004	70.5	31.6
1996	17231	71.1	32.4
1997	15532	69.3	33.1
Mean	19859	67.3	29.9

in the period between 1993 and 1996 could possibly be explained by the Lira depreciation, which occurred after the exit of the Italian currency from the Exchange Rate Mechanism (ERM) in September 1992. According to the theoretical literature which analyze the impact of exchange fluctuations on real economic variables (Obstfeld, 2002; Engel, 2002 for reviews), exchange rate fluctuations are strongly related to the export quantities of firms and, more generally, to the export flows of a country. A shift in the exchange rate regime, that makes Italian goods more price competitive, may induce both a change in the pattern of foreign market participation, by stimulating new or existing firm to become exporters, and an increase in the export shares of already established exporters (for instance by inducing a shift between domestic and foreign goods).

Coherently with this literature and with previous empirical findings for Italian manufacturing firms (Basile, 2001, Bugamelli and Infante, 2003), our data report an increase both in the share of exporting firms and in the average export intensity that began around 1993[7]. In 1997, after the large appreciation of the Lira of 1996 and the Asian and Russian financial crises, the increase in the share of exporting firms came to an end, while the average export intensity keep on increasing also in this year. This could be due to the fact that the drop in export participation was particularly concentrated among firms which were relatively less involved in international trade.

Table 2 presents the average values, distinguishing between exporters and non-exporters, for some basic variables which we will use later on in the analysis. Precisely, in addition to examining the productivity differentials (both in terms of LP and TFP), we compare the two groups of firms also with respect to firm size, capital, capital intensity, skilled labor intensity and unit labor costs.

Consistently with previous empirical results, we document the superior performance of firms that sell in the export markets with respect to the group that operates only in the domestic market (Bernard and Jensen, 1999; Bernard e Wagner, 1997; Aw, Chung and Roberts, 2000; Clerides, Lach and Tybout, 1998). We attest these differences with respect

[7] Analyzing the export pattern for a sample of Italian manufacturing firms over the period 1991-1997, Basile (2001) found an analogous trend, especially for firms belonging to scale intensive and science based sectors.

Table 2: Exporters versus Non Exporters: some descriptive statistics

Year	Average LP		Average TFP		Average Sales		Average Num. Empl.	
	Non Exp	Exp	Non Exp	Exp	Non Exp	Exp	Non Exp	Exp
1989	58.3	68.9	112.1	149.9	13208	44671	61	143
1990	58.2	69.9	111.9	151.1	14677	43404	62	138
1991	60.6	72.2	116.4	155.8	20816	42782	64	143
1992	61.1	74.6	115.3	157.4	18597	41587	56	131
1993	59.5	75.3	111.0	156.7	12427	41518	55	121
1994	61.8	80.8	114.5	166.6	12210	44623	51	118
1995	65.6	86.8	122.3	178.8	14037	49806	54	122
1996	67.4	84.9	132.4	181.0	18339	51468	58	128
1997	66.5	83.0	138.9	180.8	24983	55168	72	131
Mean	62.1	77.4	117.9	163.7	16233	45802	59	131

Year	Average Capital		Average CI		Average SLI		Average ULC	
	Non Exp	Exp	Non Exp	Exp	Non Exp	Exp	Non Exp	Exp
1989	6639	17035	84.3	92.6	16.2	23.9	0.31	0.22
1990	7426	17675	85.4	98.6	15.9	24.3	0.32	0.22
1991	9025	21500	96.9	137.4	16.7	24.8	0.33	0.23
1992	7900	20712	100.3	116.9	15.8	25.0	0.34	0.23
1993	7762	20041	101.5	119.9	16.1	25.3	0.35	0.23
1994	7283	20903	105.0	123.5	15.7	25.3	0.36	0.22
1995	8289	22243	107.1	128.3	16.0	25.4	0.34	0.21
1996	9612	26594	147.1	280.6	17.0	26.0	0.43	0.23
1997	12873	28196	166.0	274.4	19.1	26.5	0.37	0.23
Mean	8320	21453	110.4	152.5	16.5	25.2	0.35	0.22

Note: All monetary variables are expressed in millions of 1995 Italian lire and in real terms. The number of observations per year is the same as in Table 1

to a variety of firms attributes.

Indeed, a comparison of labor productivity,measured as the ratio of valued added over the number of employees, reveals the presence of an unconditional productivity differential between exporters and non exporters. Along the nine years covered by the sample, the value of labor productivity for exporting firms is on average 77 while the one for non-exporters is 62. When considering the TFP, the average value for exporters is 164, while for firms selling into domestic market is 118.

As one might expect, exporting firms are larger than non exporters, as entering the export market requires higher sunk costs. The relationship between size and export status is maintained regardless the measures used. With respect to sales, the mean level along the nine years of our sample for exporters is about three times larger than the one of non exporters. Moreover, also in terms of number of employees, exporters are on average more than twice the size of firms that serve only the domestic market.

The difference between exporters and non exporters go beyond productivity and the scale of operation and it concerns also other firm characteristics. Exporting firms are endowed with more capital and are more capital intensive, as one may notice both from the absolute value and from the capital to labor ratio. Interestingly, there are also noticeable differences in the composition of firm's labor force between the two groups of firms: white collars account for almost 25% in exporting firms against an average of 16% in non-exporting firms. Finally, exporting firms are relatively more cost competitive in terms of labor costs per unit of product.

For all the years and the variables of Table 2 we compute the p-values of t-tests for significance of the difference of means between exporters and non exporter. We are able to reject the hypothesis of equality of means, even at very conservative significance levels.

As a general message, Table 2 suggests that firms exposed to international market outperform non exporting firms with respect to different economic indicators. Further investigations are necessary in order to assess what drives this strong relationship between export behavior and performance, disentangling between the ex ante and the post-entry mechanisms. Before proceeding in the evaluation of the causal relationship between firms' characteristics and export status, we follow the literature by computing the export premia, defined as the ceteris paribus percentage difference in some characteristics between exporters and non-exporters. Indeed, one might question if the high exporters' performances survive also after controlling for the fact that exporters are bigger and are not uniformly concentrated in all sectors and regions.

Therefore, following Bernard and Jensen (1999), we estimate the export premia by performing OLS regressions of the relevant firm characteristics (in logarithm[8]) on an export dummy and a set of control variables. The estimated model takes the following forms

$$\ln(y)_{it} = \alpha_A + \beta_A ExportStatus_{it} + \gamma_A Controls_{it} + \upsilon_{it} \tag{1}$$

where y_{it} refers to firm i characteristics at period t, $ExportStatus$ is a dummy which takes value one for exporters and zero otherwise, $Controls$ is a set of control variables (indicator variables for NACE 2-digit industries, regional dummies and logarithm of employment to control for size) and υ is a random error term. Sectoral and regional dummies are included to correct for disparities across industries and location. Moreover firm size, measured by total employment, is included in order capture plausible variation in the export premia across firms of different dimensions.

Our interest lies in the value of the coefficient β_A that tells us the average premium of exporting firms with respect to non-exporters[9].In Table 3 we report the results for β_A obtained running separate regressions for each year in the sample and for all the relevant characteristics. One can observe that export behavior is positively related with business performance, no matter how measured. The coefficients on the dummy for the export status are positive (and negative, as expected, for UCL) and statistically significant at very conservative levels. As expected, even after controlling for industry, regional and size effects, firms participating into international trade are on average more productive, bigger, more endowed with capital, more capital and skilled labor intensive and they have lower unit labor costs.

[8]When using as dependent variable the skilled labor intensity we don't use the logarithmic transformation, as this variable is itself expressed in percentage points.

[9]The exact percentage differential is given by $(e_A^{\beta} - 1) \cdot 100$.

With regards to labor productivity, the positive and significant coefficients indicate clearly the higher performance of exporters: on average they are 16% more productive than non exporters. To attest that the export premia in terms of productivity is not simply the result of a capital deepening, we compute the percentage difference also in terms of TFP. As one can see from Table 3, the superior performance of exporters in terms of productivity do not remarkably change when the TFP is considered. On average, the total factor productivity of an exporter is 12% higher compared to that of non-exporter.

Table 3: Export premia: OLS regression of (the log value of) plant characteristics on export status and controls

	1989	1990	1991	1992	1993	1994	1995	1996	1997
LP	12.0	13.8	13.3	15.0	18.5	20.5	21.6	17.7	16.3
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)
TFP	7.5	8.9	8.6	10.0	12.8	15.3	16.1	11.8	10.3
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)
Sales	42.0	44.6	42.3	48.0	55.9	61.0	62.2	56.6	49.3
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)
Num. Empl.	56.3	53.2	53.4	51.2	49.6	51.0	48.8	50.5	40.9
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)
Capital	116.1	123.4	117.0	123.3	127.8	127.6	128.8	145.3	117.3
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)
CI	28.3	34.5	30.2	35.7	39.3	38.4	41.5	49.4	42.4
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)
SLI	4.7	5.1	4.8	5.5	5.6	5.9	6.0	5.6	4.7
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)
ULC	-26.3	-26.5	-25.9	-28.6	-31.5	-33.5	-34.1	-33.1	-29.6
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)
N. Obs (max)	19922	21208	19740	21301	22076	21720	20004	17231	15532

Note: P-values of t-test are in brackets below estimates (robust standard errors are used). Coefficients are transformed in exact percentage values. All regressions include, in addition to industry and region dummies, the log number of employees as another control variable (except the employment and capital regressions). The number of observations slightly varies from one variable to another. We report the maximum number of observations available for each year and performance characteristic.

The differences between the two groups of firms enlarge when considering the scale of operation. The magnitude of the coefficients for number of employees and sales substantially exceed that for productivity. Exporters employ on average 50% more workers than non exporters and produce 51% more output. As mentioned above, lager firms are more likely to have resources to overcome the fixed costs with which to enter foreign markets.

As already pointed out in Table 2, the differences between the two groups of firms go beyond productivity and size. The estimated differentials for the other variables provide additional support for the claim that exporters are associated with higher performances with respect to non exporters. Exporters are more endowed with capital and more capital intensive: they have more than twice the capital of non exporters and their workers have on average 35% more capital to work with. Also the composition of the workforce differs across the two groups of firms: exporters have on average a 6% larger share of white collar with respect to domestic firms. As expected, unit labor costs are negatively correlated with the export behavior as exporting firms have a higher level of cost competitiveness relative to firms serving the local market. The magnitude of the coefficient is relatively high and it ranges from -26% to -34%.

To summarize the findings so far, our results seem to validate the hypothesis that being an exporter implies a better performance. In particular, the positive correlation of exporting and productivity persists for every year and after controlling for a number of factors (sector, geographical location and size) that might affect efficiency. We now turn to determine the direction of causality between export behavior and firm performances. Therefore, in the following, our major aim is to evaluate whether productivity differentials between exporters and non-exporters are only due to self-selection or also to post entry mechanisms.

3 Self Selection into Exporting?

The productivity differentials between exporters and non exporters, and more generally, the differences in the specific exporters' characteristics, could reflect a self-selection mechanism according to which only the more efficient firms (or firms with certain characteristics) will enter into the export markets. It is argued that, since exporting requires additional costs and it implies to be exposed to tougher competition with respect to serve the domestic markets, only the outperforming firms will become exporters. In order to asses this hypothesis one should compare the performance of entrants vis a vis non exporters in the years before entry. Observing the dynamics of firm performances before entry into export markets allow us also to investigate if, some years prior to their entry, new exporters start to organize themselves in order to prepare to the more demanding international competition or simply to succeed in the domestic market .

As mentioned above, first of all we need to single out the firms that start to export during the time frame of observations. Hence, we define as export starters firms that do not export for at least two years, start exporting in year t and keep on exporting in the following periods[10]. Due to the time span available of nine years, we can create five cohorts of export starters, respectively from 1991 to 1995. In Table 4 we report the number of starters in each cohort. In total we obtain 612 firms that enter into the foreign markets at a certain point in time.

As a mean of comparison, i.e. as a "control group", we select in our sample firms that serve exclusively the domestic market for the entire period: the never exporters. Our control group is made up by 5441 firms.

Having selected the export starters and the never exporters, we can now turn to evaluate if ex-ante differences exist between these two groups of firms with respect to various firm characteristics. Thus, we compare starters to never exporters some years prior to entry, from $t-5$ to $t-1$[11]. Following Bernard and Jensen (1999), we implement a parametric exercise, regressing the log value[12] of firms' characteristics at time $t-\rho$ on the dummy

[10] We impose, as sample selection rule, that in the years prior to entry firms declare to be a non exporter for at least two years. Therefore, for example, if firms are considered starters in 1991 it means they didn't export in 1989 and 1990. However, due the unbalanced nature of the panel, we allow attrition of starters in the years preceding the entry if firms start exporting after 1991.

[11] An alternative solution proposed in the literature to test the self selection hypothesis is to estimate the probability of beginning to export, given the firm's characteristic some years prior to entry (Alvarez and Lopez, 2005; Girma et al, 2002).

[12] See Footnote 9.

Table 4: Export Starters by Year

Year	Number of Export Starters
1991	176
1992	177
1993	131
1994	105
1995	73
Total	662

variable indicating if a firm is an export starter at time t and on a set of controls

$$\ln(y)_{i,t-\rho} = \alpha_B + \beta_B Starters_{it} + \gamma_B Controls_{it-\rho} + \upsilon_{it} \qquad \text{with } 0 \leq \rho \leq 5 \tag{2}$$

where *Starter* is a dummy taking on value one for firms starting to export in t and zero for never exporters, and *Controls* includes dummies for calendar year, sectoral and regional effects.

In Table 5 we reports the transformed estimated coefficients of equation (2), i.e. the conditional percentage differential between starters and never exporters in levels, for all the relevant dependent variables. As a general result, we can detect that, regardless the variable analyzed and the ex ante time lag considered, future exporters display some advantages with respect to firms that will not take up exporting later on. These results are in line with the earlier empirical findings and confirm that those firms that initially are more productive, more cost competitive, larger, more capital intensive and with a higher share of white collar are more likely to become exporters. On average, the ex-ante productivity of starters is more than 15% higher than that of never-exporters, both with respect to labor productivity and TFP. Lagged firm dimension, capital stock, capital intensity and human capital endowment are also positively correlated with current export behaviour. Moreover, future exporters' labor cost per unit of product is on average comparatively lower than the one of the control group.

For the productivity proxies analyzed, the differentials between starters and never exporters appear to progressively narrow some years before entry. However, even in the year prior to the entry date into foreign market, future exporters still have a significantly higher productivity. The reverse seems to happen for the variable sales: as we approach to the entry into foreign markets new exporters appear to be more successful also in the domestic market. With respect to the other proxy for firm size, the number of employees, Table 5 shows a quite stable gap between the two groups of firms. The future exporters' average premium in terms of capital endowment tends instead to describe a U-shaped pattern that, consistently with the relative stability of the number of employees' coefficients noted above, is followed also by the capital intensity advantage of starters. No such a relatively clear trend is observable for the other firm characteristics: skilled labor intensity and unit labor cost. However, it is important to point out that a stricter test of the dynamics of future exporters premia should be based directly on a comparison of the difference in the growth rates of the relevant firm characteristics between the two groups of firms. In fact, there is the possibility that the temporal patterns just described above could be influenced by compositional effects due to the unbalanced nature of our sample.

Table 5: Self-Selection into exporting: Levels

	t-5	t-4	t-3	t-2	t-1
LP	21.0	14.8	17.2	14.3	14.7
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TFP	21.8	15.2	20.2	17.0	17.4
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales	62.6	54.1	70.1	72.3	77.3
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Num. Empl.	27.5	22.4	27.3	27.8	30.4
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Capital	84.6	52.6	62.1	63.6	78.0
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CI	44.8	24.7	27.3	28.2	36.5
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
SLI	3.0	2.3	4.5	4.2	4.6
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ULC	-15.7	-15.7	-19.9	-22.5	-21.5
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
N. Obs (max)	6426	10013	13761	17655	18386

Note: P-values of t-tests are in brackets below estimates (robust standard errors are used). Coefficients are transformed in exact percentage values. Calendar year, sectoral and regional dummies are included for all specifications. We report the maximum number of observations available for each time lag and firm's characteristics.

Therefore, looking for additional insights, we consider whether, in the years prior to entry, the performances of export starters increased more or less than those of never exporters. We explore this by estimating the following model

$$\ln(y_{i,t-s}) - \ln(y_{i,t-\rho}) = \alpha_C + \beta_C Starters_{it} + \gamma_C Controls_{it} + \upsilon_{it} \\ \text{with } 0 \leq \rho \leq 5 \qquad \text{and } 0 \leq s \leq 4 \tag{3}$$

Table 6 reports the transformed estimates of β_C, i.e. the conditional percentage differential between starters and never exporters in the growth rate, for all the relevant dependent variables. When looking at the growth rate between different time spans, we do find a significant increase in the pre-entry export premia only in terms of firm dimension and capital variables. The relevant coefficients of the regressions, employing our two productivity proxies as dependent variables, are never significant: during the pre-entry period starters and never exporters efficiency dynamics are, on average, not different.

On the other hand, in the years immediately before entering the international markets new exporters increase their size comparatively more than the firms belonging to the control group: both in terms of sales (from $t-2$ onward) and of workforce (from $t-3$ onward). Moreover, future exporters from three years before the entry onward also enlarge their capital stock more than never exporters. However, this capital accumulation

Table 6: Self-Selection into exporting: Growth Rates

	t-3/t-1	t-5/t-3	t-5/t-4	t-4/t-3	t-3/t-2	t-2/t-1
LP	0.9	-0.3	1.1	1.7	0.2	1.2
	(0.488)	(0.909)	(0.704)	(0.419)	(0.894)	(0.314)
TFP	1.3	0.8	1.4	2.0	0.7	1.1
	(0.322)	(0.75)	(0.601)	(0.318)	(0.672)	(0.381)
Sales	3.6	1.1	3.4	1.3	2.4	2.7
	(0.016)	(0.628)	(0.186)	(0.474)	(0.105)	(0.014)
Num. Empl.	2.6	3.4	2.1	2.4	2.5	1.4
	(0.011)	(0.189)	(0.152)	(0.216)	(0.002)	(0.025)
Capital	4.5	3.3	4.3	4.8	3.7	5.2
	(0.016)	(0.315)	(0.180)	(0.028)	(0.035)	(0.000)
CI	1.8	-0.1	2.1	2.3	1.1	3.8
	(0.345)	(0.982)	(0.521)	(0.309)	(0.535)	(0.007)
SLI	-0.2	2.2	4.1	1.1	-1.2	1.3
	(0.908)	(0.420)	(0.182)	(0.584)	(0.474)	(0.315)
ULC	-1.3	0.5	-1.2	1.5	-0.1	0.0
	(0.313)	(0.816)	(0.505)	(0.263)	(0.903)	(0.993)
N. Obs (max)	10545	3618	5907	8831	11762	15081

Note: P-values are in brackets below estimates (robust standard errors are used). Coefficients are transformed in exact percentage values. Sectoral, regional and calendar year dummies are included for all specifications. We report the maximum number of observations available for each time lag and firm's characteristics.

advantage of future exporters is not reflected by a capital deepening (i.e. capital intensity) premium until $t-1$. Therefore, it seems that the capital accumulation premium of new exporters is more a consequence of firm size growth than of a change in the structure of production. Moreover, the fact that neither the skilled labor intensity coefficients nor the ULC coefficients are significant confirms the last conclusion: during the pre-entrance period future exporters do not undergo relevant structural changes in terms of the organization and the technology of production (with respect to never exporters), instead they do grow (in size) comparatively more.

These findings imply that it is the "better" firms that are becoming exporters. In the spirit of self-selection, this means that prior to exporting, a firm must have certain characteristics in terms of productivity, size, human capital, and capital intensity in order to sell its goods abroad. However, we don't find relevant evidence indicating that firms prepare themselves before entering the foreign markets (consciously or simply being subject to some common shock) by changing their structure of production. It seems instead that future exporters have from the beginning comparatively "better" characteristics (with respect to "domestic" firms) and that they already benefit from these characteristics before going international. In fact, during the three years preceding the entry, firms augment their scale of production, i.e. both capital and labor usage, and their sales[13].

[13]With respect the recent literature on self selection, Bellone et al. (2007) find instead a U-shaped pattern for the TFP of French export starters, concluding that the pre-entry dip in productivity is the

4 The Post entry effects

Having ascertained the presence of a self-selection mechanism in the pre-entry period, we are now firstly interested in observing if these export premia are preserved, or reinforced, also in the post-entry period. Is it indeed possible that, irrespective of the pre-entry level, firms benefit from their exporting activities? Does exporting improve performances?

As suggested by Aw, Chung and Roberts (1998), exporting firms could in principle benefit from technological feedback provided by international clients and competitors. In order to meet foreign buyers demand and to cope with the more competitive international environment, exporters have to upgrade their production techniques and they have to adopt new processes or products innovation. As a consequence they may improve their efficiency and their productivity. In addition, exporters may exploit possible economies of scale and take advantage of a greater capacity utilization determined by international demand. If technology transfer and scale economies are at work, one would then expect to observe an increase in the post-entry exporters' performances.

As it is shown in the Appendix 2, the advantage of starters (with respect to never exporters) in terms of various economic indicators, which we have already found in the pre-entry period, is detected also in the post entry period[14]. Therefore, we firstly asses if these post-entry advantages of starters are robust to controlling for a selection mechanism that operates through firm specific heterogeneity that is constant over time. Hence, we present a set of results based on an econometric specification that exploits the panel structure of our data, by controlling for individual specific fixed effects. In other words, we want to understand if the post-entry premia of new exporters are simply a consequence of the fact that firms with higher fixed effects self-select into exporting.

We use data of firms that begin to export at some point during the period 1991-1995 ($D_{is} = 1$) and data about the comparison group of firms that never export in the sample period ($D_{iv} = 0, \forall v$) to estimate by first differencing the following linear unobserved effects model

$$Y_{it} = \phi_i + \sum_{K \geq -g}^{f} D_{it}^K \delta_K + \gamma_t + \upsilon_{it} \tag{4}$$

Y_{it} is the log of the relevant dependent variable; ϕ_i is a time-invariant individual fixed effect that is meant to control for unobserved time-constant firms' characteristics that could influence their performances. The set of dummy variables D_{it}^K represents relative time with respect to the event of beginning to export ($K = 0$). In particular, δ_K is the effect of exporting on firm performances K years following (or, if K is negative, prior to) its beginning. These coefficients approximate the percentage premia of starters in term of productivity (size, capital, etc.) with respect to the expected productivity (size, capital, etc.) levels of never exporting firms. The γ_t's are the coefficients of calendar year dummy

consequence of the specific sunk costs that new exporters have to bear in order to access the new markets. Alvarez and Lopez (2005) try to discriminate between random and conscious self-selection, however this is beyond the scope of our paper.

[14]In Table A2 we report the export premia of firms that start exporting during the period 1991-1995 with respect to never exporters at various time lags from the year of entry into foreign market. These results are purely descriptive since new exporters could have relatively better performances in the post entry period simply because the advantages we have detected in the pre-entry period are maintained. The export premia of starters seem to enlarge as they accumulate experience in the international markets, with the exception of skilled labor intensity and capital intensity whose premia are quite stable.

variables that are aimed to control for the general time pattern of productivity (and the other firm characteristics under analysis) in the whole economy.

Choosing g means imposing that there are no effects of exporting from g years before the entry backwards. Therefore, we expect that, if we have carefully controlled for all the non-ignorable[15] observable and non-observable variables influencing differences in the relevant dependent variables between the control and the treated groups, the parameter δ_K at $K = -g$ will not be significantly different from zero. Consequently, estimates of the export effects during the pre-entry years may be used as an informal specification test of the model. We have set $g = 5$ and $f = 6$.

In general, bias in the model could occur if the group of starters are not a random sample in terms of non-ignorable (observable and unobservable) characteristics we don't control for (i.e., observable time-varying characteristic and unobservable time-varying characteristics). Therefore, finding relevant and persistent premia to exporting during all the years preceding the launch of the export activity could signal that also (or only) other factors, different from exporting, are determining such premia, i.e. a causal interpretation of the estimated δ_K is not warranted (Jacobson, LaLonde and Sullivan, 1993; JLS from now).

As advocated by our informal specification test described above, the estimated effects of exporting for the pre-entry years are, in general, progressively less significant (both from an economic and a statistical point of view) as we move backward from the starting period. In other words, Table 7 shows that, once one has controlled for a selection mechanism based on individual specific heterogeneity fixed in time, export starters are not substantially different from the control group as we move back in time in the pre-exporting period. This finding is consistent with what observed in the preceding paragraph: while pre-entry levels do markedly differ in favor of export starters, the pre-entry growth rates of the relevant variables for new exporters and never exporters tend to be not statistically different. Indeed, both the equation (3) and the equation (4) are designed to eliminate the individual specific fixed effects. Hence, in general, once one accounts for individual specific fixed effects (and for the fact that every year we could have compositional effects due to the unbalanced nature of the sample), it appears that on average future exporters don't enlarge their advantage over future non-exporters during the pre-entry period. The major exceptions, both in the previous paragraph and in Table 7, are the variables related to firm size (number of employees and sales) and capital, during the years immediately before entry. Therefore, the conclusions of the previous paragraph are confirmed.

Looking at the post-entry period, we find that, with respect to never exporters, starters become more productive (both in terms of labor productivity and TFP), bigger (both in terms of sales and number of employees), they increase their capital endowment, and they reduce their ULC as they accumulate years of experience in the export markets. For example, the estimated coefficients for both regressions concerning productivity as dependent variable become statistically significant at the year firms start exporting (t) and the percentage differences become larger and larger in the periods after entry. At t export starters are about 7% more productive than the control group. Six years after entering the export markets new exporters are about 22% more productive than never exporters (both in terms of labor productivity and of TFP). A more stable, even if somehow increasing

[15] A non-ignorable characteristic is a characteristic that is correlated both with the independent variables and the outcomes.

Table 7: Ex-ante and Post-entry differences between export starters and never exporters

	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6	N. Obs	N. Firms
LP	1.1	1.9	3.4	3.2	4.5	7.2	9.7	12.5	15.2	17.7	19.9	21.7	25489	6056
	(0.695)	(0.576)	(0.334)	(0.374)	(0.212)	(0.055)	(0.011)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)		
TFP	0.2	1.4	3.1	3.3	4.5	7.5	10.3	13.5	16.4	19.2	21.4	22.0	25294	6037
	(0.938)	(0.696)	(0.387)	(0.375)	(0.229)	(0.052)	(0.009)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)		
Sales	-2.4	0.5	1.6	3.3	6.5	13.7	19.8	25.4	30.3	33.5	35.6	39.8	25475	6056
	(0.209)	(0.867)	(0.595)	(0.301)	(0.061)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
N. of Empl.	-0.4	1.8	4.3	6.8	8.5	10.8	12.4	14.0	15.6	15.9	16.0	17.6	25489	6056
	(0.749)	(0.283)	(0.020)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Capital	9.1	14.4	20.5	25.4	32.3	37.8	41.7	43.2	49.0	47.2	49.7	64.1	25306	6043
	(0.372)	(0.174)	(0.070)	(0.028)	(0.008)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.005)		
CI	9.6	12.4	15.6	17.4	22.0	24.4	26.0	25.7	28.8	27.0	29.0	39.7	25306	6043
	(0.342)	(0.234)	(0.156)	(0.117)	(0.057)	(0.038)	(0.030)	(0.034)	(0.022)	(0.040)	(0.046)	(0.055)		
SKI	-0.77	-1.09	0.28	0.02	0.20	0.92	1.39	1.23	0.68	1.11	0.28	0.02	25489	6056
	(0.132)	(0.287)	(0.330)	(0.966)	(0.623)	(0.037)	(0.005)	(0.010)	(0.238)	(0.091)	(0.192)	(0.229)		
ULC	2.60	2.10	3.90	4.20	4.10	0.30	-4.20	-7.60	-9.90	-13.20	-14.80	-13.30	25488	6056
	(0.213)	(0.446)	(0.185)	(0.182)	(0.202)	(0.935)	(0.204)	(0.024)	(0.004)	(0.000)	(0.000)	(0.002)		

Note: P-values of t-tests are in brackets below estimates (robust standard errors are used). Coefficients are transformed in exact percentage values.

pattern, is observable for the capital intensity variable: the percentage difference between starters and never exporters ranges from 24% at time t, to 29% at time $t+5$. Less clear-cut evidence is detected for the skill intensity variable: the higher level of percentage of white collar for export starters with respect to never exporters is observable in some years following entry, while in other years the coefficients, though positive, are not statistically significant.

In the next paragraph we introduce alternative econometric methodologies aimed at investigating the causal effects of beginning to export on exporters. They share with the JLS econometric strategy explained above the robustness to self-selection based on individual specific fixed effects, but they are also based on some alternative assumptions.

4.1 The Econometric Model

According to our previous results Italian manufacturing firms with higher performances are more likely to enter the export markets. That is, exporters self select into selling abroad because they are better than never exporters with respect to numerous characteristics: from productivity, to capital and non-production workers intensity. Hence, to assess the causality from export behaviour to firm performances, one needs to control for this sample selection problem. In other words, in order to determine the impact of exporting on exporters it is necessary to consider the fact that the group of export starters is not randomly selected from the entire population. A simple comparison between characteristics of export starters and never exporters can not reveal the direction of causality between productivity (and other firm's characteristics) and export status.

Indeed, the object of our analysis is to identify the average effect of the export activity on exporters with respect to firm's performances. In the evaluation literature this effect is known as the average treatment effect on the treated (ATT), which is simply a special case of the general notion of average partial effects computed for the treated part of the population (Wooldridge, 2002). In our framework this sub-sample will be the firms that begin to export.

Let's indicate as D_i a variable taking the value 1 if a firm has started exporting (i.e. the firm exposed to the treatment) and 0 if it is a never exporter. Each firm has two potential outcomes: Y_{it} $(D_i = 1)$, if it has been exposed to the treatment, Y_{it} $(D_i = 0)$ if not. Therefore, the outcome for every firm can be written as

$$Y_{it}(D_i) = D_i Y_{it}(1) - (1 - D_i) Y_{it}(0) \tag{5}$$

At time t, the average treatment effect (ATE) is the expected effect of the treatment on a randomly drawn person from the population

$$ATE_t = E(\Delta_{it}) = E(Y_{it}(1) - Y_{it}(0)) = E(Y_{it}(1)) - E(Y_{it}(0)) \tag{6}$$

while, at time t, the average treatment effect on the treated (ATT) is the expected effect of the treatment on those who were actually treated

$$\begin{aligned} ATT_t &= E(\Delta_{it}|D_i = 1) = E(Y_{it}(1) - Y_{it}(0)|D_{i0} = 1) \\ &= E(Y_{it}(1)|D_i = 1) - E(Y_{it}(0)|D_i = 1) \end{aligned} \tag{7}$$

Treatment effects can display heterogeneity connected both to firm observables and unobservable characteristics, therefore in general ATT and ATE differ. In the following we will focus our attention on the identification of the ATT, since this is the relevant effect to tackle the issues proposed in the introduction. Indeed, we are interested in testing if exporting firms benefit from starting to export, i.e. if in the hypothetical counterfactual situation of no exporting they would have had worse or better outcomes.

The problem is that in observational (non-experimental) studies one is not able to observe both outcomes for the same individual and therefore to compute directly $E(Y_{it}(0)|D_i = 1)$. What one is able to compute directly is $E(Y_{it}(0)|D_i = 0)$. The bias in computing the ATT_i is therefore

$$B(ATT_t) = E(Y_{it}(0)|D_i = 1) - E(Y_{it}(0)|D_i = 0) \tag{8}$$

that is the difference between the missing counterfactual mean and our imperfect available counterfactual mean.

If the group of the treated is randomly selected from the population, or, more precisely, the group of the treated and the group of the control have the same non-ignorable observable and non-observable characteristics, then the bias is zero. However, the main problem in observational studies is that selection into treatment is not perfectly randomized. Therefore, the treated and the non-treated may differ in non-ignorable characteristics, other than treatment intake. This implies that simply comparing the mean values of the two groups (treated and control) would determine a bias, as equation (8) shows.

Different econometric techniques have been developed in observational studies to overcome the ATT bias. A first popular estimation strategy is given by the Differences in Differences (DID) estimator. In the DID strategy one compares the differences in outcomes after and before a treatment for the treated group (export starters) to the same differences for the untreated group (never exporters), relying on the assumption that, without the treatment, the outcomes (productivity, employment, etc) would have followed parallel paths across the two groups of firms.

Let's consider two periods, one before the treatment intake ($t = 0$) and one after the treatment ($t = 1$). In presence of panel data, as in our case, the crucial identifying restriction for DID is the following

$$E(Y_{i,1}(0) - Y_{i,0}(0)|D_i = 1) = E(Y_{i,1}(0) - Y_{i,0}(0)|D_i = 0) \tag{9}$$

It states that the average outcomes for the treated and the untreated would have followed parallel dynamics over time in the absence of the treatment. If equation (9) holds, then

$$\begin{aligned} ATT_1 &= E(Y_{i1}(1) - Y_{i1}(0)|D_i = 1) \\ &= E(Y_{i1}(1) - Y_{i0}(1)|D_i = 1) - E(Y_{i1}(0) - Y_{i0}(0)|D_i = 0) \end{aligned} \tag{10}$$

The DID estimates can be easily obtained from the least squares estimation of the coefficient β in

$$\Delta Y_i = \alpha + \beta D_i + \upsilon_i \tag{11}$$

where $\Delta Y_i = Y_{i,1} - Y_{i,0}$ Therefore, in presence of panel data, selection into treatment is allowed to depend on individual specific fixed effects, as we can clearly see if we rewrite (11) as

$$Y_{it} = \alpha_i + \alpha t + \beta(D_i t) + \varepsilon_{it} \tag{12}$$

where t is a variable that indicates the pre-treatment period if it is 0 and the post treatment period if it equals 1, and α_i is a time-invariant individual specific fixed effect possibly correlated with D_i[16]. The DID formulation is often used to introduce covariates by considering the least squares estimator of

$$Y_{it} = \alpha_i + \alpha t + \beta(D_i t) + \phi_1(tX_i) + \phi_0((1-t)X_i) + \varepsilon_{it} \tag{13}$$

where X are some exogenous or predetermined observable variables that are not influenced by the treatment and that are interacted with the time indicator. By differentiating (13) with respect to t one has

$$\Delta Y_i = \alpha + \beta D_i + \phi X_i + \upsilon_i \tag{14}$$

where $\phi = \phi_1 - \phi_0$. This specification allow for different dynamics for the treated and the untreated, as long as these dynamics can be explained linearly by observed covariates. Now, assumption (9) can be reformulated as

$$E(Y_{i,1}(0) - Y_{i,0}(0)|X_i, D_i = 1) = E(Y_{i,1}(0) - Y_{i,0}(0)|X_i, D_i = 0) \tag{15}$$

Alternatively, another popular estimation method employed in observational studies to overcome the ATT bias is the propensity score matching (PSM) techniques (Rosembaum and Rubin, 1983). The main idea of this method lies in the concept of selection on observables, according to which the set of observable variables at our disposal could be sufficient to eliminate the bias stemming from the non-random selection of the firms into the exporters and non-exporters group. In other word, it is assumed that, given the set of observables, firms with the same characteristics are randomly exposed to the export activities.

Following Heckman et al. (1997, 1998), the bias can be expressed as a function of the observable characteristics , and decomposed into three parts

$$\begin{aligned} B(X_i) &= E(Y_{it}(0)|X_i, D_i = 1) - E(Y_{it}(0)|X_i, D_i = 0) \\ &= B_1 + B_2 + B_3 \end{aligned} \tag{16}$$

B_1 represents the component of the bias that is due to non-overlapping support of X, i.e. we are comparing firms that are already different also in the pre-treatment period. B_2 is due to misweighting on the common support of X. In fact, even in the common support, the distribution of the treated and of the untreated could be different. B_3 is the traditional econometric selection bias that stems from "selection on unobservables".

The aim of the matching estimator is indeed to reduce B_1 and B_2 by opportunely choosing and reweighting observations. B_3 is supposed to be absent, i.e. the matching method is based on the assumption of conditional independence (CIA)

$$Y(0) \perp D|X \tag{17}$$

[16]Equation (11) is obtained simply by differentiating (12) with respect to t.

This assumption, the so called "selection on observables", states that conditional on X the potential outcome in the non-treatment scenario is independent of the treatment status. The variables in X must be strictly exogenous, namely it is assumed that they are not affected by the treatment, either ex post or in anticipation of the treatment. The CIA will hold if X includes all of the variables that affect both the selection into treatment (*e.g.*, the decision to export) and the outcomes (*e.g.*, productivity, size, etc...). Note that equation (17) implies also *mean independence*

$$E(Y_{it}(0)|X_i, D_i = 1) = E(Y_{it}(0)|X_i, D_i = 0) \tag{18}$$

In the standard setting of a linear model with an additively separable error term, equation (17) becomes

$$E(U_{it}|X_i, D_i = 1) = E(U_{it}|X_i, D_i = 0) \tag{19}$$

Note that this is slightly weaker than the assumption that underlies OLS. Indeed, the OLS assumption $E(U_{it}|X_i, D_i) = 0$ implies the assumption required for matching, but it is not implied by the latter. Moreover, standard OLS do not address possible problems of common support of the distribution of X_i between treated and control group, extrapolating counterfactual outcomes that are outside the common support (thanks to its functional assumptions). In presence of heterogeneity of the treatment effect, OLS gives more weight to the heterogeneous values of this partial effect for which the conditional variance of D_{it} given X_{it} is largest[17]. Thus, given equation (17) , the ATT_t can be identified by estimating

$$\begin{aligned} ATT_t &= E(Y_{i,1}(1) - Y_{i,1}(0)|D_i = 1) \\ &= E_{X|D=1}\{E(Y_{i,1}(1) - Y_{i,1}(0)|X_i, D_i = 1)\} \\ &= E_{X|D=1}\{E(Y_{i,1}(1)|X_i, D_i = 1)\} - E_{X|D=1}\{E(Y_{i,1}(0)|X_i, D_i = 1)\} \\ &= E_{X|D=1}\{E(Y_{i,1}(1)|X_i, D_i = 1)\} - E_{X|D=1}\{E(Y_{i,1}(0)|X_i, D_i = 0)\} \end{aligned} \tag{20}$$

where in the third line we applied the CIA. When the dimension of X_i is high, the practical computation of (20) becomes unfeasible. However, Rosembaum and Rubin (1983) showed that

$$Y(0) \perp D|X \Rightarrow Y(0) \perp D|P(X) \tag{21}$$

where $P(X) = Pr(D = 1|X)$ is called the *propensity score*. This means that, if treatment is random conditioning upon X, it is random also conditioning upon $P(X)$. Therefore the "curse of dimensionality" can be solved and the ATT_t identified by estimating

$$\begin{aligned} ATT_t &= E_{P(X)|D=1}\{E(Y_{i,1}(1)|P(X_i), D_i = 1)\} - \\ &- E_{P(X)|D=1}\{E(Y_{i,1}(0)|P(X_i), D_i = 0)\} \end{aligned} \tag{22}$$

In practice, there exist many different matching procedures which can be used to estimate 22. A typical matching estimator takes the form

[17]See for example Angrist and Krueger (1998).

$$M_{ATT_t} = \frac{1}{n_1} \sum_{i \in \{D_i=1\}} \left[Y_{it} - \sum_{j \in \{D_j=0\}} w(i,j) \cdot Y_{jt} \right] \quad (23)$$

where $w(i,j)$ is the weight placed on the jth observations in constructing the counterfactual for the jth treated observation and n_i is the number of treated observations. Matching estimators differ in how they construct the weights $w(i,j)$.

In the *Nearest Neighbour* (NN) method the match between treated and untreated units consists on searching for the control with the closest propensity score. The *Radius Matching* matches each treated unit only with the control units whose propensity score falls in a predefined neighbourhood of the propensity score of the treated unit. The *Kernel Matching* matches all the treated with a weighted average of all controls (if using a Gaussian kernel), with weights that are inversely proportional to the distance between the propensity score of the treated and controls (Becker and Ichino, 2002).We show the results obtained by implementing the single nearest neighbour matching with replacement. However, similar treatment effects are found with the kernel matching and radius matching techniques.

The true propensity score normally is not known and must be estimated. Any standard probability model can be used. The "balancing test" introduced by Rosembaum and Rubin (1983) helps to choose a specification of the probability model given the chosen X. It relies on the fact that, if $P(X)$ is the propensity score, then it must be that $D \perp X|P(X)$.

The balancing test we use is based on the routine developed by Becker and Ichino (2002). First we split the sample in intervals such that the average propensity score for the treated and the control does not differ in each interval. Then, within each interval, we test that the means of each characteristics don't differ between treated and control units. The balancing property is satisfied in all of our estimates.

Matching should impose the condition of pointwise common support. We adopt the simplest strategy to exclude from the treated group the observations whose P(x) values lie outside the support of the distribution of the controls.

Finally, the robustness of the matching estimator can be augmented by taking advantage of the panel structure of the data. In fact, one can implement a Propensity Score Matching-Differences In Differences (PSM-DID) (Heckman et al. 1997, 1998), which is a particular kind of matching estimator based on the assumption (15) and on the result (21). Indeed, if the point-wise bias due to B_3 is constant in time, i.e. unobserved heterogeneity is fixed in time, we have that

$$B^{post}(X_i) - B^{pre}(X_i) = 0 \quad (24)$$

The practical implementation of this estimator is straightforward

$$M_{ATT}^{DID-PSM} = \frac{1}{n_1} \sum_{i \in \{D_i=1\}} \left[(Y_{i,post} - Y_{i,pre}) - \sum_{j \in \{D_j=0\}} w(i,j) \cdot (Y_{i,post} - Y_{i,pre}) \right] \quad (25)$$

4.2 Are there any post-entry effects?

To analyze the impact of the export activities on exporters we perform the propensity score matching differences in differences estimator. We compute the PSM-DID estimator at every period k after the entry into the export markets, with respect to the year prior to entry $(t-1)$. The first step in implanting the PSM-DID strategy requires modelling and estimating the probability of starting to export for each of the five cohorts. It is important to estimate propensity score for each cohort separately because the drivers of the decision to export could differ in the various years. Moreover, as discussed in Dehejia and Wahba (1999, 2002), there is no reason to believe that the same specification of the propensity score will balance the covariates in different samples. Our specification of the propensity score can be represented as follows

$$\begin{aligned} Pr(Start_{it}) \;\; = \;\; & \Phi\{h(LP_{i,t-1}; TFP_{i,t-1}; Sales_{i,t-1}; N.Empl_{i,t-1}; Capital_{i,t-1}; \\ & KPE_{i,t-1}; PWC_{i,t-1}; ULC_{i,t-1}; Sectors; Regions; \ldots)\} \end{aligned} \tag{26}$$

where $\Phi()$ is the Normal cumulative distribution function.

In estimating the propensity score we include all the relevant variables: productivity, employment, sales, capital and skilled labor intensity and unit labor costs (*Sectors and Regions* refers to sectoral and regional dummies). To free up the functional form of the propensity score we include higher order polynomials and interaction terms, and search for a specification that balances the pre-treatment covariates between the treatment and the control group conditional on the estimated propensity score (using the methodologies described above). The variables we match on cannot be affected by the treatment, either ex post or in anticipation of treatment. Otherwise, if the exporting firms adjust their characteristics in anticipation of the beginning of the export activity, then we would end up matching on endogenous variables. Therefore, to overcome this problem, we had initially chosen to match on pre-treatment variables at year $t-3$. However, in our case, matching at $t-1$ leaves the estimation results basically unchanged but enlarge the size of the sample (cause we don't have to additionally impose that starters have a valid observation at $t-3$). Moreover, the risk to match on endogenous variable is, in our case, extremely low as many starters' pre-treatment characteristics at year $t-3$ closely resemble those at $t-1$: as we have already seen, we find clear-cut evidence of pre-exporting adjustments only with respect to size and capital stock. Therefore we have chosen to present the results deriving from matching at $t-1$.

Once the sample of matched firms and the corresponding controls has been selected for each of the five cohorts, we compute the average treatment effects at different relative temporal distance from the entry time, pooling together these treated and matched control firms of different calendar years.

As mentioned above, in applying the matching technique one needs to choose a counterfactual group as similar as possible to the treated group. Several procedures have been proposed in order to check the quality of the matching procedure. To test the goodness of our matching we first implement the balancing test, as proposed by Becker and Ichino (2002), which we already described above. We verify that the balancing property is satisfied for every specification of the propensity score (and therefore for each cohort of starters and never exporters separately). Second, we implement a standard t-test for equality of means for the covariates to check if significant differences remain after conditioning on the propensity score. We compute the t-test for the mean values at $t-1$, $t-2$ and $t-3$. [18] The results, shown in Table 8, give us confidence that we have identified the appropri-

[18]Note that, for a matter of simplicity, in Table 8 we present only the results of t-test for the sample

Table 8: Assessing the matching quality

	N.Firms	LP	TFP	Sales	N.Empl.	Capital	CI	SLI	ULC
					Value at t-1				
All Treated	662	4.1	4.8	9.1	3.8	8.17	4.3	21.2	-1.55
All Controls	5441	3.9	4.5	8.4	3.6	7.43	3.8	14.5	-1.20
P-value		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Treated on Common Support	656	4.1	4.8	9.1	3.8	8.13	4.3	21.0	-1.55
Matched Controls	656	4.2	4.8	9.1	3.8	8.15	4.3	21.0	-1.56
P-value		0.62	0.72	0.69	0.71	0.78	0.94	0.93	0.68
					Value at t-2				
All Treated	626	4.1	4.7	9.1	3.8	8.1	4.2	20.6	-1.6
All Controls	5441	3.9	4.5	8.4	3.6	7.44	3.8	14.6	-1.23
P-value		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Treated on Common Support	620	4.1	4.7	9.0	3.8	8.02	4.2	20.4	-1.58
Matched Controls	563	4.1	4.7	9.1	3.8	8.10	4.3	20.4	-1.56
P-value		0.62	0.80	0.70	0.62	0.33	0.37	0.98	0.47
					Value at t-3				
All Treated	385	4.2	4.8	9.1	3.9	8.1	4.2	21.1	-1.6
All Controls	5441	3.9	4.5	8.4	3.6	7.5	3.8	14.6	-1.2
P-value		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Treated on Common Support	381	4.2	4.8	9.1	3.8	8.1	4.2	20.9	-1.6
Matched Controls	362	4.2	4.7	9.1	3.8	8.1	4.3	20.9	-1.6
P-vallue		0.72	0.51	0.99	0.40	0.99	0.55	0.99	0.33

Note: At time $t-2$ the number of treated decreases to 620 because of missing observations in the relevant variables. At $t-3$ it reduces to 381 also because the cohort of firms starting to export in 1991 is not included since it has not observations at $t-3$. P-values refer to t-tests for the significance of the difference of means between the two relevant groups. The number of matched controls refers to the number of firms that are matched to the treated firms on the common support, however in the t-test we replicate the controls that are used as multiple matches (that are used as control for more than one treated).

ate matched control group. In fact, after matching no differences are found in covariate means of treated and untreated. We are not able to reject the null hypothesis of equality of means for all the relevant variables and regardless of the time lag considered. Finally, it also useful to look at the density functions of the propensity scores for the treated and the matched controls to get a sense of the overlap between them. Figure 1 shows how the propensity score matching increases the comparability between the two groups. While prior to matching, the estimated kernel densities are quite different, after matching we can observe very similar values [19].

Table 9 displays the estimated ATTs obtained by employing the PSM-DID method-

obtained by matching firms that have non missing observations at $t-1$ and at t. However, the equality of means between the matched treated and controls is confirmed also for all the other samples used in the ATT estimation: matched firms that have no missing observations both at $t-1$ and $t+k$, with $k \in [0,6]$.

[19] In Appendix 3, Figure A3, we report the kernel densities of the propensity score for each of the five cohorts within we matched treated and controls. All the kernel density shown in this work were performed using *gbutils*, a package of programs for parametric and non-parametric analysis of panel data, distributed under the General Public License and freely available at *http://www.cafed.eu/gbutils*. If not else specified, density estimation is performed using Epanenchnikov kernel and setting the bandwidth following the "rules" suggested in Section 3.4 of Silverman (1986).

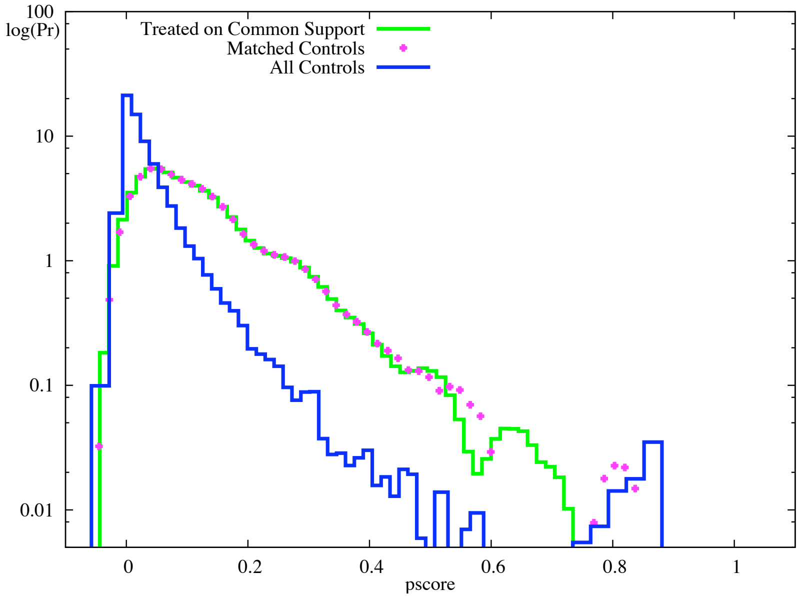

Figure 1: Kernel density estimates of the propensity score

ology as described above. In line with the results of Table 7, we find that the labour productivity growth of starters is higher than that of the never exporters. Firms that start exporting growth more than firms that serve only the domestic markets. An important issue to point out regards the evolution of the rate of growth as we move forward from entry period. While we observe a labor productivity growth of about 2 percent after one year exporting, the percentage reach 13 percent after 5 years. This implies that, though the effect of export activities on productivity is immediate, it enlarges after some years following the entry period. Moreover, considering TFP as dependent variable confirms that export starters have an higher productivity rate of growth with respect to their domestic counterpart and that this gap is increasing after some years of exports. Beginning to export has a similar effect also on firm's size. Once more, this effect is larger as we move forward from the year of entry into foreign markets. The rate of growth of sales (employment) of new exporters from $t-1$ to t, is about 6% (3%) higher than that of never exporters; the premium of starters with respect to the growth rate of sales (employment) from $t-1$ to $t+5$, increases to about 32% (11%).

We also uncover evidence of a positive treatment effect of exporting on the capital endowment. The estimated ATTs are positive and increasing and they are in general statistically significant with the exception of the last three estimates ($t-4$, $t-5$, $t-6$). However for the capital intensity variable we never find significant post-entry effects. This estimation results are consistent with the presence of post-entry effects on the scale of production (both on labor and capital) but not on capital intensity. This conclusion is coherent with the estimation results of the JLS model: capital intensity advantage of exporters is quite stable from the year before entry onward.

Regarding the skill labor intensity variable we find that the rate of growth of skill intensity of the treated group is in general higher than that of the control group. However, the estimated ATTs are statistically significant only in two cases, namely for ATT($t-1/t+$

Table 9: PSM-DID estimates

		t-1/t	t-1/t+1	t-1/t+2	t-1/t+3	t-1/t+4	t-1/t+5	t-1/t+6
LP	ATT	0.020	0.043	0.040	0.085	0.109	0.132	0.077
	SE	0.019	0.025	0.032	0.035	0.049	0.067	0.101
	P-value	0.293	0.091	0.211	0.015	0.027	0.049	0.445
TFP	ATT	0.024	0.047	0.055	0.102	0.112	0.170	0.086
	SE	0.018	0.026	0.033	0.035	0.048	0.067	0.112
	P-value	0.178	0.074	0.093	0.004	0.02	0.011	0.446
Sales	ATT	0.062	0.112	0.136	0.208	0.210	0.278	0.413
	SE	0.021	0.027	0.040	0.044	0.054	0.063	0.095
	P-value	0.003	0.000	0.001	0.000	0.000	0.000	0.000
N.Empl.	ATT	0.027	0.035	0.059	0.075	0.068	0.108	0.135
	SE	0.010	0.017	0.022	0.026	0.032	0.045	0.061
	P-value	0.007	0.038	0.009	0.004	0.033	0.016	0.027
Capital	ATT	0.056	0.083	0.104	0.113	0.088	0.113	0.120
	SE	0.020	0.030	0.041	0.066	0.088	0.144	0.189
	P-value	0.005	0.006	0.012	0.087	0.317	0.433	0.526
CI	ATT	0.029	0.048	0.046	0.034	0.025	0.001	-0.023
	SE	0.022	0.035	0.043	0.067	0.083	0.138	0.161
	P-value	0.186	0.169	0.277	0.617	0.761	0.995	0.887
SLI	ATT	0.018	0.047	0.017	0.050	0.081	0.066	0.096
	SE	0.020	0.027	0.034	0.035	0.041	0.063	0.089
	P-value	0.362	0.081	0.624	0.148	0.050	0.288	0.277
ULC	ATT	-0.054	-0.086	-0.110	-0.133	-0.152	-0.164	-0.264
	SE	0.017	0.019	0.029	0.033	0.042	0.056	0.082
	P-value	0.001	0.000	0.000	0.000	0.000	0.004	0.001
N.Firms	Treated	654	629	604	455	325	204	97
	Controls	589	550	525	398	288	178	78

Note: For details on the estimation procedure see the text. We report bootstrapped standard errors (200 replications), P-values, the number of treated on the common support and the number of matched controls (remember one control can be matched to more than one starter).

1) and ATT($t-1/t+4$). Therefore we tend to exclude a causal effect of exporting on the percentage of white collars.

Finally, we also detect that exporting has a labor (cost) saving effect: the estimated ATT for the variable ULC is negative and increasing in absolute value. However, this reduction in unit labor costs is not the results of a decrease in the number of employees (as we have already seen) nor a consequence of a reduction of average wages (the ATT for average wages is not reported cause it is never significant). It is instead associated with a positive causal effect of exporting on the scale of production (both capital and labor) and on productivity.

Using the traditional parametric DID estimator, the main results of the DID-PSM estimator are confirmed (see Appendix 4). In Table A4 we report the results obtained by a specification that includes, as controls at $t-1$, productivity, number of employees, capital and skilled labour intensity and unit labour costs.

In conclusion, we have detected robust evidence of positive average effects of the export activity on productivity, sales, number of employees and capital. We have found that, with respect to these variables, the positive effects of exporting on firms' performances increases as firms accumulate experience in the export market. Remarkably, the results seems to be robust to applying either the fixed effects specification *a la JLS*, the standard parametric

DID and the PSM-DID methods.

4.3 Conclusions and further research agenda

The paper contributes to add evidence to the growing empirical literature that attests the superior performances of exporters relative to non-exporters. In line with previous studies, we find that exporters outperform non-exporters and that self selection is at work also in the case of Italian manufacturing firms. Indeed, we describe the differences between exporters and non exporters with respect to a variety of firms attributes. We find that firms serving foreign markets have on average an higher productivity level, they are larger, they are more capital and skill labour intensive and they are more (labour) cost competitive than firms serving only the domestic market. Controlling for sectoral, geographical location and dimension heterogeneity the picture remains unchanged. To consistently estimate productivity we employ the semiparametric technique developed by Levenisohn and Petrin (2003) that takes into account the simultaneity and the unobserved heterogeneity problems. The export productivity premia persist using different proxies of firm productivity.

In order to test the self-selection hypothesis we differentiate between firms that start to export during the time frame of observation (export starters) and firms that serve exclusively the domestic markets for the entire period (never exporters). We find that, for all the variables under analysis and despite the different time lags, future exporters display advantages with respect to firms that will not take up exporting later on. However, when looking at the growth rates (of the relevant characteristics) in the pre-entry period we observe that starters and never exporters in general do not differ in terms of their dynamic path, with the exception of the scale of production and the sales.

In order to test the presence of post entry effects we exploit our longitudinal micro-level dataset, implementing various panel data techniques. We detect evidence of performance improvements either in terms of labor productivity, TFP, number of employees, capital endowment and ULC. Remarkably, the results seem to be robust to applying either the fixed effects specification a la JLS, the standard parametric DID and the PSM-DID methods. No such relatively clear evidence is found for the variable skill intensity. Only with the parametric DID model, but in contrast with the fixed effects specification a la JLS and the PSM-DID, we uncover some signals of quantitatively modest post entry effects on the percentage of white collars.

Though the relationship between export behaviour and firm performance has been widely investigated, the mechanisms underlying the effects of exporting on productivity have been only partially studied by the empirical literature. Our future research agenda is therefore aimed to deeply investigate the sources of the productivity gains due to exporting and, hence, the heterogeneity of the treatment effect of exporting on productivity. We have at our disposal additional variables on firm characteristics such the export markets served (both in terms of destinations and sectors) and import flows (with information also about the different countries and sector from which the firms import). The possibility to add new dimensions in the analysis could allow us to understand how and in which way firms improve their performances by exporting. Which is the role played by firm heterogeneity? Is it a matter of firm specific absorptive capacity? Are the effects of exporting different by foreign market served (both in term of destination and sector)? These will be our topics for future research.

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Appendix 1: Estimating Total Factor Productivity

Throughout the empirical analysis we evaluate firm's productivity through a measure of labour productivity, proxied by the value added over number of employees and through the Total Factor Productivity calculated applying the semi-parametric techniques implemented by Levinson and Petrin.

We assume a two factor Cobb Douglas production function containing labor and capital, and construct the TFP measure taking the residual of the estimate. Since the proportion of inputs and output may differ across sectors, we estimate the production function for each of the four Pavitt 's categories separately. We estimate the following equation

$$y_{it} = \beta l_{it} + \gamma k_{it} + \upsilon_{it}$$

where y_{it} is the log of value added of firm i at time t ; l_{it} is the log of number of employees and k_{it} is the log of firm's capital stock. The main problem that arises when we estimate the TFP is usually referred as the simultaneity problems and it is due to the fact that firms choose inputs knowing their own level of productivity. Thus, more productive firms are likely to use a greater amount of production inputs. The possible correlation between the productivity and the choice of factor inputs (i.e. the correlation between the error term and the regressors) will give bias parameter estimates and, consequently, bias productivity estimates when using the Ordinary Least Square.

Different methodology has been proposed in order to rise above this endogeneity problem (Van Biesebroeck, 2003 for a review of the possible techniques implemented by the literature). Though the fixed effect technique we can consistently estimate partial effects in the presence of time invariant component of productivity that can be arbitrarily related to the production inputs. However, the robustness of the fixed effect estimators comes at a price of requiring productivity shock to be fixed over time. An alternative method to solve the endogeneity problem has been proposed by Blundell and Blond (1998) which used a GMM-SYS estimator. Weak instrumental variables which has to be correlated with firm-level input and uncorrelated with productivity, is the main drawback of this method, other than it requires a longer panel.

Olley and Pakes (1996) proposes a semi-parametric techniques which estimates the coefficient taking into account the simultaneity and the unobserved heterogeneity problems. Precisely, they consider firm's investment decision to proxy unobserved productivity shocks. Following Olley and Pakes (1996) the error term can be written as $\upsilon_{it} = \varepsilon_{it} + \eta_{it}$, where ε_{it} is the productivity observed by the firms and η_{it} a random shock to productivity. Firm's investment decision depends on the observed productivity ε_{it} and on the current stock of capital ($i_{it} = i_{it}(k_{it}, \varepsilon_{it})$). In order to consistently estimate the production function the condition of a strict monotonous relationship between investment and output must hold. Given that, we can express the productivity observed by the firms as un unknown function of investment and capital, $\varepsilon_{it} = \varepsilon_{it}(k_{it}, i_{it})$, and the previous equation becomes:

$$y_{it} = \beta l_{it} + \phi(k_{it}, i_{it}) + \eta_{it}$$

Approximating $\phi(k_{it}, i_{it})$ by a third-order polynomial we can consistently estimates the labour coefficient. As a second step, in order to consistently estimates coefficients on capital, Olley and Pakes estimate the probability of staying in the markets conditional on perception of productivity realization. The probability is needed in the third and last step in which the capital coefficient is estimated.

The estimation strategy proposed by Olley and Pakes (1996) presents the disadvantages that very often datasets have numerous observations with zero investments. This causes a drop of numerous observations when estimating the TFP. Alternatively, Levenisohn and Petrin (2003) use intermediate inputs as a proxy for unobserved productivity instead of using investment, solving the problem of firms reporting zero investment. Assuming that intermediate inputs can be expressed as a function of the capital stock and the transmitted productivity components ε_{it} , that is $m_{it} = m_{it}(k_{it}, \varepsilon_{it})$ and given that this relationship is monotonically increasing in the productivity shocks, again ones can express productivity as a function of capital and intermediate inputs,$\varepsilon_{it} = \varepsilon_{it}(k_{it}, m_{it})$.

Appendix 2: Post entry export premia in Levels

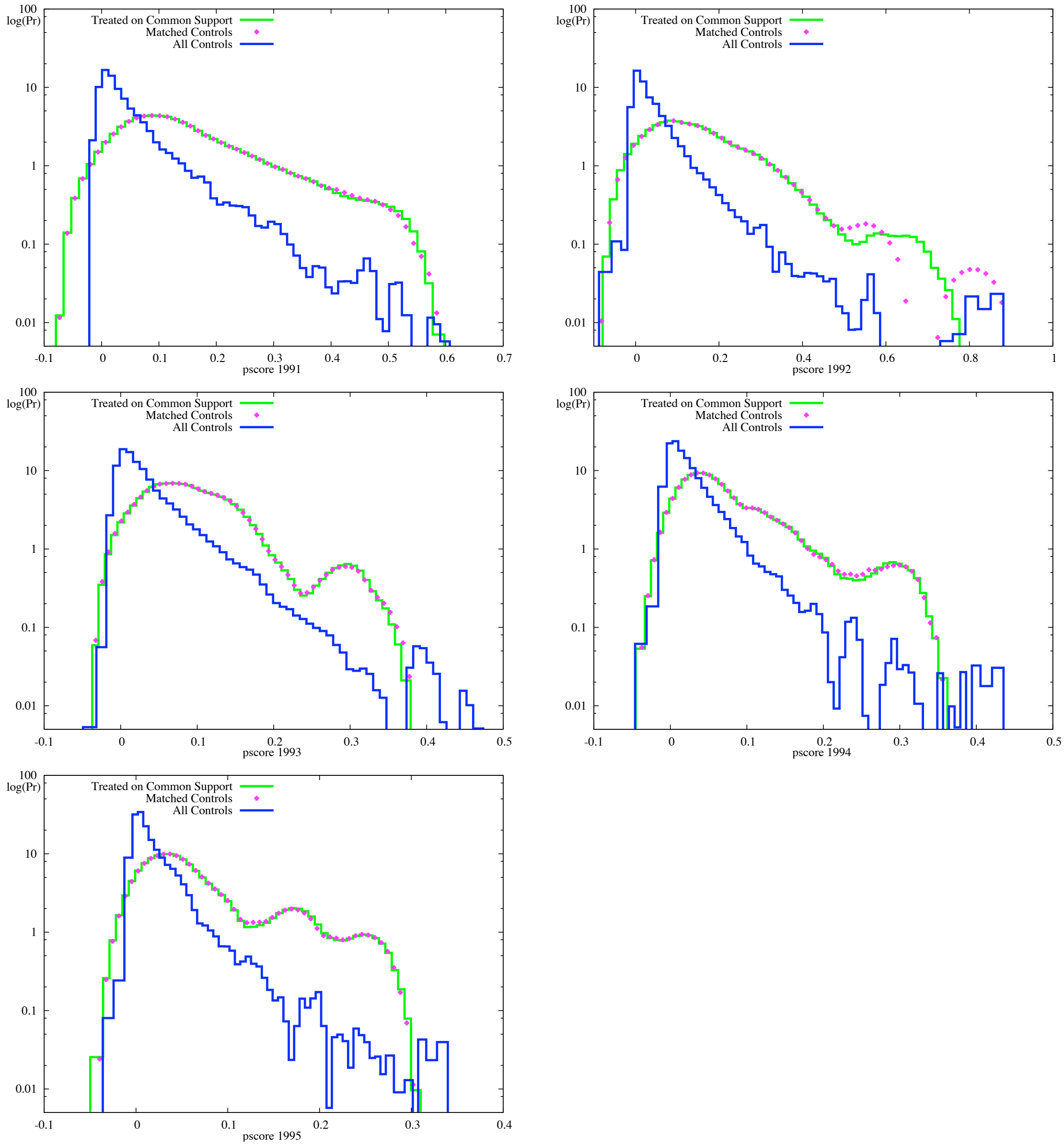
Table A2: Post entry export premia in Levels

	t+1	t+2	t+3	t+4	t+5	t+6
LP	15.7	16.4	17.0	15.5	19.2	29.0
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TFP	19.0	19.1	23.8	24.1	26.7	32.9
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales	94.9	102.1	125.7	130.7	145.1	154.1
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Num. Empl.	35.6	36.3	50.2	52.5	56.2	43.9
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Capital	99.9	103.6	129.3	113.6	151.2	113.6
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CI	47.4	49.5	52.6	40.7	60.5	48.8
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SLI	6.3	6.4	5.8	7.1	6.2	7.5
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ULC	-24.6	-26.4	-27.2	-27.7	-30.9	-35.8
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. Obs (max)	17201	15721	11916	8203	4895	2237

Note: Export premia of firms that start exporting during the period 1991-1995 with respect to never exporters at various time lags from the year of entry into foreign markets. Coefficients are transformed in exact percentage values. Sectoral, regional and calendar year dummies are included for all specifications. P-values of t-tests are in brackets below estimates (robust standard errors are used). We report the maximum number of observations available for each time lag and performance characteristics.

Appendix 3:Kernel density estimates of the propensity score

Figure A1: Kernel density estimates of the propensity score



Appendix 4: Post entry effects: differences in differences estimates

Table A4: Post-entry effects: differences in differences estimates

	t-1/t	t-1/t+1	t-1/t+2	t-1/t+3	t-1/t+4	t-1/t+5	t-1/t+6
LP	1.9	2.7	4.0	5.6	4.0	7.6	13.1
	(0.077)	(0.036)	(0.004)	(0.001)	(0.069)	(0.010)	(0.006)
TFP	2.3	3.3	4.7	6.4	6.4	9.5	13.4
	(0.032)	(0.013)	(0.001)	(0.000)	(0.006)	(0.002)	(0.010)
Sales	6.6	11.5	16.0	21.8	21.9	25.1	31.4
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Num. Empl.	2.1	3.3	4.4	7.2	8.2	9.2	5.1
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.228)
Capital	4.0	7.0	9.2	16.4	7.2	15.7	4.5
	(0.006)	(0.000)	(0.000)	(0.000)	(0.204)	(0.035)	(0.747)
CI	1.8	3.6	4.7	8.6	-0.8	5.7	-0.5
	(0.183)	(0.063)	(0.053)	(0.014)	(0.884)	(0.389)	(0.970)
SLI	5.2	7.2	6.7	5.4	6.1	4.0	13.4
	(0.000)	(0.000)	(0.000)	(0.007)	(0.014)	(0.279)	(0.022)
ULC	-4.6	-7.8	-10.5	-12.6	-12.7	-14.9	-20.6
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. Obs (max)	15215	11913	9779	6747	4265	2419	1121

Note: The Table presents the results of DID regressions, estimated pooling the cohorts of export starters across time. We compute the DID estimator at every period k after the entry into the export markets, with respect to the year prior to entry ($t-1$). As mentioned in the text, the parametric DID estimator is based on the strong assumption that, in absence of the treatment, the average outcome of the export starters and that of never exporters would have followed the parallel path. However, the parametric DID estimation could over or under estimates the treatment effect if the pre-treatment characteristics are unbalanced between the treated and the untreated groups. In order to solve this problem, and to increase comparability with the PSM-DID estimates, we introduce as controls the same regressors (at $t-1$) used in the computation of the Propensity Scores, following equation (15). P-values of t-tests are in brackets below estimates (robust standard errors are used). Coefficients are transformed in exact percentage values. Sectoral, regional and calendar year dummies are included for all specifications. We report the maximum number of observations available for each time lag and performance characteristics.