# Self selection vs learning: Evidence from Indian exporting firms

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November 9, 2010

**Abstract**

This paper studies the export behavior of a panel of Indian manufacturing firms for a period of 17 years from 1990 to 2006. Specifically, we look at whether exporting firms differ from domestic firms in size, productivity, capital intensity, remuneration levels, etc. We find that exporters systematically outperform non-exporters over a number of characteristics. We find evidence of "self-selection" for Indian manufacturing firms, i.e., firms that are more productive enter the export market as they are more capable of meeting the challenges of an international market. We also find evidence of learning and growth for a number of variables.

*Keywords: HFMCF trade models, Total Factor Productivity, Self-Selection, Export-led growth.*
*JEL codes: F10, F12, C23, C14.*

## 1. Introduction

In the past few years, a large number of empirical studies have shown that exporting firms outperform non-exporting firms over a number of characteristics, productivity being the most important one. A key question in this literature is to figure out whether this difference in performance outcomes between exporting and non-exporting firms is effectively a consequence of self-selection of the more productive firms into exporting or a case of exporting firms learning by exporting and hence becoming more productive over time. This question of "self-selection" versus "learning by exporting" is important from a policy point of view because an affirmative answer to the latter supports a policy of export promotion to enhance productivity growth. This paper attempts to answer this question using a panel data set of manufacturing firms from India.

We first document evidence of substantial differentials in the performance of exporters over non-exporters in terms of labor productivity, total factor productivity, capital intensity and a number of other firm characteristics. Next, we look at the growth in performance characteristics of exporting firms, firms that export in all years of our sample and firms that never export in any of these years. We find evidence of faster growth of exporters for some firm characteristics. We find that perpetual exporters grow faster than other firms. We also find that firms that never export grow slower than other firms. These results provide preliminary evidence in support of learning by exporting. We then conduct a simple exercise to separate out the selection effect from the learning effect. Using a simple probit specification we find that future exporters already have some of the desirable characteristics before their entry into the export market, suggesting some evidence of self-selection. Next, we conduct a more robust exercise to isolate the learning effect from self-selection by using a new matching technique from the micro-econometric evaluation literature. Viewing treatment as export participation we isolate the effects of receiving this treatment, controlling for self-selection. Doing so helps us identify the causal effects of the treatment or exporting on the treatment group (the exporting firms), i.e., to help establish if there are any learning effects after controlling for selection. The results of our matching analysis indicate that once we control for non-random selection bias into the treatment group, there is evidence for learning effects after controlling for selection.

Our study confirms a few results well established in this literature. It also suggests some evidence for learning of which instances are somewhat limited. Thus for example, a large number of empirical studies have already well documented that exporting firms are larger, more productive and more capital intensive than non-exporting firms[1]. In an attempt to explain these empirical findings, Melitz (2003) and Bernard, Eaton, Jensen and Kortum (2003) develop models of firm

[1]See for example, Handoussa, Nishimizu and Page (1986), Chen and Tang (1987),Aw and Hwang (1995), Aw, Chen and Roberts (1997), Bernard and Jensen (1997*a*), Bernard and Jensen (1997*b*), Clerides, Lach and Tybout (1998), Bernard and Jensen (1999).

heterogeneity, in which differences in firm productivity in combination with fixed export costs ensure that only the most productive firms *self select* into export markets. Corroborating evidence for the self-selection of firms into export markets is also quite well established by a number of empirical studies.[2]While the question of self selection of better firms into the export market is well established, the extant empirical literature, as mentioned earlier, has documented fewer instances of learning by exporting. However, some recent studies find evidence of productivity gains and/or improved firm performance after a firm starts exporting.[3] The rationale behind this "learning by exporting hypothesis" is mainly technical or managerial skill or knowledge transfers from foreign to domestic firms that lead to improvement in manufacturing practices and/or better production or product design for domestic firms (for example, see the WorldBank (1993) report) or the gains from trade to exporting firms resulting from an increase in the scale of production (Bernard and Jensen (1999)). Also, a very small number of studies find evidence of both learning by exporting and self-selection. For example, van Biesebroeck's (2005) study of sub-Saharan African manufacturing firms finds *ex-ante* productivity differentials between exporters and non-exporters as well as productivity gains post exporting. This last result is similar to our finding. However, in contrast to van Biesebroeck's (2005) method which uses the standard procedure to control for selection, we use a matching technique based on nearest neighbor matching which is relatively new in the literature.

We believe that our work is important in light of the recent emergence of India as a major exporter in the international market. After India deregulated its economy in 1991, manufacturing output in India has steadily accelerated to a growth rate of almost 9% a year and the service sector growth rate has also increased to over 10% percent a year. The total growth in exports (services and manufacturing taken over) has been over 8% a year. Also, the bulk of the Indian exports have been dominated by manufactured goods which account for more than 76% share in the late nineties (Sharma (2000)). In light of these facts, our study, which is amongst the first studies looking at the export behavior of manufacturing firms in India, fills an important deficiency in the literature that has concentrated mainly on firm performance in developed economies. We note that a very recent working paper, Tabrizy and Trofimenko (2010), obtains qualitatively similar results on the export premium that we obtain in our analysis. However, this paper relies on the old technique of looking at post entry productivity gains to separate out the selection effect from the learning effect in contrast to the matching techniques that we use in our analysis.[4] We also

[2]See for example, Clerides et al.'s (1998) study involving manufacturing firms in Columbia, Mexico and Morocco or Bernard and Jensen's (1999) study of a panel of U.S. manufacturing firms.

[3]Examples include Kraay (1997) for China, Bigsten (2004) for sub-Saharan Africa (involving a different sample of firms from van Biesebroeck (2005)) and Aw, Chung and Roberts (2000) for Taiwan, and De Loecker (2007) for Slovenia.

[4]We thank an anonymous referee for bringing this recent paper to our attention.

note that this paper covers a smaller time period of 10 years (1998-2008) than our data set which is of 17 years (1990-2006). Also, this paper uses the wage bill as a proxy for employment. The authors (to their credit) acknowledge the weakness of this proxy (Tabrizy and Trofimenko (2010), pp.11-pp.12). In contrast, we use actual employment data.[5]

The paper is organized as follows. Section 2 outlines the data. Section 3 outlines some issues in productivity estimation and describes two measures of productivity that we use in our analysis. Section 4 shows the differentials in levels of performance between exporters, perpetual exporters and non-exporters compared to other firms not in these categories and also looks at the growth rate differentials of these firms. Section 5 looks at the evidence on self-selection of better firms into export markets using a simple probit model of firm export behavior. Section 6 tries to identify the effects of learning or performance improvements from exporting. Section 7 concludes.

## 2. Data

The data for this paper are from the database of the Centre for Monitoring Indian Economy (Prowess(CMIE) (2007)) which covers major firms in most organized industrial activities in India accounting for almost 70% of all economic activity in the organized industrial sector.[6] The database also categorizes firms by industry according to the 4-digit 1998 NIC code (Indian equivalent of the SIC classification scheme). The list of firms span the industrial composition of the Indian economy.

Our panel of firms observed over a period of 17 years from 1990 to 2006. Table 1 shows the summary statistics for all variables. All nominal variable figures in the summary table are

**Table 1**. Summary statistics

| Variable | Mean | Std. Dev. | N |
|---|---|---|---|
| Sales | 624.430 | 1817.455 | 3698 |
| No. of employees | 3708.181 | 13009.686 | 3698 |
| Net Value Added | 117.067 | 469.647 | 3698 |
| Net fixed assets | 335.021 | 1231.631 | 3698 |
| Salaries and wages | 54.508 | 207.902 | 3698 |
| Forex earnings goods | 57.757 | 205.016 | 3698 |
| Raw material expenses | 242.815 | 739.504 | 3698 |

[5]For India, other notable papers in this area include Krishna and Mitra (1998) who find that trade liberalization in the 90's increased competition from cheaper imports lowering the price-cost margin of firms (pro-competitive effects of trade) and Topalova (2004) who finds that exogenous reductions in tariff barriers during the Indian trade policy reform of the 90's improved firm productivity.

[6]As given on the CMIE website at http://www.cmie.com/.

denominated in Rs. crores (1 crore = 10 million) and deflated by the GDP deflator for the year taken from India's national accounts statistics.[7] We also tabulate exporters and non-exporters by 2-digit industry category for all industries in table 2. We show percentage figures (for easy comparison across the years) for each of the three years : 1990 the first year of our sample, 1998 the middle year in our sample and 2006 the final year of our sample. As usually found in the extant literature, the percentage of firms in exporting is usually less than the percentage of non-exporting firms across all sector over all these years. The final year 2006 shows slightly high percentage of exporters. The percentage of exporters increases from an average of about 33% in the earlier years to 40%. Such large percentage of exporters is unusual and obtains here because the data is for large and medium size firms. The highest percentage of exporters is in chemical industries (including both the basic and other chemical categories), in food products and in spinning (the last two being traditional export sectors of comparative advantage). Motor vehicles and parts and (general) machinery are also leading export sectors. Some sectors, like footwear and textiles, which are also traditional advantage sectors have low export percentages probably because there are not too many firms from these sectors in our sample.

## 3. Productivity Estimation

One important measure of firm performance in our paper is total factor productivity. We first consider simple measures of industry-level total factor productivity (TFP, hereafter). We assume that the production function at the firm level is Cobb-Douglas of the form:

$$Y_{ijt} = A_{ijt}\, K_{ijt}^{\beta_k}\, L_{ijt}^{\beta_l} \tag{1}$$

where $Y_{ijt}$ represents the net value added (i.e., net of material inputs) of firm $i$ in industry $j$ in period $t$; $K_{ijt}$ and $L_{ijt}$ are inputs of capital and labor respectively and $A_{ijt}$ is the Hicks neutral

[7] We note that our data has large number of missing observations on employment for almost all firms from the earlier years of our sample. Missing data on employment is a problem that has plagued almost all micro-econometric studies of firm performance in India. In the study of the effects of India's trade liberalization by Krishna and Mitra (1998), the authors obtain figures of real labor by deflating the total wage bill by the public sector employee wage rate. We use a simple method to impute employment data to check the robustness of our results. We impute data on employment from values of salaries and wages. We use all the observations on salaries and wages within a 2-digit NIC group to impute values for employment by using the predicted values of employment from a regression of employment on salaries and wages. If the value on the dependent variable in this regression (i.e., employment) is not missing then the non-missing value itself is imputed. If not then the predicted value of employment is (generated by using all observations for a certain NIC code) is used as an imputed value. Thus our method of imputation is different from Krishna and Mitra (1998). One advantage of our method over Krishna and Mitra (1998) is that we use the actual manufacturing wages to impute values of employment instead of using the public sector wage to back out employment data. Note that we do not report our results with these imputed values in this paper. These results are qualitatively similar to the results reported in this paper.

efficiency level of firm $i$ in in industry $j$ in period $t$. While all other quantities in the above regression are observed, $A_{ijt}$ is unobservable to the researcher. Taking the natural logs of Equation 1 above, we get the following linear form of the production function :

$$y_{ijt} = \beta_0 + \beta_k\, k_{ijt} + \beta_l\, l_{ijt} + \epsilon_{ijt} \tag{2}$$

where lower-case letters refer to natural logarithms, $ln(A_{ijt}) = \beta_0 + \epsilon_{ijt}$ where $\beta_0$ measures the mean efficiency level across firms over time and $\epsilon_{ijt}$ is the time and firm specific deviation from that mean (this formulation is borrowed from Petrin, Levinsohn and Poi (2003)). The quantity of interest here is the residual from the estimation of the above equation. Following previous studies we estimate Equation 2 using log net value added as the dependent variable, log net fixed assets as capturing the capital stock and log number of employees as labor. The estimated value of TFP is calculated as follows:

$$\widehat{TFP}_{ijt} = y_{ijt} - \widehat{\beta_0} - \widehat{\beta_k}\, k_{ijt} - \widehat{\beta_l}\, l_{ijt} \tag{3}$$

Therefore, TFP is calculated as the difference between actual and predicted output. The productivity in levels can be obtained as the exponential of the above residual. This procedure gives us a measure of TFP that we call TFP-OLS.

It is, however, well known that Equation 3 cannot be consistently estimated using simple OLS and that the resulting estimates for TFP calculated this way are very likely to be biased due to a number of endogeneity problems. To fix these problems, several estimators have been proposed in the literature. However, traditional fixes like fixed effects, GMM or IV/2SLS methods have not proved very satisfactory for estimating the production function.[8] A workable solution to these problems has therefore been to use non-parametric or semi-parametric methods to estimate TFP. Olley and Pakes (1996) and Levinsohn and Petrin (2003) (LP hereafter) have developed semi-parametric estimators for TFP estimation that address the aforementioned estimation problems. In this paper we use the the LP estimator to correct for the simultaneity bias in the firms' production function. Following the LP methodology we use a firm's raw material input usage as an instrument to correct for this simultaneity.[9] We use log net value added as the dependent variable, log net fixed assets as capturing the capital stock and log number of employees as labor. We estimate the TFP equations at the industry level (i.e., by using all observations for firms of an

[8] For details on the drawbacks of these estimators and the underlying reasons for these drawbacks see Van Beveren (2007).

[9] For additional details about the Levinsohn-Petrin method of estimation and the assumptions required, refer to the original paper Levinsohn and Petrin (2003). Levinsohn-Petrin make available a Stata program "levpet" that produces estimates of beta coefficients for labor and capital of the production function Petrin et al. (2003). We use the package "levpet" in Stata to estimate the TFP by Levinsohn-Petrin methodology.

industry to estimate industry-level TFP) at the 2-digit NIC level. We thereby derive consistent estimates of the parameters of the production function for each industry $j$ and consequently estimates of TFP for a firm $i$ in that industry. This process gives us the measure of TFP that we call TFP-LP. We report our results for both these measures of TFP: TFP-OLS and TFP-LP.

# 4. Relative Performance of Exporters

### 4.1 *Differential exporter performance in levels*

In this section we document the differences between exporters and non-exporters. We look at the magnitude of the performance gap between exporters and non-exporters (and also at the performance gap between perpetual exporters and other firms and again between perpetual non-exporters and other firms) for a number of firm attributes like labor productivity (measured by sales/worker), employment, netvalueadded/worker, capital/worker, average salaries and wages and the two measures of total factor productivity–TFP-OLS and TFP-LP. Following Bernard and Jensen (1999), we first consider regressions of the form below, for a variety of firm attributes:

$$\begin{aligned} ln(X)_{ijt} &= \beta_0 + \beta_1 D_{ijt} + \sum_t \beta_t Year\ Dummy_t + \\ &\quad + \beta_2 ln(Employ)_{ijt} + \delta_j I_j + \epsilon_{ijt} \end{aligned} \tag{4}$$

where $ln(X)_{ijt}$ is the characteristic of firm $i$ in year $t$ in industry $j$, $D_{ijt}$ is the export status dummy of firm $i$ in year $t$ in industry $j$, defined as follows:

$$D_{ijt} = \begin{cases} 1 & \text{if firm } i \text{ in industry } j \text{ exported in year } t \\ 0 & \text{otherwise.} \end{cases}$$

for $i = 1, 2, \ldots, N_j, t = 1, 2, \ldots, T$ for each industry $j$. $Year\ Dummy_t$ are time dummies that control for time trends and/or economy wide shocks common to all firms, $ln(Employ)_{ijt}$ is a control for firm size using the log employment level of the firm as a control and $I_j$ denotes the industry dummy at 2-digit level.[10] The coefficient on the export dummy $\beta_1$ measures the percentage difference, over a certain performance characteristic, between exporters and non-exporters, or the *export premia* for exporting firms. The results of these regressions are given in row 1 of table 3. Rows 2 and 3 of table 3 give us the performance differentials between $PerpetualExporter$ (i.e., firms with $ExportDummy = 1$ for $t = 1990, 1991, \ldots, 2006$) and all other firms and between $Perpetual\,Non-exporters$ (or firms that never export, i.e., firms with $ExportDummy = 0$ for $t =$

[10]We estimate TFP at 2-digit level and hence include industry dummies at the 2-digit level.

1990, 1991, . . . , 2006) and all other firms respectively.

In table 3, $S/L$ denotes sales per worker, $L$ stands for employment, $NVA/L$ denotes net value added per worker, $K/L$ denotes capital per worker, $W/L$ denotes average salaries and wages, $TFP - OLS$ and $TFP - LP$ denote the two measures of productivity mentioned earlier. As shown in row 1 of table 3 firms that are exporters have about 75% higher labor productivity than non-exporting firms.[11] Exporting firms hire more workers, pay higher wages to workers than non-exporters, have higher net value added/worker than non-exporting firms, are more capital-intensive than non-exporters and have higher TFP (as indicated by both measures of TFP). In general, many of the coefficients in the first row of table 3 are positive, large in an economic sense and significant at the 1% significance level. These results are typical of the results obtained in the literature (for example, see Bernard and Jensen (1999)).

The coefficients in row 2 and 3 of table 3 show starkly how perpetual exporters outperform all other firms on one hand and also how perpetual non-exporters are under performers compared to firms that export at some time in the sample period. Interestingly, perpetual exporters have a larger coefficients for both measures of total factor productivity than exporters, while perpetual non-exporters have lower total factor productivity compared to exporters.

### 4.2 *Differential exporter performance in growth rates*

Next, to obtain initial evidence on learning effects we re-run the same regressions, using annual growth rates of the same variables. That is, we run a regression of the change in a performance measure, $ln(X_{ijt}) - ln(X_{ijt-1}) = \%\Delta X_{ijt}$ (where $X_{ijt}$ denotes a performance characteristic at year $t$) on exporter and subsequently on perpetual exporter and perpetual non-exporter dummies, controlling for firm characteristics like employment level. Thus, we consider regressions of the form:

$$\begin{aligned} \%\Delta X_{ijt} &= \beta_0 + \beta_1 D_{ijt} + \sum_t \beta_t Year\ Dummy_t + \\ &\quad + \beta_2 ln(Employ)_{ijt} + \delta_j I_j + \epsilon_{ijt} \end{aligned} \tag{5}$$

We report these results in rows 4-6 of table 3. We note that while better firms might self-select into the export market based on difference in their performance characteristics in levels, it is extremely unlikely that a similar argument can be given for self-selection in growth rates. Thus, positive

[11]Note that although one would expect that exporters would outperform non-exporters, it is not unlikely that the converse might also hold. As Bernard and Jensen (1999)[pp. 14] point out that other than a sunk cost of exporting "...if there were no additional costs to selling in foreign markets then exports at the industry and firm level could be determined by unsystematic variation in product attributes and comparative advantage. Exporters and non-exporters would make different goods but could have similar productivity, size and wage levels and growth rates."

differential growth rates for exporters would suggest some evidence of learning by exporting for exporters. From row 4 of table 3 we see that exporters have higher growth rates over non-exporters for almost all performance measures (although not all coefficients are statistically significant at the conventional levels). Thus, from the coefficients of these differential annual growth rates, we infer the presence of learning effects for most firm performance variables. In particular, both measures of TFP growth are positive (but not statistically significant). The other rows give the growth rates for the performance indicators for perpetual exporters (row 5) and perpetual non-exporters (row 6). For perpetual exporters, from row 5 we see the same pattern of signs and comparable magnitudes for the performance indicators as with the exporters on row 4. For perpetual non-exporters in row 6, not surprisingly, we have negative signs for most of the coefficients. The only exceptions are the coefficients on employment which is positively signed. To sum up, the results obtained suggest that exporters perform better than non-exporters over all performance measures. Also, we can justifiably conclude that for almost all variables, exporters and perpetual exporters have higher annual growth rates and perpetual-non-exporters have lower annual growth rates than other firms not in these categories.

# 5. Do better firms become exporters?

## 5.1 *The decision to export*

To figure out the selection effects we follow the extant literature and consider a simple model of the firm's exporting decision with sunk costs of exporting.[12] Let $y_{ijt}$ denote a binary variable as to whether or not a firm exports, where $i = 1, 2, \ldots, N$ denotes the firm, $t = 1, 2, \ldots, T$ denotes time and $j$ denotes industry. This export dummy is the dependent variable in our specification. Since the dependent variable is dichotomous, we use a probit model to estimate the structural parameters. The probit specification for the sunk costs model in our case is given by :

$$\Pr(y_{ijt} = 1) = \Phi\left(\beta_0 y_{it-1j} + \beta_1 I_j + \sum_t \beta_t Year\ Dummy_t + \boldsymbol{\beta}' \mathbf{x}_{it-1j} + \epsilon_{ijt}\right) \tag{6}$$

In the above specification, $y_{it-1j}$ is the export status of the firm in period $t-1$, $\mathbf{x}_{it-1j}$ is a vector of covariates that consisting of firm characteristics at period $t-1$ and $\boldsymbol{\beta}$ is the corresponding vector of coefficients. $\Phi$ denotes the standard normal cdf. It can be shown that the above specification considers the probability of exporting by a firm in the current period, given that it did not export in the previous period as a function of firm characteristics in the previous period.[13] We are

[12]This formulation follows Bernard and Jensen (1999).

[13]Our model specification is based on the sunk cost model wherein a firm will export when the sum of discounted revenues is greater than costs. Following Bernard and Jensen (1999) the specification equation 6 above is equivalent

testing for selection effects here, since we study how past firm characteristics affects the future export probability of a firm. The variables that we include in the vector $\mathbf{x_{i,t-1,j}}$ are standard in the literature (for example see Bernard et al. (2003) and Bernard and Jensen (2006)). Since we are dealing only with selection effects we include the measures of total factor productivity-TFP-OLS and TFP-LP (in two alternative specifications). To control for size effects the log of the number of employees is also included. The log of the capital-labor intensity in period $t-1$ is included to capture firms' capacity build-up prior to entry for cost smoothing (see Bernard and Jensen (1999)). Also, average salaries and wages is included as an explanatory variable because average wages are a proxy for skilled labor. To capture the individual effects or the unobserved heterogeneity among cross-sectional units or firms we also use industry dummies in our probit specification. We use time dummies to capture general time effects that are not specific to an individual firm. All variables are in logs, lagged by one period and are deflated for comparison. To check the robustness of our results, we also repeat the earlier regressions but without the lagged export status variable.

The results of the probit regressions with lagged export status included and without lagged export status are given in table 4. Columns 1 and 2 of table 4 are the specifications that include lagged export status as an explanatory variable while columns 3 and 4 do not include lagged export status as an explanatory variable. Also, column 1 and column 3 use TFP-LP as the measure of TFP while column 2 and 4 use TFP-OLS as a measure of TFP. We report the coefficients of the probit regression (not the marginal effects in table 4).[14] From table 4 we see that most of the coefficients are positive and significant. In the first two specifications with lagged export status as an explanatory variable, it is clear that this variable is a key determinant of present export status. This result is in accordance with the prediction of the sunk cost model mentioned earlier. The magnitude of the effect of the lagged export status variable is, in real terms, quite large. If all other predictor values in the specification are held at their mean values then the magnitude of the lagged export status seems to indicate that a change in the lagged export status of a firm

to the model :

$$\Pr\left(y_{ijt}=1|y_{it-1j}=0\right)=\Phi\left(\beta_1 I_j+\sum_t \beta_t Year\ Dummy_t+\boldsymbol{\beta}'\mathbf{x}_{it-1j}+\epsilon_{ijt}\right)$$

We also note here that values of the variables in period $(t-1)$ as explanatory variables also helps reduce simultaneity problems.

[14]Since the probit model is non-linear, interpretation of the coefficients for any of the specifications is not straightforward. If there are $K$ explanatory variables in the vector $\mathbf{x}_{it-1}$ (we suppress the industry notation for convenience), then the marginal effect of the $k^{th.}$ explanatory variable for the probit models outlined above, is $\frac{\partial Pr\left(y_{it}=1|\mathbf{x}_{it-1}\right)}{\partial x_{it-1k}}=\phi\left(\boldsymbol{\beta}'\mathbf{x}_{it-1}\right)\beta_k$, where $\phi\left(\boldsymbol{\beta}'\mathbf{x}_{it-1}\right)$ is the probability density function of the normal distribution evaluated at $\boldsymbol{\beta}'\mathbf{x}_{it-1}$. Therefore, the value of the marginal effect depends on the level of all other variables in the model. The sign of the marginal effect is, however, determined by $\beta_k$ since $\phi\left(\boldsymbol{\beta}'\mathbf{x}_{it-1}\right)$ is always positive. Therefore, the signs of the variable coefficients gives the direction of effect of the covariates on the response (for details see Wooldridge (2005)). In this study we will focus only on the general direction of these effects rather than their magnitudes and hence we report the probit coefficients themselves and not the marginal effects.

increases the future probability of exporting by almost 80% (here we are referring to the marginal effect of the lagged export status). These results are similar to those obtained by Robert and Tybout (1997) for Columbian firms and more recently Arnold and Hussinger (2005) for German manufacturing.

In general all probit specifications in table 4 give us the same signs for the coefficients and hence tell a consistent story of selection into exporting. Large size and capital intensity increase the probability of future exporting. Not surprisingly both productivity measures, TFP-LP and TFP-OLS have a significant and positive effect on a firms's future export decision. Also, firms that have a larger skilled workforce (proxied by average salary) are more likely to export in the future, although this result is not statistically significant at the conventional levels of significance. On balance, the probit regressions show that the probability of exporting increases for firms that are larger, use more capital per worker, pay higher wages and which are more productive, even after controlling for industry effects. Therefore, firms with better characteristics in the past are more likely to enter export markets in the future. These results point to some evidence of self-selection.

# 6. The effect of exporting on performance

## 6.1 *Identifying exporter learning using propensity score matching*

The results from the growth regressions in table 3 earlier seem to point out to the presence of learning for most of the variables. In this section we check the robustness of these learning effects by controlling for selection effects and examining the causal links from exporting to several firm performance indicators. To this end, we employ a matching technique using nearest neighbor matching developed by Abadie, Drukker, Herr and Imbens (2004).[15] Viewing export participation as treatment our objective is to isolate the effects of receiving the treatment, controlling for non-random self-selection of firms into exporting. Doing so helps us identify the causal effects of the treatment or exporting on the treatment group (the exporting firms), i.e., to help establish if there are any learning effects from exporting after controlling for selection.

Let $Export\ Dummy_{it}$ denote as before the export status of a firm $i$ in year $t$ (we suppress the industry indicator for notational convenience).[16] Using the formulation in Angrist and Pischke (2008), let $X^1_{it}$ denote an outcome (performance indicator) of the firm and let $X^0_{it}$ denotes the *counterfactual* outcome of the *same* firm had it not started exporting. Then, the observed outcome

[15]Matching techniques have recently been used in a number of studies to control for selection effects. In a recent study De Loecker (2007) finds evidence of learning by exporting for a panel of Slovenian firms by using matching techniques. Girma, Greenaway and Kneller (2004) finds similar evidence for a panel of firms in the U.K. using the same methodology.

[16]In writing this section we closely follow the general structure, notation and terminology in Angrist and Pischke (2008)[pp. 10-12] and again Angrist and Pischke (2008)[pp. 51-53].

$X_{it}$ can be written in terms of these potential outcomes as (Angrist and Pischke (2008)[pp. 11]) :

$$X_{it} = \begin{cases} X_{it}^1 & \text{if } \textit{Export Dummy}_{it} = 1 \\ X_{it}^0 & \text{if } \textit{Export Dummy}_{it} = 0 \end{cases} \tag{7}$$

Then, the effect of exporting on firm $i$'s performance, or the treatment effect for firm $i$, is given by the difference $X_{it}^1 - X_{it}^0$. The average treatment effect on the treated (ATT) which in this case is the average effect of exporting on exporters is $E[X_{it}^1|\textit{Export Dummy}_{it} = 1] - E[X_{it}^0|\textit{Export Dummy}_{it} = 1]$, i.e., the difference in the average performance outcome between exporters that participated in exporting at time $t$ and the average performance outcome that would have resulted (in the counterfactual situation) had the same group of exporters not participated in exporting. However, the counterfactual $E[X_{it}^0|\textit{Export Dummy}_{it} = 1]$ which is the outcome exporters would have experienced, on average, had they not entered the export market is not observable. The *observed* difference in average exporting performance $E[X_{it}|\textit{Export Dummy} = 1] - E[X_{it}|\textit{Export Dummy} = 0]$ (that we obtained in the "export premia" regressions) which compares simple averages of the treatment group (exporters) with the control group (non-exporters) can produce biased results, because of *non-random* selection into exporting. Quantitatively, the observed difference in average exporting performance is related to the average treatment effect by the following equation (see Angrist and Pischke (2008)[pp. 11-12]):

$$\begin{aligned} E[X_{it}|\textit{Export Dummy}_{it} = 1] \; - \; & E[X_{it}|\textit{Export Dummy}_{it} = 0] = \\ & E[X_{it}^1|\textit{Export Dummy}_{it} = 1] - E[X_{it}^0|\textit{Export Dummy}_{it} = 1] \\ + \; & E[X_{it}^0|\textit{Export Dummy}_{it} = 1] - E[X_{it}^0|\textit{Export Dummy}_{it} = 0] \end{aligned} \tag{8}$$

where the last term in the above equation is the selection bias that confounds identification of the ATT.

Matching methods offer a technique to identify the aforementioned unobserved counterfactual state of the world (under reasonable assumptions) by comparing the outcomes of exporting firms with very similar non-exporting firms. We assume that that all the differences between the exporter treatment group and the control group of non-exporters that influence the selection decision into exporting can be captured by a vector of *observable* firm characteristics. We summarize these different characteristics into a single number called the propensity score by using a predicted score generated through a simple probit regression using the following specification:

$$P(\textit{Export Dummy}_{it} = 1) = \Phi(\textit{TFP}_{it-1}, \textit{Size}_{it-1})$$

where, $\Phi(.)$ denotes the cumulative normal density. On the basis of the probit specification above we calculate the predicted export probability of a firm $i$ exporting at time $t$.[17] Based on this propensity score, each exporting firm $i$ that exports at $t$, is matched with one non-exporting firm $j$ using the nearest neighbor method which minimizes the within-pair difference in the propensity scores. After having matched exporting firms with the non-exporting counterparts this way, that ATT is obtained as the difference in the average outcomes of exporters (i.e., the outcome averaged over all elements of the treatment group) and matched non-exporters. Therefore, we finally compare the average outcomes of treated firms with an appropriately matched control group where the matching is conditional on a vector of observable variables.[18] In this conditional sample, the observed differences between treated and control groups can be given a causal interpretation as identifying the ATT, since we assume that conditional on the propensity score there are no systematic differences relevant to the selection process, between these two groups.

One area of concern in such matching exercises is how good the match has been. Ideally, one would want "exact matching" where for each matched observation we find a corresponding member of the opposite group which has the same value for the variable on which the matching is done. However, over the entire data set such exact matches would be difficult to find with reasonable sized samples. The simple matching estimator estimates the (average) treatment effect as the (average) difference between the actual outcome for the treated unit $i$ and the counterfactual outcome for this unit approximated by the taking the average of the $m$ matches for this unit $i$ in the opposite treatment group (see Abadie et al. (2004), pp 294). Abadie et al. (2004) point out that using a simple matching estimator in this case may not lead to a good match in finite samples. In fact, in such cases the estimator might be biased. To compensate for this bias following the methodology outlined in Abadie et al. (2004) we use a bias-corrected matching estimator on the matched sample. By using this regression adjusted bias-correction we can control for the quality of the match in the matched sample (for details of the bias-adjusted estimator and how it corrects for the bias stemming from the quality of match see Abadie et al. (2004), pp. 298-300).

Table 5 presents the results of the matching exercise. The first row reveals that for labor productivity the ATT is 0.29. Since we control for non-random selection into the treatment group, this result can be given a causal interpretation. This result is statistically significant at the 1% level of significance. Not surprisingly, the magnitudes of the treatment effects are smaller than those obtained from the "export premia" regressions earlier . Similar results are obtained for almost all performance indicators and notably for TFP-OLS and TFP-LP. The only variable which is insignificant is employment, but we do recall that it is significant in table 4 suggesting

[17] We include industry dummies in the matching function to accommodate industry effects. We also include time dummies in our specification.

[18] We use the program "nnmatch" in Stata to implement this method. This method has to our knowledge not been used in the relevant literature.

that observed labor differentials are a result of selection effects only. Thus, on the whole, the results of our matching analysis indicate that once we control for non-random selection bias into the treatment group, there is evidence of learning for almost all variables of firm performance.[19]

## 7. Conclusion

Using a panel data set from India, this paper shows that exporters tend to outperform non-exporters over performance characteristics like labor productivity, size, capital intensity, remuneration levels and total factor productivity. These differences persist even after controlling for firm size and industry effects. We find some evidence to indicate that exporters already have better performance over a number of characteristics before they enter the export market. We also find evidence that suggests that there are gains from learning by exporting for most performance characteristics of firms.

[19] To check the robustness of our results for the matching exercise, we repeat our analysis using propensity score matching with the STATA command "attnd" made available by Becker and Ichino (2002). Using a common support for matched firms only and using the nearest neighbor matching algorithm we find similar effects for most variables. Most importantly, for TFP-OLS the ATT is 0.16 with a $t$-value of 2.619 (significant at 1%) while for TFP-LP the ATT is 0.12 with a $t$-value of 1.141 (not significant). We note that the "nnmatch" allows for bias correction of the average treatment effect, as mentioned earlier, while "attnd" does not. Therefore, we report the results using "nnmatch".

**Table 2. Percentage exporters and non-exporters across industries**

| | **Export Status (0 : Non-exporter ; 1 : Exporter)** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Economic Activity** | 0%(1990) | 1%(1990) | Total%(1990) | 0%(1998) | 1%(1998) | Total%(1998) | 0%(2006) | 1%(2006) | Total%(2006) |
| Basic Chemicals (incl. fertilizers) | 7.53% | 2.72% | 10.25% | 6.33% | 2.75% | 9.09% | 4.76% | 3.82% | 8.59% |
| Beverages | 1.91% | 0.27% | 2.18% | 1.86% | 0.20% | 2.06% | 1.16% | 0.26% | 1.42% |
| Domestic Appliances | 1.18% | 0.27% | 1.45% | 0.43% | 0.36% | 0.80% | 0.64% | 0.26% | 0.90% |
| Electric Machinery/Apparatus | 3.54% | 1.63% | 5.17% | 2.62% | 1.26% | 3.88% | 2.32% | 1.46% | 3.79% |
| Food Products,Diary & Feed | 6.17% | 2.90% | 9.07% | 8.03% | 2.65% | 10.68% | 8.74% | 2.92% | 11.66% |
| Footwear | 0.00% | 0.09% | 0.09% | 0.20% | 0.40% | 0.60% | 0.26% | 0.26% | 0.52% |
| Glass | 0.54% | 0.27% | 0.82% | 0.46% | 0.40% | 0.86% | 0.41% | 0.37% | 0.79% |
| Iron and Steel | 5.54% | 1.45% | 6.99% | 4.58% | 2.22% | 6.80% | 4.65% | 2.92% | 7.57% |
| Leather | 0.00% | 0.18% | 0.18% | 0.07% | 0.33% | 0.40% | 0.22% | 0.34% | 0.56% |
| Machinery (except Electrical) | 5.72% | 3.09% | 8.80% | 4.25% | 2.29% | 6.53% | 3.11% | 3.34% | 6.45% |
| Metal Products | 1.36% | 1.00% | 2.36% | 1.82% | 1.00% | 2.82% | 1.69% | 1.12% | 2.81% |
| Motor Vehicles & Parts | 4.26% | 2.45% | 6.72% | 3.35% | 1.96% | 5.31% | 2.66% | 3.15% | 5.81% |
| Non-ferrous Metals | 2.09% | 0.73% | 2.81% | 1.63% | 1.00% | 2.62% | 1.46% | 1.39% | 2.85% |
| Non-metallic products (incl. pottery) | 4.99% | 1.27% | 6.26% | 2.79% | 1.29% | 4.08% | 2.59% | 1.50% | 4.09% |
| Other Chemicals (incl. drugs) | 4.72% | 4.81% | 9.53% | 7.56% | 4.44% | 12.01% | 5.89% | 5.40% | 11.29% |
| Paper and Paper products | 2.72% | 0.27% | 2.99% | 2.92% | 0.40% | 3.32% | 2.40% | 0.67% | 3.07% |
| Plastic Products | 2.54% | 0.64% | 3.18% | 3.98% | 1.49% | 5.47% | 3.64% | 1.84% | 5.47% |
| Professional/Scientific Equipment | 0.45% | 0.27% | 0.73% | 0.90% | 0.30% | 1.19% | 0.97% | 0.37% | 1.35% |
| Rubber Products | 1.18% | 0.82% | 2.00% | 1.16% | 0.73% | 1.89% | 1.09% | 0.79% | 1.87% |
| Spinning | 5.54% | 4.63% | 10.16% | 4.74% | 5.61% | 10.35% | 6.34% | 4.61% | 10.95% |
| Synthetic Fibres | 2.45% | 1.63% | 4.08% | 2.02% | 1.29% | 3.32% | 1.46% | 1.09% | 2.55% |
| T.V.,Radio & Electro.Commun. | 2.36% | 0.54% | 2.90% | 2.32% | 0.83% | 3.15% | 1.99% | 1.09% | 3.07% |
| Textiles and Fibres | 0.36% | 0.27% | 0.64% | 1.06% | 1.00% | 2.06% | 0.82% | 0.90% | 1.72% |
| Watches | 0.09% | 0.09% | 0.18% | 0.13% | 0.07% | 0.20% | 0.11% | 0.11% | 0.22% |
| Wood Products | 0.27% | 0.18% | 0.45% | 0.36% | 0.17% | 0.53% | 0.41% | 0.19% | 0.60% |
| **Total** | 67.51% | 32.49% | 100.00% | 65.57% | 34.43% | 100.00% | 59.81% | 40.19% | 100.00% |

*Note:* 0 denotes non-exporter 1 denotes exporter. All figures in percentages. Total denotes the total percentage of firms in a year in an industry.Year is given in parenthesis.

**Table 3**. Export Performance of firms. [a]

| | (1) $S/L$ | (2) $L$ | (3) $NVA/L$ | (4) $K/L$ | (5) $W/L$ | (6) $TFP-OLS$ | (7) $TFP-LP$ |
|---|---|---|---|---|---|---|---|
| **Levels** | | | | | | | |
| 1.Export Dummy | 0.75*** | 0.94*** | 0.61*** | 0.55*** | 0.28*** | 0.30*** | 0.28*** |
| | (0.04) | (0.05) | (0.04) | (0.04) | (0.02) | (0.03) | (0.04) |
| 2.Perpetual Exporter | 0.70*** | 1.65*** | 0.70*** | 0.38*** | 0.45*** | 0.47*** | 0.49*** |
| | (0.05) | (0.07) | (0.05) | (0.06) | (0.03) | (0.04) | (0.05) |
| 3.Perpetual Non-exporter | -0.80*** | -1.00*** | -0.65*** | -0.74*** | -0.40*** | -0.21*** | -0.20*** |
| | (0.05) | (0.06) | (0.05) | (0.05) | (0.03) | (0.04) | (0.05) |
| Observations | 3684 | 3698 | 3368 | 3694 | 3695 | 3365 | 3365 |
| | (1) $\Delta S/L$ | (2) $\Delta L$ | (3) $\Delta NVA/L$ | (4) $\Delta K/L$ | (5) $\Delta W/L$ | (6) $\Delta TFP-OLS$ | (7) $\Delta TFP-LP$ |
| **Growth Rates** | | | | | | | |
| 4.Export Dummy | 0.06*** | 0.04** | 0.05+ | 0.02 | 0.04** | 0.03 | 0.03 |
| | (0.02) | (0.01) | (0.03) | (0.02) | (0.01) | (0.03) | (0.03) |
| 5.Perpetual Exporter | 0.06** | 0.01 | 0.06+ | 0.04+ | 0.04* | 0.03 | 0.03 |
| | (0.02) | (0.02) | (0.03) | (0.02) | (0.02) | (0.03) | (0.03) |
| 6.Perpetual Non-exporter | -0.05* | 0.01 | -0.06 | -0.03+ | -0.06*** | -0.04 | -0.04 |
| | (0.02) | (0.02) | (0.03) | (0.02) | (0.02) | (0.03) | (0.03) |
| Observations | 2430 | 2438 | 2161 | 2434 | 2435 | 2159 | 2159 |
| Time Dummies | YES | YES | YES | YES | YES | YES | YES |

[a] Dep. vbl. is measure of firm performance (in levels or growth rates) for firm characteristics given in cols. Indep. vbl. in Rows (1) and (4) is the export dummy. Rows (2) and (5) report results of the same regression of firm characteristics on a perpetual export dummy while rows (3) and (6) report results of the regression of firm characteristics on a perpetual non-exporter dummy. Regressions include industry effects w/ time dummies& size controls except for col.(2) that includes time dummies but does not include size controls. **Note** : $^{+}$ $p < 0.10$ $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$. Std. errors in parentheses.

**Table 4**. Probit Model: Decision to Export [a]

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Lagged Export Status | 2.66*** | 2.66*** | | |
| | (0.07) | (0.07) | | |
| NoofEmployees_(t-1) | 0.14*** | 0.14*** | 0.31*** | 0.32*** |
| | (0.03) | (0.03) | (0.02) | (0.02) |
| Average Salary_(t-1) | 0.05 | 0.01 | 0.06 | 0.02 |
| | (0.07) | (0.07) | (0.05) | (0.05) |
| Capital Intensity_(t-1) | 0.15*** | 0.16*** | 0.27*** | 0.27*** |
| | (0.04) | (0.04) | (0.03) | (0.03) |
| Log TFP-Levpet_(t-1) | 0.11* | | 0.20*** | |
| | (0.04) | | (0.03) | |
| Log TFP-OLS_(t-1) | | 0.16** | | 0.26*** |
| | | (0.05) | | (0.04) |
| Observations | 2716 | 2716 | 2716 | 2716 |
| Time Dummies | YES | YES | YES | YES |
| Industry Dummies | YES | YES | YES | YES |

[a] Dep. vbl. is export status of firm in $t$. Indep. vbls. are in rows.
[b] Cols.(1)and(2): Probit model including lagged export status as an explanatory variable.
[c] Cols. (3)and(4): Probit model without lagged export status as an explanatory variable.
[c] **Note** : $^{+}$ $p < 0.10$ $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$. Std. errors in parentheses.

**Table 5**. Nearest Neighbor Matching: Average Treatment Effects on the Treated [a]

| Variable | (1) ATT | (2) Std. Error | (3) $z$-Stat | (4) $p$-value | (5) Obvs. |
|---|---|---|---|---|---|
| S/L | 0.29 | 0.06 | 4.93 | 0.00*** | 2235 |
| L | 0.01 | 0.02 | 0.82 | 0.41 | 2236 |
| NVA/L | 0.29 | 0.06 | 5.11 | 0.00*** | 2160 |
| K/L | 0.27 | 0.08 | 3.43 | 0.00*** | 2235 |
| W/L | 0.10 | 0.03 | 3.24 | 0.00*** | 2236 |
| TFP-OLS | 0.16 | 0.04 | 4.18 | 0.00*** | 2159 |
| TFP-LP | 0.11 | 0.03 | 3.07 | 0.00** | 2159 |

[a] ATT denotes the average treatment effects on the treated after controlling for selection effects and is reported in the column ATT.
[b] **Note:** Matching is using nearest neighbor method. Treatment is export participation. Firm characteristics are given in the rows. Obvs. denotes observations used in the matching exercise.
[c] Matching characteristics is based on lagged TFP-LP, lagged firm size, year and industry dummies.
[f] **Note** : $^{+}\ p < 0.10$ $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$.

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