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

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Abstract

Our paper adds empirical evidence on the causal effects of exporting on firms' performances. Using a rich database on Italian manufacturing firms, we test the self-selection and the post-entry effects hypotheses with respect to various firms' characteristics. Our analysis supports the idea that the superior performance of the exporters is due not only to a market selection mechanism, but also to efficiency improvements following the export activity. We find heterogeneous post entry effects with respect to characteristics as geographical location, size and sector. To test the post entry hypothesis we implement the 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. A large body of empirical research documented the high and persistent level of heterogeneity across firms and establishments (Foster et al., 1998; Baily et al., 1996; Bartelsman 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, 2001). 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.

Two different theoretical interpretations have been proposed to explain such a productivity "export premium": the self-selection hypothesis and the post-entry mechanisms. On the empirical side, while most of the studies supported for the self-selection hypothesis, [1] less widespread evidence has been found in favour of the post-entry mechanisms. Nonetheless, recent research by Aw et al. (1998) for Taiwan, Van Biesebroeck (2006) for Cote d'Ivoire and De Loecker (2007) for Slovenia have found evidence of an increase in productivity as a result of firms' exposure to exporting. [2]

One of the issues only marginally tackled by the empirical literature has been the heterogeneity in the post-entry effects. The question whether the effect of export (*treatment*) is equal for all subpopulations of firms or whether it differs for some sub-samples may be of substantive importance. In particular, the heterogeneity issue may be relevant for researchers interested in assessing the potential channel through which trading activities raises firm's performances. In a recent paper Lileeva and Trefler (2007) have raised the problem of heterogeneity in the impact of exporting on productivity gains. They link the decisions to export and invest and they observe how the different degrees of complementarities between exporting and investing activities may determine diverse post-entry productivity effects. De Loecker (2007) exploits the information on firm-level destination of exports in order to better understand the mechanism through which the learning by exporting takes place.

Following most of existing empirical work our paper tests the two possibly complementary explanations - the self selection and the post entry hypothesis - by using a large panel for Italian manufacturing, which covers the universe of firms with more than 20 employees over the period 1989-1997. Although other empirical research for Italian manufacturing firms have documented the differences between exporters and non exporters (Castellani, 2002; 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. By employing the

[1] Bernard and Jensen (1999) for the US, Bernard and Wagner (1997) for Germany, Aw et al. (1998) for Taiwan and South Korea, Clerides et al. (1998) for Colombia, Mexico and Morocco, Alvarez and López (2005) for Chile, Delgado et al. (2002) for Spain, De Loecker (2007) for Slovenia, Castellani (2002) for Italy,Van Biesebroeck (2006) 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] Other papers find evidence of a post entry-effect but only when limiting their analysis to some firms. For instance young firms in the case of Spain (Delgado et al., 2002) or exporters with a high share of export intensity for Italy (Castellani, 2002).

propensity score matching jointly with the Differences in Differences estimator (PSM-DID) (Heckman et al., 1997), we can solve potential endogeneity problems and evaluate the causal effect of export activities on firms' performances. Indeed, a credible test of the post-entry explanation should try to take into account possible biases stemming from self-selection.

In particular, 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's characteristics as capital endowment, workforce composition and labor cost competitiveness. More importantly, we contribute to the existing literature by verifying the presence of heterogeneous post-entry mechanisms. As already mentioned, few empirical work look at possibile differentiated productivity gains from entering the export markets. Indeed, in our paper some sources of heterogeneity in the treatment effect are investigated. The effects of exporting activities on firms' performances are computed separately with respect to characteristics such as sector, regional location and size dimension. We submit that part of the variance observed in the estimated productivity gains may be related to firms' differences along these observable characteristics.

The reminder of the paper is organized as follows. Section 2 presents our theoretical framework. In Section 3 we describe our data and we present the estimation results of the export premia with respect to different firms' characteristics. In Section 4 we investigate econometrically whether ex ante firms' characteristics influence the decision to enter into export markets and validate the self-selection hypothesis. In Section 5 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. Some sources of post-entry heterogeneity are considered in Section 5.2. Finally, in the last section the main findings are summarized.

2 Conceptual Framework

At least two strands of theoretical explanations about how firms' performances are related to export status have been put forward. The first theoretical approach 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 the domestic market (Jovanovic, 1982; Roberts and Tybout, 1997; Melitz, 2003). The self-selection hypothesis has been incorporated by Melitz (2003) in a theoretical model that combines firm heterogeneity with a monopolistic competition framework. This model assumes that exporters incur sunk costs, so only some firms, those with a sufficiently high level of productivity, can make positive profits in international markets. In other words, firms that will be able to export are those sufficiently productive to bear the fixed cost needed to start exporting, while less productive firms will restrict their activity to their home market. Besides the self-selection mechanisms of more productive firms as the one proposed by Melitz, the empirical literature have shown that also other firms' characteristics such as the size, the capital and the skilled labor intensity, are crucial to understanding differences in foreign market entry decisions. That is the self-selection mechanism operates through productivity and other important firms' performances which may fundamentally affect the decision to export.

An alternative theoretical explanation for the link between exporting and productivity is related to 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 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.

It is worth mentioning here then the increased productivity in the post entry period could be detected as a consequence of marks-ups and demand shock effects in addition to "true" productivity changes. To properly measure the productivity differences between exporters and non-exporters (and more generally between firms), ones should ideally observe the quantities and the qualities of varieties produced by a firm (Marschak and Andrews, 1944; Melitz, 2001). [3] In order to partially solve this problem the empirical literature has used deflated sales as a proxy for firm production analysis, assuming that goods produced by firms in a given industry are homogeneous. The productivity obtained as a residual from an estimated production function, has then been considered as a measure combining real productivity and pricing strategies.

In our paper we evaluate firm's productivity through the Total Factor Productivity (TFP) calculated applying the semi-parametric estimation technique implemented by Levinsohn and Petrin (2003). As the Olley and Pakes (1996) methodology, this approach has the advantage to control for the simultaneity bias without having to rely on instruments. However, both the methodologies have some drawbacks since they assume that all firms within the same industry face the same prices and they do not make any assumptions on how exporting versus non-exporting could influence firms' investment decision or intermediate inputs demand. [4] Recently, empirical and theoretical works have more carefully tackle the issue of the possible distortions and mis-interpretations raised when estimating the firm productivity level. Melitz (2001) developed a new methodology, strongly related to the one proposed by Klette and Griliches (1996), which allow to re-interpret the productivity estimates even in the context of differentiated - multi product mix firms within the same industry. De Loecker (2007) argues that unobserved productivity shocks correlated to export status and differences in markets structures and demand conditions between exporters and non-exporting firms may have important consequences when investigating the export-productivity link. In attempting to solve this problem he introduces the firm export status in the Olley and Pakes (1996) estimation algorithm. Moreover, both the Olley and Pakes (1996) and the Levinsohn and Petrin (2003) methodologies assume an exogenous productivity process that is in contradiction with the learning by exporting hypothesis that we aim to test. In order to deal with this inconsistency, De Loecker

[3] The Italian dataset provides information in nominal terms and without plant-specific pricing data. It is indeed impossible to perfectly separate changes in quantities from changes in prices/mark-ups.

[4] Ackerberg et al. (2004) show that both the Olley and Pakes (1996) and the Levinsohn and Petrin (2003) methodologies may suffer from collinearity problems which may further be problematic for the interpretations of the results.

(2007) decomposes the productivity shock in two components, one following an exogenous Markov process and another one following an endogenous Markov process determined by past export experience. In Appendix we briefly show how we introduce these two innovations (i.e., export status as an additional state variable and the possibility of learning by exporting) in the Levinsohn and Petrin (2003) methodology . We submit that, as in De Loecker (2007), this two robustness checks left our main estimation results on self-selection and post-entry mechanisms practically unaltered.

3 Data description and Export premia

The research we present draws upon the MICRO 1 databank developed by the Italian Statistical Office (ISTAT) [5] 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. Over the period covered by the data there are, for certain years, missing values in part due to the fact that some firms may come out in the database as they reach the threshold criteria of 20 employees or, on the contrary, they may exit as they reduce their size and fall below the threshold. The existence of missing values makes of MICRO 1 an unbalanced panel, containing information for an average of around 20.000 firms per year. As documented in Bottazzi and Grazzi (2007), despite the unbalanced nature, the validity of the database is largely supported by its census nature, which avoid possible biases in the data collection process, and by the fact that there are no particular trend or changes in the structure and performances of firms that do not appear for some years (i.e. firms that exit and re-appear again in the database).

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.

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 firms 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.*

Table 1 presents the number of active firms within the Manufacturing sector in each of the nine years, the percentage of exporting firms (i.e. the participation rate), the export intensity (EI) and,

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

in the last column, the fraction of the total manufacturing export covered by our sample. Overall, along the nine years, exporters represents on average 67% of the firms. [6] Though the 20 employees threshold do not allow us to consider the totality of exporting firms and prevent us from analyzing the behavior and the performances of smaller units, the representativeness of MICRO 1 is endorsed by the fact that a large amount of the aggregate Italian export is generated by large firms. As reported by the Italian Statistical Office [7], in 2005 the firms with less than 20 employees accounted for 10% of the total manufacturing export while nearly 90% of the aggregate value was generated by firms with more than 20 employees. Besides, as reported in the last column of Table 1, our data cover more than the 60% of the total manufacturing export. [8]

The number of active firms remains substantially stable over time, with a minor reduction in the period between 1993 and 1997. The percentage of exporting firms increases: while in the 1989 about 64% of firms were exporting, by 1996 the percentage raised to 71%. The increase in the participation rate in the period between 1993 and 1996 could possibly be explained by the exit of the Italian currency from the Exchange Rate Mechanism (ERM) in September 1992, coupled with the Lira depreciation. 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.

Before proceeding in the evaluation of the causal relationship between firms' characteristics and export status, we show 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). 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.

Following Bernard and Jensen (1999) we estimate the export premia, defined as the ceteris paribus percentage difference in some characteristics between exporters and non-exporters, by performing OLS regressions of the relevant firm characteristics (in logarithm [9]) on an export dummy and a set of control variables (indicator variables for NACE 2-digit industries, regional dummies and logarithm of employment to control for size). In Table 2 we report the results obtained running separate

[6] According to the figures reported by Ferragina and Quintieri (2000) for a stratified sample representative of the whole universe of Italian manufacturing firms, including firms with less than 20 employees, the average export participation rate of the period 1995-1997 was of about 40.

[7] www.coeweb.istat.it

[8] Note that the percentage is computed on the aggregate value which includes also firms with less than 20 employees. It follows that the percentages reported in Table 1 are likely to be underestimated. Information on the total export generated by firms above the 20-threshold criteria is not available for the years covered by our database.

[9] When using as dependent variable the skilled labor intensity we do not use the logarithmic transformation, as this variable is itself expressed in percentage points.

regressions for each year in the sample and for all the relevant characteristics. [10] 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 and Wagner, 1997; Aw et al., 1998; Clerides et al., 1998). We now turn to determine the direction of causality between export behavior and firm performances.

4 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. 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. 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. [11] The rationale behind this definition of export starters stems from the literature dealing with sunk costs and export markets participation (Roberts and Tybout, 1997). Accordingly, the decision to export is based on a comparison between the sunk costs of entry (e.g. information required to export, distributional channels, ecc.) and the benefits of such choice (the expected profits). However, the gathered information is likely to depreciate and, after a suitably long absence from the export markets, the re-entry costs of a past-exporter are not different from those that a new exporter have to bear. Therefore, the same selection mechanisms should operate both for new exporters that never exported in the past and new exporters that quitted exporting. [12] Roberts and Tybout (1997) estimate that on average, in their sample of Colombian firms, after a 2 year absence the re-entry costs are not different from those faced by a new exporter. Bernard and Wagner (2001), in a sample of German manufacturing firms, find evidence that on average the capital needed to enter foreign markets depreciate by two thirds in a year.

Due to the time span available of nine years, we can create five cohorts of export starters, respectively from 1991 to 1995. In Table 3 we report the number of starters in each cohort. In total we obtain 662 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-

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

[11] 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. Increasing the number of non exporting years does not change our main results.

[12] The magnitude and the depreciation rate of the gathered information are likely to depend on firm characteristics and destination market characteristics.

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 $t-1$. [13] Following Bernard and Jensen (1999), we implement a parametric exercise, regressing the log value [14] of firms' characteristics at time $t-\rho$ on the dummy variable indicating if a firm is an export starter at time t and on a set of controls

$$\ln(y)_{i,t-\rho} = \alpha_B + \beta_B Starters_{it} + \gamma_B Controls_{it-\rho} + \upsilon_{it} \qquad \text{with } 0 \leq \rho \leq 5 \tag{1}$$

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 4 we reports the transformed estimated coefficients of (1), 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.

In order to shed some light on the dynamics of future exporters' premia, we now test if, 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

$$\ln(y_{i,t-s}) - \ln(y_{i,t-\rho}) = \alpha_C + \beta_C Starters_{it} + \gamma_C Controls_{it} + \upsilon_{it}$$
$$\text{with } 0 \leq \rho \leq 5 \qquad \text{and } 0 \leq s \leq 4 \tag{2}$$

Table 5 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 and of workforce from $t-2$ onward. Moreover, future exporters from three years before the entry onward also enlarge their capital stock more than never exporters. However, this capital accumulation 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.

[13] 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 López, 2005; Girma et al., 2004).

[14] See Footnote 10.

Moreover, the fact that neither the skilled labor intensity coefficients nor the ULC coefficients are significant tends to confirm the last conclusion. However, these observed measures are only indicative of the technology of production and direct data on innovation behavior and R&D expenditures would be needed to draw a stronger conclusion.

These findings imply that it is the "better" firm that is becoming exporter. 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 do not find evidence on productivity improvements and skilled labor intensity deepening that predates the entry. We do find instead that, during the three years preceding the entry, firms augment their scale of production, i.e. both capital and labor usage, and their sales. [15]

5 The Post entry effects

Having ascertained the presence of a self-selection mechanism in the pre-entry period, we are now interested in observing if these export premia are preserved, or reinforced, also in the post-entry period. Is it indeed possible that firms benefit from their exporting activities? As suggested by Aw et al. (1998), exporting firms could in principle benefit from technological feedback provided by international clients and competitors. In addition, exporters may exploit possible economies of scale or they 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.

We want first to asses if the 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

$$Y_{it} = \phi_i + \sum_{K \geq -g}^{f} D_{it}^{K} \delta_K + \gamma_t + v_{it} \tag{3}$$

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

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

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 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 [16] 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 et al. (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 6 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 (2) and (3) 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 6, 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. 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 (from 7% at t to 22% at $t+6$). A more stable, even if somehow increasing 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:

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

the higher level of the percentage of white collars 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.

5.1 Are there any post-entry effects?

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 behavior 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 (Wooldrige, 2002). 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. The problem is that in observational (non-experimental) studies one is not able to observe both outcomes for the same individual, i.e to compute directly $E(Y_{it}(0)|D_i = 1)$. What one is able to compute directly is $E(Y_{it}(0)|D_i = 0)$.

Different econometric techniques have been developed in observational studies to overcome the bias generated when computing the ATT. 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 to the same differences for the untreated group, relying on the assumption that, without the treatment, the outcomes would have followed parallel paths across the two groups of firms.

Another popular estimation method employed in observational studies to overcome the ATT bias is the propensity score matching (PSM techniques (Rosenbaum and Rubin, 1983). The aim of the matching estimator Heckman et al. (1997) is to reduce, first, 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) and, second, the component that 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. The traditional econometric selection bias that stems from "selection on unobservables" is supposed to be absent, i.e. the matching method is based on the assumption of conditional independence (CIA). The "selection on observables" assumption states that, conditional on X, the potential outcome in the non-treatment scenario is independent of the treatment status. [17] However, when the dimension of X is high, the practical computation of the ATT becomes unfeasible. Rosenbaum and Rubin (1983) showed that if treatment is random conditioning upon X, it is random also conditioning upon $P(X) = Pr(D = 1|X)$, the propensity score. Therefore the "curse of dimensionality" can be solved and the ATT identified.

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). Indeed, if the point-wise bias due to "selection on unobservables" is constant in time, i.e. unobserved heterogeneity is fixed in time, we have that

$$B^{post}(X) - B^{pre}(X) = 0 \tag{4}$$

A typical PSM-DID estimator takes the form

$$M_{ATT}^{DID-PSM} = \frac{1}{n_1} \sum_{i \in \{D_i=1\}} \left[(Y_{i,post} - Y_{i,pre}) - \sum_{j \in \{D_j=0\}} w(i,j) \cdot (Y_{i,post} - Y_{i,pre}) \right] \tag{5}$$

where $w(i, j)$ is the weight placed on the j th observations in constructing the counterfactual for the j the treated observation and n_i is the number of treated observations. Matching estimators differ in how they construct the weights $w(i, j)$. [18]

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 modeling 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), there is no reason to believe that the same specification of the propensity score will balance the covariates in different samples.

International trade models based in heterogeneous firms assume that selection into exporting is mainly determined by firms' size and productivity (e.g. Melitz (2003)). However, the empirical evidence, including the one provided by the previous pages, has shown that also capital intensity, skilled labor intensity and sectoral and regional characteristics are important dimensions in explaining the decision to begin to export. According to the theory of matching, the independent variables that one should use in estimating the propensity score, i.e. the X, are all the factors that affect both the selection into treatment (e.g., the decision to export) and the outcomes under analysis (e.g., productivity, size, etc.). Indeed, the CIA will hold only if a credible counterfactual situation can be

[17] 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...). For the difference between multivariate OLS and matching see for example Angrist and Krueger (1999).

[18] 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 neighborhood 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).

constructed, which take into account all the non-ignorable exogenous firms' characteristic. Lagged productivity, sales, employment, capital endowment, capital intensity, skilled labor intensity, unit labor costs and sectoral and geographical characteristics are important drivers of the decision to export and surely influence the subsequent outcomes of starters (the treated) and never exporters (the control group). Our specification of the propensity score can therefore be represented as follows

$$\begin{aligned} Pr(Start_{it}) \quad = \quad & \Phi\{h(LP_{i,t-1}; TFP_{i,t-1}; Sales_{i,t-1}; N.Empl_{i,t-1}; Capital_{i,t-1}; \\ & KPE_{i,t-1}; PWC_{i,t-1}; ULC_{i,t-1}; Sectors; Regions; \ldots)\} \end{aligned} \tag{6}$$

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

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 below). The variables we match on can not 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 do not 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. We show the results obtained by implementing the single nearest neighbor matching with replacement. However, similar treatment effects are found with the kernel matching and radius matching techniques.

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 based on the property that if $P(X)$ is the propensity score, then it must be that $D \perp X|P(X)$ Rosenbaum and Rubin (1983). To test the goodness of our matching we implement a balancing test proposed 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 do not differ between treated and control units. 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). Additionally, we realize 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 $t-3$. [19] The results shown in Table 7 give us confidence that we have identified the appropriate 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. [20]

Table 8 displays the estimated ATTs obtained by employing the PSM-DID methodology as described above. The standard errors are computed by boostrapping the entire estimation procedure, including the propensity score stage, using 200 replications. 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. In line with the results of Table 6, we find that the labour productivity growth of starters is higher than that of the never exporters. 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($t-1/t+1$) and ATT($t-1/t+4$). Therefore, at this stage, we tend to exclude a generalised causal effect of exporting on the percentage

[19]Note that, for a matter of simplicity, in Table 7 we present only the results of t-test for the sample 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 $k \in [0,6]$.

[20]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 (1981).

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. [21]

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* and the PSM-DID method.

5.2 Post entry effects: only for some groups of firms

To assess the robustness of our findings we conduct a sensitivity analysis that takes into account the possible heterogeneity in the treatment effects. It is indeed possible that the effects of export on various firms performances, as those found in the previous section, are not homogeneous but rather they vary in some symptomatic way. Export activities could have a large impact on those firms located in certain areas, or belonging to some sectors or class dimension. To control for the various sources of heterogeneity, we compute the effect of export activity for some subpopulations of the treated individuals. In particular, we consider the firms' location, distinguishing between northern firms from those localised in the center and southern regions; the firms' size, classifying as *small* firms those with less then 50 employees and *medium-large* firms those with more than 50 employees; and the sectoral dimension, grouping firms according the Pavitt (1984) taxonomy.

Tables 9-11 report the results of the treatment effects computed for the different groups of export starters. Our analysis reveals a set of interesting results. For many of the variables and the groups considered we detect some heterogeneity in the treatment effects: the average impact of export on firms' performances is likely to vary across the considered groups of firms. However, some regularities are observable. For example, the post-entry effects in terms of sales and unit labor costs, with the exception of the science based firms, are always statistically significant and positive, regardless of the group selected. Therefore it seems that exporting allows firms to increase their volume of production and, by increasing their capacity utilization, to reduce their unit labor costs.

Table 9 shows that, while for the northern firms the impact of export is positive and significant for almost all variables, for firms localised in the centern and southern regions we find non-significant effects, except for sales and unit labor costs. In particular northern firms, as a consequence of entry in export markets, increase also the percentage of skilled workers, the number of employees and the use of capital. Therefore, on average, positive and significant treatment effects in terms of productivity growth are associated with positive and significant effects in terms of capital, employment and non-production workers share growth, and not simply with sales increases and unit labor costs reduction. Instead, firms localised in the center-south regions do not upgrade their capital and skill structure and they do not increase their workforce. As a consequence of the export activities these firms increase their sales and reduce the unit labour costs, by exploiting their unused capacity.

In Table 10 the ATTs for firms of different size are computed separately. The medium-large firms are the ones benefit more from the export activities. They have higher treatment effects than small firms both with respect to TFP (at least in the long run) and size growth (employees and

[21] Using the traditional parametric DID estimator, the main results of the DID-PSM estimator are confirmed. These results are available from the authors upon request.

sales). Moreover, our results show positive and significant effects for this group of firms also in terms of capital accumulation and skill labor intensity. Once again, we observe a positive relationship between productivity increases, and capital and skilled intensity growth. In fact, contrary to the medium-large firms, the group of small firms, which do not upgrade their capital and skill structure, are the one that gain less in terms of TFP. As regards the reduction in unit labor costs, we detect homogeneous treatment effect across firms of different size.

In Table 11 we differentiate ATTs in terms of sectoral characteristics. Sectors are defined according to Pavitt (1984) taxonomy. Some interesting results emerge from the heterogeneity analysis. First, the sectoral classification in general reveals no significant treatment effects for both the capital endowment and intensity. Second, with the exception of the science based firms, all sectors benefit from exporting in term of size growth (both sales and number of employees) and reduction in unit labor costs. Third, only supplier dominated firms robustly display positive and statistically significant effects in terms of productivity and skill intensity growth, and some positive effects in terms of capital growth.

Concluding, the impact of the treatment is not homogeneous, rather it is varies with respect to firms' characteristics as region, size and sector. From this deeper "heterogeneity" analysis two main findings emerge. Substantially all groups of firms benefit in terms of sales growth and unit labor cost reduction. However, as the productivity growth concerns our results show mixed treatment effects. Precisely, we detect the presence of post-entry effects in terms of TFP only for firms that display positive effects with respect to the skill intensity and the capital endowment variables. These additional findings give more robustness and support to the average post-entry effects for productivity, size and unit labor costs that we estimated in the aggregate analysis.

6 Conclusion

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. Firms serving foreign markets have 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. To consistently estimate productivity we employ the semiparametric technique developed by Levinsohn and Petrin (2003) that takes into account the simultaneity problem. 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 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 and the PSM-DID methods. No such relatively clear evidence is found for the variables skill and capital intensity.

However, according to our "heterogeneity" analysis, the treatment effects are not homogeneous, rather they vary with respect to firms' characteristics as region, size and sector. All groups of firms benefit in terms of sales and unit labour costs. By contrast, we detect the presence of post-entry productivity improvements only for firms that display positive effects with respect to the skill intensity and capital endowments variables. This additional results suggest that the productivity post-entry effects are not merely associated with the scale of operation enlargements. Indeed, firms that simply increase their size as a consequence of exporting display significant treatment effects only in terms of a reduction in unit labor costs.

Appendix : Estimating Total Factor Productivity

The Levinsohn and Petrin (2003) (L-P) methodology assumes 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 following production function for each of the four Pavitt 's categories separately.

$$y_t = \beta_{0+}\beta_l l_t + \beta_k k_t + \upsilon_t$$

where y_t is the log of the firm value added of at time t ; l_t is the log of number of employees and k_t 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.

Levinsohn and Petrin (2003) proposes a semi-parametric techniques which estimates the coefficient taking into account the simultaneity problem. Labor and intermediate inputs are assumed to be perfectly variable; capital is chosen the period before production takes place. Following Levinsohn and Petrin (2003) the error term is written as $\upsilon_t = w_t + \eta_t$, where w_t is the productivity observed by the firms and η_t a random shock to productivity. They assume that w_t evolves exogenously following a first order Markov process ($w_t = E[w_t|w_{t-1}] + u_t$) and that firm's intermediate inputs demand depends on the observed productivity w_t and on the current stock of capital: $m_t = f_t(w_t, k_t)$. Moreover they demonstrate that, under perfect competition in output markets and competitive inputs markets, this demand is monotonically increasing in w_t, conditional on k_t. Therefore they can invert ($w_t = f_t^{-1}(m_t,\, k_t)$) and use firm's intermediate inputs to proxy w_t. The firm's intermediate inputs demand is treated non parametrically and therefore in the following first stage regression only the coefficient on labor is identified by estimating

$$y_t = \beta l_t + \phi_t(k_t, m_t) + \eta_t$$

where $\phi_t(k_t, m_t) = \beta_{0+}\beta_k k_t + f_t^{-1}(m_t,\, k_t) + \eta_t = \sum_{i=0}^{3}\sum_{j=0}^{3-i} \alpha_{RS} \cdot k_t^i m_t^j$.

The second stage of the estimation procedure is aimed to identify the coefficient β_k exploiting the assumptions about the timing of the choice of capital and about the expectation of the future productivity shock w_t, i.e. the moment condition $E[u_t|k_t] = 0$.

A first possible weakness of this productivity measure is related to the assumption of perfect competition in the output markets. As a consequence, our TFP measures are close to revenue per unit input bundle and, therefore, close to both true efficiency and price-cost mark-ups. If these mark-ups enlarge with efficiency, our TFP measures will be correlated with plant efficiency. Bernard et al. (2003) and Katayama et al. (2003) develop models with differentiated products that are characterized by a positive relationship between plant size, price-cost mark-ups, and efficiency. Moreover, DeSouza (2006) demonstrates the validity of the L-P procedure under monopolistic competition with constant demand price elasticity. Even if monopolistic competition may not be always appropriate to model imperfect competition, the assumptions underlying monopolistic competition are certainly less restrictive than the ones underlying perfect competition. These studies provide a rationale to expect our revenue-based TFP measures to capture true plant efficiency.

A basic assumption of this estimation procedure is that firms face the same demand conditions and the same prices. Our TFP estimates uses deflated value added as dependent variable and it is estimated separately for the four Pavitt's sectors. However, if demand conditions and prices vary at a more disaggregated sectoral level and also according to the export status of firms, then the reliability of our ATT estimates of the effects of exports on productivity would be undermined. Hence, as a robustness check, we take into account this problem by estimating productivity separately for each 2-digit sector and, following De Loecker (2007)'s strategy (that was developed in the context of an Olley and Pakes routine), by incorporating the export dummy in the L-P estimation algorithm as an additional state variable. In fact, in each sector, exporting firms face different market structures and prices when decisions are made about intermediate inputs. This possibility is captured by allowing the coefficients of the polynomial $\phi_t(k_t, m_t)$ to differ between exporters and "domestic" firms: $\phi_{e,t}(k_t, m_t)$ now include the export dummy and all terms interacted with the export dummy. We will call this alternative productivity measure TFP_e. We want also to recall that, more in general, our ATT estimation strategy (PSM-DID) indirectly takes into account the possible bias of our estimated productivity if this bias is constant in time for a given firm in a given two-digit industry (De Loecker, 2007).

Another possible relevant flaw of our productivity measure is directly related to the contradiction between the learning by exporting hypothesis that we aim to test and the L-P assumption of an exogenous Markov process governing productivity dynamics. Self-selection does not introduce this problem since future productivity is not endogenously determined; however if current productivity is instead in part determined by the past exporting activity via learning, then part of the unobservable w_t is not captured by $\phi_{e,t}(k_t, m_t)$. Following De Loecker (2007), w_t can be decomposed in two independent terms, one following an exogenous Markov process w_t^N and another one following an endogenous Markov process determined by past exporting experience w_t^E. In the first stage of the estimation , the unobserved productivity related to learning is proxied non-parametrically by a third order polynomial in the number of year exported until t-1 (T) and the average export share until t-1 (ES): $\varphi_t(T_{t-1}, ES_{t-1})$. Therefore in the first stage of the estimation of this additional alternative productivity measure, that we will call $TFP_{e,l}$, we have an additional term capturing the endogenous productivity component related to learning by exporting:

$$y_t = \beta l_t + \varphi_t(T_{t-1}, ES_{t-1}) + \phi_{e,t}(k_t, m_t) + \eta_t$$

As a robustness check of our estimated ATT for productivity, we have applied the PSM-DID methodology to the TFP_e and the $TFP_{e,l}$ finding no relevant change in the estimated treatment effects.

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Table 1: *Number of active firms, of exporting firms and export intensity*

Year	Number of firms	Exporting firms (%)	Average export intensity (%)	% of aggregate manuf. export (%)
1989	19922	64.2	28.4	61.7
1990	21208	63.5	27.9	62.1
1991	19740	64.5	28.2	62.2
1992	21301	66.6	27.0	64.4
1993	22076	67.7	30.0	64.8
1994	21720	68.5	30.8	64.3
1995	20004	70.5	31.6	62.1
1996	17231	71.1	32.4	58.8
1997	15532	69.3	33.1	53.1
Mean	19859	67.3	29.9	61.5

Table 2: *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)	(0.000)	(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)	(0.000)	(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)	(0.000)	(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)	(0.000)	(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)	(0.000)	(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)	(0.000)	(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)	(0.000)	(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)	(0.000)	(0.000)
N. obs[a] (max)	19922	21208	19740	21301	22076	21720	20004	17231	15532

*a*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.

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).

Table 3: *Export starters by year*

Year	Number of export starters
1991	176
1992	177
1993	131
1994	105
1995	73
Total	662

Table 4: *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[a] (max)	6426	10013	13761	17655	18386

a We report the maximum number of observations available for each time lag and firm's characteristics.
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.

Table 5: *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[a] (max)	10545	3618	5907	8831	11762	15081

a We report the maximum number of observations available for each time lag and firm's characteristics.
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.

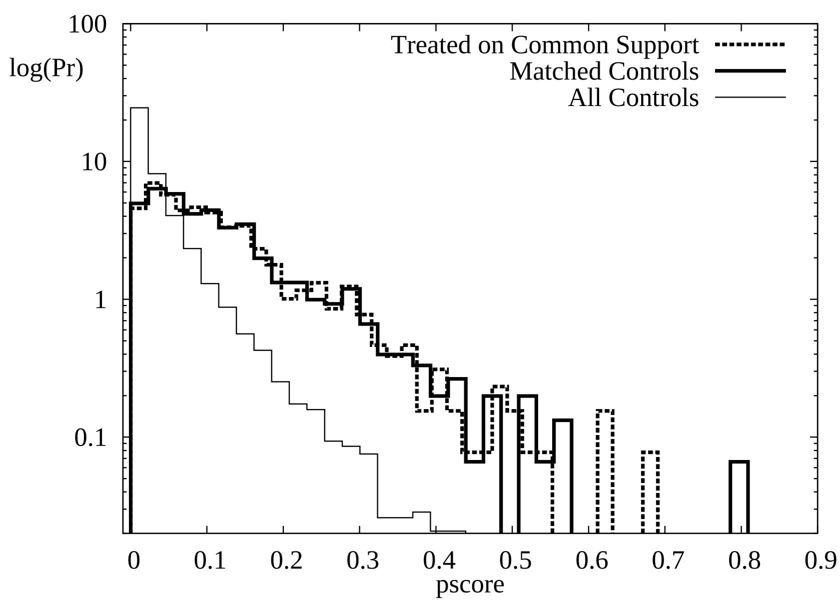

Figure 1: *Kernel density estimates of the propensity score*

Table 6: *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)		
Num. 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.

Table 7: *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[a]				
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 cupport	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[b]				
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

a At time $t-2$ the number of treated decreases to 620 because of missing observations in the relevant variables - *b* 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 $t-3$. *Note*: 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).

Table 8: *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)
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)
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)
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)
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)
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)
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)
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)
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), 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) Coefficients significant at leas at 0.10 level are in bold.

Table 9: *Heterogeneity of the treatment effect: region*

		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
TFP								
North	ATT	**0.048**	**0.076**	**0.090**	**0.123**	**0.118**	**0.145**	0.113
	stand.err	(0.020)	(0.025)	(0.035)	(0.039)	(0.055)	(0.071)	(0.107)
Center	ATT	0.024	-0.064	0.034	0.046	0.057	0.126	-0.053
	stand.err	(0.052)	(0.051)	(0.055)	(0.074)	(0.088)	(0.101)	(0.169)
South	ATT	-0.111	0.040	0.096	0.201	0.158	0.216	0.005
	stand.err	(0.095)	(0.080)	(0.093)	(0.169)	(0.150)	(0.241)	(0.202)
Sales								
North	ATT	**0.073**	**0.116**	**0.149**	**0.259**	**0.208**	**0.298**	**0.405**
	stand.err	(0.023)	(0.029)	(0.035)	(0.048)	(0.065)	(0.065)	(0.101)
Center	ATT	0.049	0.064	**0.133**	**0.112**	**0.188**	0.120	-0.097
	stand.err	(0.041)	(0.052)	(0.060)	(0.072)	(0.095)	(0.133)	(0.226)
South	ATT	0.069	**0.140**	**0.247**	**0.245**	**0.312**	-0.032	-0.047
	stand.err	(0.054)	(0.061)	(0.081)	(0.127)	(0.186)	(0.232)	(0.133)
Num. empl.								
North	ATT	**0.035**	**0.049**	**0.083**	**0.114**	**0.080**	**0.141**	**0.186**
	stand.err	(0.012)	(0.017)	(0.020)	(0.029)	(0.036)	(0.048)	(0.071)
Center	ATT	-0.009	-0.007	-0.007	-0.007	0.034	0.060	-0.136
	stand.err	(0.023)	(0.028)	(0.037)	(0.049)	(0.067)	(0.115)	(0.132)
South	ATT	-0.032	-0.010	0.045	**0.095**	0.090	-0.010	-0.035
	stand.err	(0.036)	(0.044)	(0.042)	(0.057)	(0.082)	(0.150)	(0.114)
Capital								
North	ATT	**0.071**	**0.080**	**0.117**	**0.138**	**0.128**	0.147	0.041
	stand.err	(0.025)	(0.036)	(0.046)	(0.071)	(0.106)	(0.160)	(0.240)
Center	ATT	0.043	0.079	0.017	0.016	0.090	-0.070	-0.064
	stand.err	(0.079)	(0.076)	(0.091)	(0.100)	(0.148)	(0.182)	(0.416)
South	ATT	-0.019	-0.005	0.194	0.221	-0.218	0.000	0.106
	stand.err	(0.073)	(0.087)	(0.180)	(0.208)	(0.208)	(0.300)	(0.507)
CI								
North	ATT	**0.035**	0.031	0.034	0.017	0.048	-0.006	-0.144
	stand.err	(0.025)	(0.036)	(0.045)	(0.070)	(0.104)	(0.147)	(0.210)
Center	ATT	0.052	0.085	0.028	0.024	0.056	-0.091	0.034
	stand.err	(0.079)	(0.075)	(0.092)	(0.111)	(0.146)	(0.153)	(0.368)
South	ATT	0.015	0.005	0.149	0.139	-0.306	0.009	0.141
	stand.err	(0.076)	(0.092)	(0.185)	(0.198)	(0.201)	(0.283)	(0.505)
SLI								
North	ATT	**0.047**	**0.077**	0.012	**0.055**	**0.085**	0.068	0.126
	stand.err	(0.022)	(0.026)	(0.029)	(0.037)	(0.046)	(0.067)	(0.103)
Center	ATT	0.015	-0.010	0.036	0.068	0.086	0.110	0.088
	stand.err	(0.039)	(0.044)	(0.062)	(0.075)	(0.079)	(0.078)	(0.147)
South	ATT	-0.010	0.009	0.013	0.002	0.011	0.000	0.126
	stand.err	(0.057)	(0.073)	(0.069)	(0.095)	(0.120)	(0.202)	(0.245)
ULC								
North	ATT	**-0.053**	**-0.068**	**-0.104**	**-0.130**	**-0.157**	**-0.181**	**-0.147**
	stand.err	(0.017)	(0.023)	(0.026)	(0.036)	(0.052)	(0.050)	(0.074)
Center	ATT	**-0.052**	**-0.095**	**-0.104**	**-0.087**	-0.084	0.025	-0.041
	stand.err	(0.032)	(0.044)	(0.051)	(0.060)	(0.082)	(0.099)	(0.168)
South	ATT	**-0.077**	**-0.176**	**-0.234**	**-0.232**	**-0.223**	-0.095	-0.258
	stand.err	(0.043)	(0.057)	(0.092)	(0.114)	(0.138)	(0.228)	(0.185)

Note: We report bootstrapped standard errors (200 replications), 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). Coefficients significant at leas at 0.10 level are in bold.

Table 10: *Heterogeneity of the treatment effect: size*

		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
TFP								
Small	ATT	**0.037**	**0.056**	**0.046**	**0.092**	0.053	**0.180**	0.051
	stand.err	(0.023)	(0.016)	(0.032)	(0.040)	(0.054)	(0.069)	(0.084)
Medium-large	ATT	0.016	0.040	**0.123**	**0.116**	**0.282**	**0.221**	0.083
	stand.err	(0.040)	(0.040)	(0.051)	(0.057)	(0.106)	(0.118)	(0.166)
Sales								
Small	ATT	**0.057**	**0.119**	**0.115**	**0.160**	**0.166**	**0.257**	**0.330**
	stand.err	(0.020)	(0.028)	(0.033)	(0.046)	(0.070)	(0.068)	(0.125)
Medium-large	ATT	0.033	**0.085**	**0.194**	**0.252**	**0.321**	**0.363**	**0.426**
	stand.err	(0.044)	(0.051)	(0.060)	(0.074)	(0.081)	(0.094)	(0.139)
Num. empl.								
Small	ATT	0.008	**0.021**	**0.030**	**0.050**	**0.085**	**0.105**	**0.110**
	stand.err	(0.010)	(0.014)	(0.017)	(0.026)	(0.034)	(0.046)	(0.069)
Medium-large	ATT	**0.039**	**0.067**	**0.118**	**0.151**	**0.121**	**0.210**	**0.169**
	stand.err	(0.025)	(0.035)	(0.041)	(0.050)	(0.060)	(0.078)	(0.115)
Capital								
Small	ATT	0.022	0.050	0.053	**0.149**	0.099	0.153	0.315
	stand.err	(0.025)	(0.035)	(0.063)	(0.066)	(0.121)	(0.152)	(0.202)
Medium-large	ATT	**0.098**	**0.149**	**0.285**	**0.176**	**0.317**	0.005	0.095
	stand.err	(0.036)	(0.061)	(0.099)	(0.097)	(0.160)	(0.168)	(0.381)
CI								
Small	ATT	0.014	0.029	0.023	0.091	0.018	0.043	0.203
	stand.err	(0.025)	(0.036)	(0.045)	(0.063)	(0.119)	(0.144)	(0.191)
Medium-large	ATT	**0.059**	**0.082**	**0.167**	0.029	0.199	-0.204	-0.068
	stand.err	(0.035)	(0.064)	(0.097)	(0.101)	(0.153)	(0.154)	(0.321)
SLI								
Small	ATT	0.012	**0.069**	0.030	0.061	0.056	0.021	0.160
	stand.err	(0.021)	(0.028)	(0.034)	(0.040)	(0.050)	(0.075)	(0.120)
Medium-large	ATT	**0.060**	0.038	**0.072**	0.048	**0.109**	**0.111**	0.102
	stand.err	(0.036)	(0.039)	(0.044)	(0.048)	(0.059)	(0.077)	(0.127)
ULC								
Small	ATT	**-0.047**	**-0.100**	**-0.096**	**-0.107**	**-0.096**	**-0.159**	**-0.203**
	stand.err	(0.016)	(0.023)	(0.027)	(0.037)	(0.058)	(0.057)	(0.103)
Medium-large	ATT	**-0.060**	**-0.075**	**-0.122**	**-0.116**	**-0.180**	**-0.129**	**-0.151**
	stand.err	(0.029)	(0.035)	(0.041)	(0.048)	(0.053)	(0.076)	(0.104)

Note: We report bootstrapped standard errors (200 replications), 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). Coefficients significant at leas at 0.10 level are in bold.

Table 11: *Heterogeneity of the treatment effect: Pavitt's taxonomy*

		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 [a]
TFP								
Supplier dominated	ATT	**0.056**	**0.061**	**0.076**	**0.123**	**0.158**	**0.157**	**0.170**
	stand.err	(0.024)	(0.028)	(0.040)	(0.046)	(0.060)	(0.096)	(0.109)
Scale intensive	ATT	0.032	0.035	0.088	0.031	0.049	0.224	0.115
	stand.err	(0.036)	(0.041)	(0.058)	(0.051)	(0.086)	(0.113)	(0.147)
Specialised suppliers	ATT	0.048	-0.019	0.095	0.097	0.198	0.257	0.077
	stand.err	(0.071)	(0.058)	(0.079)	(0.099)	(0.137)	(0.197)	(0.177)
Science based	ATT	0.051	**0.298**	**0.353**	0.239	0.176	-0.063	-
	stand.err	(0.180)	(0.155)	(0.170)	(0.160)	(0.153)	(0.183)	-
Sales								
Supplier dominated	ATT	**0.090**	**0.152**	**0.163**	**0.223**	**0.237**	**0.261**	**0.381**
	stand.err	(0.024)	(0.030)	(0.035)	(0.047)	(0.071)	(0.079)	(0.131)
Scale intensive	ATT	**0.061**	**0.079**	**0.118**	**0.125**	**0.163**	**0.348**	**0.447**
	stand.err	(0.035)	(0.041)	(0.051)	(0.060)	(0.077)	(0.093)	(0.204)
Specialised suppliers	ATT	0.039	0.111	**0.211**	**0.362**	**0.470**	**0.512**	**0.479**
	stand.err	(0.072)	(0.097)	(0.105)	(0.139)	(0.145)	(0.212)	(0.145)
Science based	ATT	0.036	0.108	0.148	0.285	0.086	-0.078	-
	stand.err	(0.123)	(0.154)	(0.173)	(0.205)	(0.177)	(0.135)	-
Num. empl.								
Supplier dominated	ATT	**0.022**	**0.038**	**0.054**	**0.080**	**0.091**	**0.062**	0.068
	stand.err	(0.013)	(0.018)	(0.024)	(0.031)	(0.043)	(0.055)	(0.099)
Scale intensive	ATT	**0.030**	**0.046**	**0.058**	**0.089**	**0.111**	**0.194**	0.118
	stand.err	(0.016)	(0.023)	(0.029)	(0.041)	(0.047)	(0.073)	(0.094)
Specialised suppliers	ATT	0.009	0.039	0.049	**0.157**	**0.110**	**0.207**	**0.386**
	stand.err	(0.042)	(0.054)	(0.062)	(0.072)	(0.071)	(0.117)	(0.145)
Science based	ATT	0.006	-0.055	-0.005	0.118	-0.093	-0.220	-
	stand.err	(0.084)	(0.142)	(0.153)	(0.206)	(0.192)	(0.169)	-
Capital								
Supplier dominated	ATT	0.026	0.045	**0.147**	**0.226**	0.117	0.135	0.081
	stand.err	(0.027)	(0.041)	(0.056)	(0.078)	(0.120)	(0.138)	(0.334)
Scale intensive	ATT	0.024	0.068	0.102	0.113	0.010	-0.176	0.074
	stand.err	(0.029)	(0.053)	(0.075)	(0.104)	(0.135)	(0.199)	(0.250)
Specialised suppliers	ATT	0.028	0.159	-0.004	0.199	0.155	0.274	0.795
	stand.err	(0.082)	(0.128)	(0.153)	(0.171)	(0.220)	(0.349)	(0.605)
Science based	ATT	0.001	-0.040	-0.019	0.450	-0.218	0.627	-
	stand.err	(0.073)	(0.127)	(0.146)	(0.455)	(0.505)	(0.753)	-
CI								
Supplier dominated	ATT	0.004	0.007	**0.092**	**0.139**	0.027	0.069	0.023
	stand.err (0.027)	(0.041)	(0.056)	(0.076)	(0.115)	(0.124)	(0.297)	
Scale intensive	ATT	-0.006	0.022	0.046	0.021	-0.099	-0.376	-0.040
	stand.err	(0.030)	(0.053)	(0.074)	(0.104)	(0.138)	(0.191)	(0.233)
Specialised suppliers	ATT	0.019	0.120	-0.055	0.041	0.045	0.063	0.352
	stand.err	(0.071)	(0.125)	(0.151)	(0.155)	(0.200)	(0.337)	(0.449)
Science based	ATT	-0.004	0.015	-0.015	0.340	-0.126	0.888	-
	stand.err	(0.074)	(0.178)	(0.180)	(0.492)	(0.516)	(0.646)	-

a Not enough observation for the Science based group at t+6.
Note: We report bootstrapped standard errors (200 replications), 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). Coefficients significant at leas at 0.10 level are in bold.

		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[a]
SLI								
Supplier dominated	ATT	**0.055**	**0.106**	**0.072**	**0.112**	**0.114**	-0.005	0.035
	stand.err	(0.027)	(0.039)	(0.046)	(0.048)	(0.056)	(0.074)	(0.133)
Scale intensive	ATT	0.013	-0.040	-0.040	-0.041	-0.060	-0.054	0.179
	stand.err	(0.036)	(0.036)	(0.042)	(0.052)	(0.064)	(0.084)	(0.112)
Specialised suppliers	ATT	0.091	0.087	0.051	0.085	0.179	0.079	0.343
	stand.err	(0.069)	(0.079)	(0.096)	(0.121)	(0.134)	(0.190)	(0.396)
Science based	ATT	0.019	0.120	-0.055	0.041	0.045	0.063	-
	stand.err	(0.058)	(0.072)	(0.173)	(0.134)	(0.173)	(0.000)	-
ULC								
Supplier dominated	ATT	**-0.072**	**-0.104**	**-0.115**	**-0.126**	**-0.133**	**-0.205**	**-0.290**
	stand.err	(0.019)	(0.026)	(0.028)	(0.040)	(0.057)	(0.058)	(0.096)
Scale intensive	ATT	**-0.042**	**-0.052**	**-0.113**	**-0.084**	**-0.091**	-0.089	**-0.252**
	stand.err	(0.025)	(0.031)	(0.041)	(0.046)	(0.059)	(0.068)	(0.173)
Specialised suppliers	ATT	-0.017	**-0.098**	**-0.137**	**-0.208**	**-0.327**	**-0.254**	-0.268
	stand.err	(0.049)	(0.061)	(0.068)	(0.080)	(0.102)	(0.152)	(0.200)
Science based	ATT	-0.003	-0.126	**-0.202**	**-0.217**	-0.146	-0.138	-
	stand.err	(0.063)	(0.093)	(0.126)	(0.142)	(0.152)	(0.135)	-

*a*Not enough observation for the Science based group at t+6.

Note: We report bootstrapped standard errors (200 replications), 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). Coefficients significant at leas at 0.10 level are in bold.