Learning to export

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Abstract

There is strong evidence that exporting firms are better. This correlation can potentially arise from many alternative casual models. In this paper, we utilise the natural experiments offered by transitioning into export in a dataset of Indian firms from 1990 to 2011, where each firm which made the transition is matched against one which did not. While exporting firms become bigger, there is no evidence that they improve productivity. On the other hand, we find a rise in productivity in the year prior to embarking on export. Indian firms learn to export.

JEL Classification: F43, L1, D24

Keywords: Exports, Self-selection, Learning by exporting, Firm productivity

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Contents

1 Introduction

Following Bernard et al. (1995), a growing body of empirical studies showed that exporters are more productive than non-exporters. This correlation has led to many suggestions about policy interventions, ranging from microeconomic interventions (e.g. subsidised purchases of high technology) to macroeconomic interventions (tax breaks, exchange rate undervaluation). Intuitively, it is felt that once a firm steps into the international market, learning takes place through exposure to better technology, increased competition in foreign markets, scale effects, etc. If the 'learning by exporting' (LBE) hypothesis were true – that exporting had a causal impact upon productivity – then these policy interventions could be considered.

However, the apparent correlation between exporting and productivity could come about through alternative causal mechanisms. The standard models of modern trade theory, Melitz (2003); Bernard et al. (2003) are based on the notion that firms are heterogeneous, productivity is immutable, and the most productive ones self-select themselves into exporting. If this model is correct, then policy interventions are futile as firm productivity cannot change.

This paper utilises a dataset of large Indian manufacturing firms observed from 1990 to 2011. This is an interesting period as many firms made the transition from serving the domestic market to exporting. This permits the construction of a dataset with firms that transitioned into sustained exporting matched against similar firms that did not. The event of starting to export is found across diverse years, which permits the use of the event study methodology in identifying the trajectory of parameters of interest – such as firm productivity – before and after the year when exporting commenced.

Datasets in this field have many firms that intermittently transition in and out of exporting. The advantage of our large dataset, with 10,685 firms, is that within it are a large number of firms with clean trajectories. We see 1695 firms which are sustained non-exporters: who are observed for seven consecutive years with zero export in all of them. There are 527 firms who have three years of no export followed by four years of exporting. With propensity score matching, we construct a dataset of 280 firms who made the transition with controls that did not. The dataset has high quality match balance; the treatments and controls are much alike. This offers a unique quasi-experimental opportunity to examine the phenomena of interest.

As has been observed in the recent decade by numerous papers, export starters are bigger, younger, and pay higher wages, prior to exporting. Exporting has a positive impact upon size. But there is no evidence of learning by exporting. We explore the possibility of heterogeneity in learning based on firm characteristics such as age or export intensity. There is no evidence of improved productivity after exporting here also.

We find striking evidence that the firms that export in year t have a surge in productivity in the year $t - 1$. This suggests that firms undertake actions that improve their productivity prior to embarking upon exporting. Firms learn in order to export.

Our results are inconsistent with the Melitz and HMY models in that firm productivity is not immutable. Second order questions are now suggested, in understanding why some firms obtain a surge in productivity while others do not. At the same time, our results raise questions about the policy consensus that policies should be designed to subsidise exporting firms. Aiding firms that are *presently* exporting will target the wrong firms. It may be useful to shift focus from exporting to the *transition of non-exporters into exporting*, and the productivity surge that precedes exporting.

The rest of the paper proceeds as follows. Section 2 reviews the evidence thus far on self-selection and learning by exporting. Section 3 outlines the data and sample characteristics. Section 4 discusses the methodology we have used to study learning effects of exporting and the results we obtain. Section 5 discusses the robustness tests. Section 6 concludes.

2 Empirical research on firm productivity and exporting

The empirical evidence for self-selection and LBE now spans many countries. Wagner (2007) reports that most studies have found evidence for self-selection, while the debate on post-entry productivity growth remains inconclusive.

Exporting by a firm in a developing country may be particularly important, as this gives the firm exposure to global technology, sophisticated inputs, and the pressure to produce sophisticated outputs. While a purely domestic firm in an advanced economy faces competition from sophisticated firms, and hence may not gain knowledge by exporting, a purely domestic firm in a developing country might gain a lot by competing in exporting to advanced economies.

A second source of cross-country diversity could be market size. In a small country, firms that step out into the global market have a greater opportunity to achieve scale effects. On the other hand, this may not be an issue for firms in large countries.

The existing evidence for LBE from developed economies is mixed. Bernard and Jensen (1999) and Hung et al. (2004) for America, Delgado et al. (2002) for Spain, Wagner (2002) and Arnold and Hussinger (2005) for Germany, find little or no evidence for LBE. On the other hand, Baldwin and Gu (2003) for Canada, Girma et al. (2004) and Greenaway and Kneller (2008) for UK, find evidence for both self selection and LBE.

Evidence from emerging economies is also mixed. De Loecker (2007) for Slovenia, Van Biesebroeck (2005) for Sub-Saharan Africa, and Blalock and Gertler (2004) for Indonesia report post entry increase in productivity for the firms. Aw et al. (2000) shows that while learning by exporting is seen in Taiwan, this is not the case in Korea. On the other hand, Isgut (2001) for Colombia, and Clerides et al. (1998) for Colombia, Mexico and Morocco, do not find evidence in favour of LBE.

The lack of evidence for learning by exporting has often been attributed to the argument that learning is specific only to a certain kind of firm, and studying average treatment effect can nullify these differences in learning. Learning from exporting has been found to be more pronounced for firms that belong to an industry which has high exposure to foreign firms (Greenaway and Kneller, 2008), are younger (Delgado et al., 2002), or have a greater exposure to export markets (Kraay, 1999; Castellani, 2002). Another line of thought suggests that firms do not learn from exporting but learn to export. Alvarez and Lopez (2005) argue that productivity changes occur after the decision to start exporting, and firms most likely invest in new technologies before entering foreign markets to be able to compete internationally. Iacovone and Javorcik (2012) find that firms improve quality exactly one year prior to entering export markets and there is no upgrade after entry.

Recently, two studies have analysed self-selection and LBE for Indian firms. Tabrizy and Trofimenko (2010) use a sample of 1822 firms from 1998 to 2008 and find evidence for self-selection but not for learning by exporting. Ranjan and Raychaudhuri (2011) find evidence for both self-selection and learning by exporting. We improve upon the work of these papers in many aspects of methods and data.

Table 1 Summary statistics

All variables are in Rs. million. While the maximum sales are Rs. 3579 billion, the mean sales is only Rs. 2680 million. The distribution for all variables is positively skewed. This indicates that there is a large number of small firms in the dataset.

	Min	0.25	Median	Mean	0.75	Max
Sales	0	82	306	2669	1066	3579000
Gross fixed assets	0	46	144	1350	506	2213000
Total Assets	0	77	239	2372	866	2849000
Wage Bill	0	4	16	118	59	62410
Exports	0	0	0	305	38	1405000
Rawmaterial expenses	0	40	156	1277	539	1932000
Power expenses	0	3	11	111	45	42080

3 Data and descriptive statistics

We source firm level data from the Prowess database provided by the Centre for Monitoring Indian Economy (CMIE). We restrict the analysis to manufacturing firms since their exporting activity is easily distinguishable. CMIE Prowess currently has data for 10,685 manufacturing firms since 1990, however, data is sometimes not available or are reported as missing. Table 1 provides the summary statistics of the data. There is a lot of heterogeneity in the data in terms of firm size, age, capital intensity etc [1].

In this sample, about 47-60% of the firms in each year report positive earnings from export. The mean export value to domestic sales ratio for the sample is stable at 12-13% (see table 7 in the appendix). There are exporters in all industrial sectors, but there is considerable variation in the internationalisation of each sector. For the year 2007, 59% of the firms in Chemicals, 66% in Transport equipment and 71% in Non-electrical machinery industry were exporting, while only 30% in Paper and Pulp industry were exporting[2].

[1]Manufacturing companies in CMIE Prowess form 79% of the value of output of the registered manufacturing sector of India in 2008-09. CMIE also has a well-developed 'normalisation' methodology which ensures inter-year and inter-firm comparability of accounting data. Many empirical papers for India have been written using this database such as Bertrand et al. (2002); Ghemawat and Khanna (1998); Goldberg et al. (2010). The reporting by firms is sometimes not continuous and can lead to problems of missing data.

[2]The pattern is similar in all years.

Table 2 Transition probability from t to $t+1$

	0	1
0	89.46	10.54
1	7.42	92.58

3.1 Productivity measurement

To measure firm level productivity, we assume that the production function at the firm level is the logarithm of the Cobb-Douglas function.

$$y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + w_{it}$$

where y_{it} represents the logarithm of firm output, k_{it} and l_{it} represents the logarithm of capital and labour respectively, and w_{it} is the productivity component. But this equation cannot be estimated consistently using simple OLS due to endogeneity problems. We use the semi-parametric estimator for total factor productivity developed by Levinsohn and Petrin (2003) (TFP-LP henceforth). This measure uses intermediate inputs as proxies to control for the correlation between input levels and the unobserved productivity shocks.

We estimate TFP-LP for each industry separately and use raw material expenses deflated by Wholesale Price Index for Manufacturing firms (WPI-M) as a proxy. Output is calculated as the sales deflated by WPI-M, and capital is calculated as the gross fixed assets divided by WPI-M. Labour is estimated by deflating the total wage bill by Consumer Price Index for the Industrial Workers. The productivity measure is made comparable across industries by demeaning the TFP-LP values of each firm by its industry mean (Petkova, 2012). We use the stata command *levpet* for the estimation[3].

3.2 Transitioning in and out of exporting

We look at the transition probability of firms between exporter and non-exporter status from year t to $t+1$. In table 2, 0 depicts non-export status and 1 depicts export status. There is significant on-diagonal mass (89.46 and 92.58), which means that since entering export markets is costly, firms do not easily switch from one state to another over a one year horizon. But there is also non-zero probability of entering and exiting export markets. When a firms starts out as a 0, there is

[3]The estimation in Stata, when gross revenue is the dependent variable, is discussed in Petrin et al. (2004).

Table 3 Are exporters different?

LHS Variable	Beta
Gross fixed assets	1.1 (0.036) ***
Wages	1.33 (0.033) ***
Sales	1.55 (0.039) ***
Investment	1.08 (0.07) ***
Total assets	1.22 (0.034) ***
Total factor productivity	0.05 (0.007) ***

1)*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$
2)Robust clustered standard errors are reported in brackets

a 10.5% probability of it moving to exporting. The probability of exiting from export markets is 7.42% over a one year horizon.

These entries and exits from exporting are an important source of difficulty for measuring LBE. If learning by exporting has to be observed, the firm must undertake sustained exporting, through which there is the possibility of observing the impact upon productivity over a multi-year period. This requires observing a clean trajectory of a firm which makes one jump into exporting, and then sustains exporting for many years.

Conversely, firms which make the transition into exporting need to be compared against firms which have uncontaminated trajectories of zero export.

3.3 Superior exporter performance

The literature has established that exporters are different from non-exporters in important ways Bernard et al. (1995). We replicate this analysis with our dataset. Following Bernard and Jensen (1999), we run the following specification:

$$y_{it} = \alpha + \beta EXP_{it} + \gamma Controls_{it} \tag{1}$$

where y_{it} is the firm characteristic for firm i at time t. EXP_{it} is an export dummy equal to one if firm i reports positive earnings from exports in period t and $Controls_{it}$ includes the number of employees (Wages deflated by CPI-IW), age and ownership type. We also add industry, year and location fixed effects. The β for different firm characteristics is reported in Table 3. It is clear that exporters are superior to non-exporters. They are bigger, have a higher wage bill, sales, and investment, and are also more productive than the non-exporters.

4 Results

Studying self-selection and learning by exporting is not trivial since the two hypotheses create a two-way causality between firm performance and its export status. Self-selection looks at the pre-entry characteristics of exporters as compared to non-exporters, and LBE looks at the post-entry performance of export starters in comparison to non-exporters.

In our sample, there is both an inward and outward movement of firms from export markets. Moreover, about 4139 firms report discontinuously and as many as 1301 enter and also exit the export market, atleast once. We factor these issues in our analysis and define an export starter and a non-exporter using a clean trajectory definition. A firm is considered an export-starter if it reports zero export earnings for atleast three consecutive years followed by a transition into exports, and remains in the export market for atleast the next 3 years. A firm is a sustained non-exporter if it reports zero earnings from exports for atleast seven consecutive years. Our dataset yields a rich collection of 527 export starters and 1695 non-exporters using these definitions.

4.1 Self-selection

To study the self-selection effects, we look at how firm characteristics in $t-1$ affect the probability to export. Here $START_{it}$ is the dependent variable. It is a dummy variable which is equal to 1 when firm i begins to export in year t, and 0 otherwise. Since the dependent variable is binary, we use a probit specification as follows.

$$Pr(START_{it} = 1) = F(Productivity_{it-1}, size_{it-1}, wagebill_{it-1}, ownership_{it-1}) \tag{2}$$

where $F(.)$ is the normal cumulative distribution function. We control for productivity, size of the firm[4], the wage bill (as a proxy for skill of the labour force) and ownership type in $t-1$. To control for industry specific comparative advantage and proclivity to internationalise, we add industry fixed effects. We also add year fixed effects to control for macroeconomic changes. All variables are in logs.

The results of the probit are shown in Table 4. Our results indicate that the probability of beginning to export increases in the productivity, size, and wage bill of the firm, and decreases in the age of the firm. Thus firms with better

[4]Size is defined as the log of total assets.

Table 4 Self-selection

	Estimate	Std.Error	z-value	p-value
$Prod_{i,t-1}$	0.33	0.10	3.13	0.00
$Age_{i,t-1}$	-0.01	0.00	-3.47	0.00
$Size_{i,t-1}$	0.15	0.04	4.06	0.00
$WageBill_{i,t-1}$	0.18	0.04	4.67	0.00

characteristics in $t-1$ are more likely to enter the export market or get self-selected into exporting.

4.2 Do firms learn by exporting?

To study the causal impact of exporting on firm performance, we need to evaluate the $w^1_{is} - w^0_{is}$, where w is the firm productivity for firm i at time s, and the superscript is equal to 1 when firm i exports and 0 when it is a non-exporter. But for an exporter, we do not observe w^0_{is} i.e. the outcome had it not exported. Hence, we need to create a counterfactual to estimate the firm productivity of exporters had they not exported. Since exporters are *a priori* better than non-exporters, we need to match the export starter to a non-exporter that is similar to the exporting firm in the year prior to the year of entry. We use propensity score matching (Rosenbaum and Rubin, 1983) to control for this self-selection and construct a counterfactual for the exporting firms[5].

The export starters as defined at the beginning of this section form the treatment group and the non-exporters form the control group. The model discussed in section 4.1 gives the propensity to export for all firms in the treatment and control group. We use this propensity score to do nearest-neighbour matching with replacement in each year such that if P_{it} is the predicted probability of entry at time t for firm i (a firm in the treatment group), a non-exporter j is chosen as its matched partner if its probability to enter export markets is closest to P_{it} amongst all non-exporters in year t[6]. We use a caliper matching method to ensure a region of common support. If for a treated firm we do not find a close enough control unit, we drop the firm from subsequent analysis. We get 242 matched pairs

[5] Girma et al. (2004) and De Loecker (2007) use a similar methodology for UK and Slovenia, respectively, to study the learning from exporting.

[6] We do the matching in each year to control for macroeconomic effects. The year of treatment is the year in which the treated firms transition from a non-exporter to exporter. This treated firm is matched with a firm from the control group in the same year as the year of treatment.

Table 5 Matched Pairs year wise

Since we impose a caliper, we get matches for a fewer number of treated firms than the total firms in the treatment group. For example, in 2006, the number of treated firms is 36, but we get matches for only 32 firms. This leads to a loss in data, but we get a better match balance and a can do a more robust analysis for the outcome variable.

Year	Number of controls	Number of treated	Matched pairs
1994	10	2	1
1996	22	4	1
1997	26	3	1
1998	40	2	2
1999	79	6	4
2000	98	7	6
2001	372	28	23
2002	495	32	29
2003	507	24	20
2004	536	42	38
2005	568	33	27
2006	696	36	32
2007	710	37	36
2008	427	24	22
Total	4586	280	242

using this technique. Table 5 shows the number of firms in the control group and treatment group, and the number of matched pairs in each year.

The caliper matching ensures that we get good matches i.e. the difference in propensity scores of the treated firm and its counterfactual is not substantially different. Table 6 shows the match balance statistics. We use the Standardised difference and Kolmogorov Smirnov-test (KS-test) to check if the treatment and control group are not significantly different based on the calculated propensity score and firm characteristics in the year prior to treatment. We achieve good match balance with the distribution of the propensity scores, productivity, size and wage bill being very similar in both groups after matching. For example, the standardised difference for propensity score before matching is 0.71 and almost 0 after matching. Similarly, in the KS-test, while the p-value is 0 before matching, it is almost 1 after matching for the propensity score, showing that the distribution for the treated and the corresponding control firms is not significantly different.

For the matched pairs, we calculate the following statistic

$$LBE_s = \sum_i (\delta w_{is} - \delta w_{js}) \tag{3}$$

where i is the treated firm, and j is the corresponding matched control firm. $s = -3, -2, -1, 0, 1, 2, 3$ is the rescaled time where 0 is the time at which a treated firm

Table 6 Match Balance

The values in brackets are p-values. Both tests show that before matching treated and control firms are significantly different in terms of different firm characteristics, while after matching they are similar.

Standardised difference

	Before Matching	After Matching
Propensity Score	0.71	-0.00
$TFP_{i,t-1}$	0.35	0.12
$Log(Size)_{i,t-1}$	0.66	0.08
$Log(Salary)_{i,t-1}$	0.62	-0.07

Kolmogorov Smirnov test

	Before Matching	After Matching
Propensity Score	11.8052	-0.0088
	(0)	(0.993)
$TFP_{i,t-1}$	5.6477	1.14
	(0)	(0.2549)
$Log(Size)_{i,t-1}$	14.6147	0.8684
	(0)	(0.3856)
$Log(Salary)_{i,t-1}$	10.4012	-0.7813
	(0)	(0.435)

starts exporting. δw is the change in productivity of the firm. We bootstrap[7] this statistic to obtain significance at 95% level. We plot the bootstrapped difference in difference (DID) statistic and check if it is significantly different from zero.

Learning by exporting?

Figure 1 shows the impact of exporting on productivity for the event window -3 to 3. On the aggregate we do not see learning by exporting since the difference in productivity growth of the treated and the control firm (black line in the graph) is not significantly different from zero at a horizon of one, two and three years after treatment date.

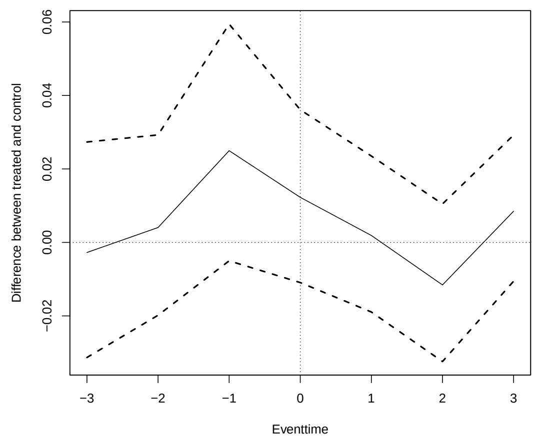
Heterogeneity in learning

The above analysis only considers learning as an average treatment effect across all matched pairs. But as discussed in Section 2, learning can vary across firms based on certain characteristics. In this section we explore if learning is heterogenous and what firm characteristics are correlated with high learning effects.

[7]We calculate the average treatment effect as described in Becker and Ichino (2002) and find that our results (discussed later) still hold.

Figure 1 DID for productivity

The black line in the graph is the estimate of the statistic calculated using equation 3. The dotted lines depict the 95% confidence interval. The vertical line shows the event date i.e. the year of treatment and the horizontal line is a reference line for no statistically significant difference between the control and the treated firms.



We divide matched pairs into quartiles based on firm characteristics in the period before entry (t -1). The three variables we consider are age, size of the firm, and productivity level. For the matched pairs in each quartile, we study difference in productivity growth of the matched pairs.

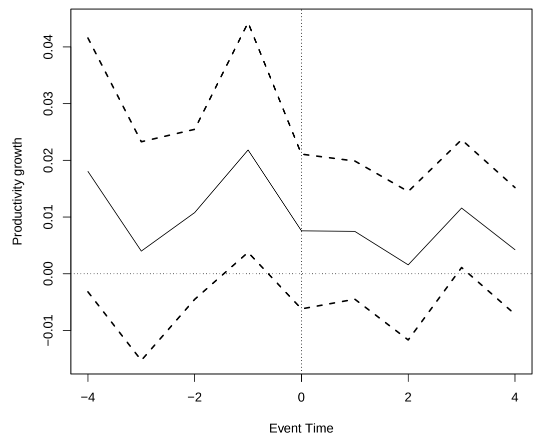
Figures 6 to 8 in the appendix show that for quartiles by each firm characteristic, there is no learning by exporting at a horizon of one and two years i.e. the difference in productivity growth of the matched pairs is not significantly different from zero. However, for quartile 2 w.r.t. age and quartile 2 w.r.t. size, there is a significant difference in the productivity of treated and control at a horizon of three years after treatment. This suggests that there might be some long term gains in productivity for some specific firms.

Learning to export

An alternate explanation for not seeing LBE is that firms learn to export. Figure 2 shows the productivity trajectory of export starters, before and after they become exporters. We see that firms that become exporters, experience a significant rise in productivity one year prior to entering the foreign markets. This suggests that firms prepare themselves to enter foreign markets, i.e. they learn to export.

Growth in size

Figure 2 Productivity growth of treated firms



We calculate the statistic in equation 3 for the size of firms. In figure 3 we see that treated firms have a significantly higher growth rate in terms of size both prior to and after the firm enters foreign markets. It is interesting, that prior to entry, the DID is increasing, suggesting again that the firms prepare themselves for foreign markets. After entry, the growth is positive but the DID is on a downward trend.

5 Robustness Tests

To check the robustness of our results, we perform the following tests.

5.1 Stronger Trajectory definition

Similar to the definition of treatment and control group in section 4, we now consider a firm in the treatment group if after four years of being a non-exporter, the firm becomes an exporter and remains one for atleast the next four years. Similarly, a firm is in the control group if it was a non-exporter consecutively for atleast 9 years. We repeat all the above steps with our new treatment and control group and get 140 matched pairs.

Figure 4 shows that even with a stronger trajectory definition, we do not observe any LBE. However, the treated firms grow at a considerably higher rate than the

Figure 3 DID for size

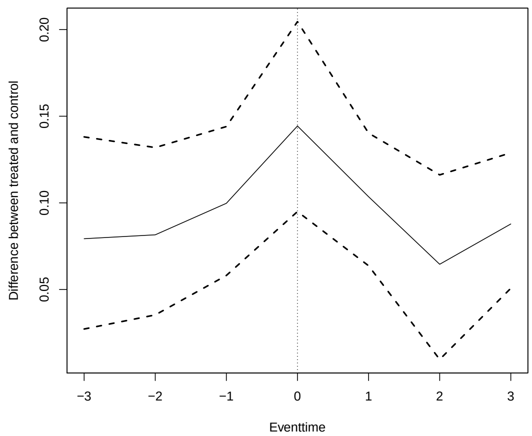


Figure 4 Stronger trajectory definition

Productivity Growth

Size Growth

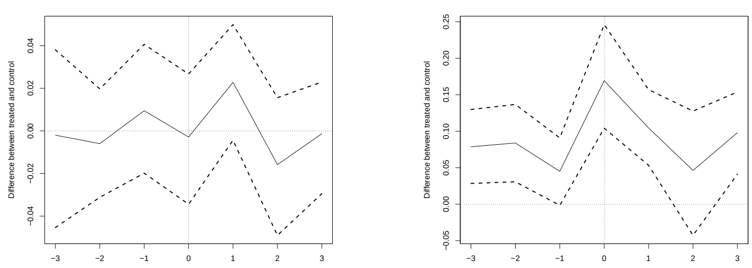
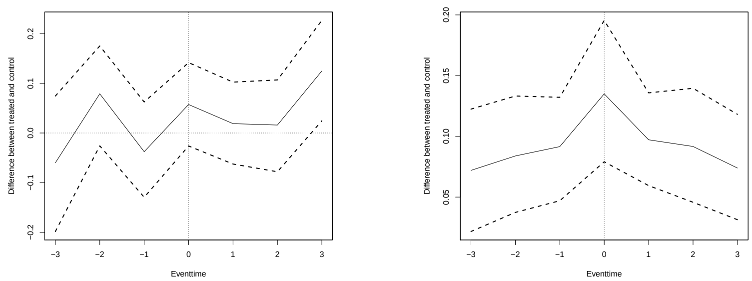


Figure 5 Labour Productivity

Productivity Growth | Size Growth



controls at a horizon of one and two years after entry.[8]

5.2 Labour productivity

As an alternate measure of productivity, we follow Tabrizy and Trofimenko (2010), who use the same dataset to build a proxy for labour productivity. Data for the number of employees is often missing as it is not mandatory for firms to report this series. Hence we use the wage bill as a proxy for labour input. We calculate labour productivity as follows:

$$log(\phi_{it}) = log(VA_{it}) - log(W_{it}) \tag{4}$$

where, ϕ_{it} represents the labour productivity. VA_{it} is the firm-level value added, computed as total sales minus power and fuel expenditures, and raw material expenses; and W_{it} is the total wage bill.

We get 240 matched pairs in this case and the results are shown in figure 5. Here too, we see that firms are not learning from exporting at a horizon of one and two years after exporting, but at a three year horizon, the DID is significantly different from zero. This is different from our earlier result (figure 1), and could be because labour productivity does not account for the switch from being labour intensive to capital intensive. Also, the treated firms are growing in size at a significantly higher rate than the controls.

[8] These results also hold if we weaken the trajectory definition and define exporter starters as those who after being a non-exporter for more than 2 years, have been an exporter for atleast one year.

Our results are robust to other alterations to the empirical strategy defined in section 4, such as matching firms in the same industry and in the same year, or tightening the caliper, or changing the probit model.

6 Conclusion and Policy implications

Do firms learn by exporting? This is an important question which shapes our understanding of trade theory, and influences many policy questions ranging from micro-economic interventions to exchange rate undervaluation. If firm productivity is immutable (as in the HMY model), or if firms increase productivity in order to export, then there is no value in subsidising present exporters.

The lack of consensus in this field suggests this is a question that requires further research. This paper explores this question, starting from a large database of firms in India, where many firms have made the transition into exporting. The unique feature of the paper is an unusually clean design using this the phenomenon of interest is identified.

We start with a large database of 10685 Indian manufacturing firms from 1990 to 2011, a period in which a large number of firms made the transition into exporting. We define export starters as firms who have been domestic for atleast three years, followed by entry into export markets and an export status for three years hence. We match each export starter with a non-exporter in *each year* to control for any macroeconomic changes. The inference procedure is done in an event study framework with bootstrapping to study the outcome variable at a one, two, and three year horizon from the date of entry into exporting.

This paper examines the reasons for the differential performance of exporters as compared to non-exporters. While we do find that more productive firms self select themselves into participating in foreign markets, our analysis does not provide evidence for learning by exporting. Learning is also not heterogenous or specific to a certain kind of firm. However, we do find preliminary evidence of learning to export. The productivity for the exporters increases significantly in the period prior to entry, suggesting that firms learn to export. This is a particularly interesting result, and further research can shed light on the investment decisions of firms prior to exporting.

For policy-makers, these findings are important. Evidence in favour of self-selection of firms and learning to export suggest that policy should focus on enabling firms to improve their productivity by reducing the distortionary costs of government intervention, investing in infrastructure, promoting investment in R&D etc. The higher the productivity of firms, the more likely they are to export and compete in global markets. Also, since we find that firms grow faster after entering export markets, the gradual increase in market share of these firms would force the less productive firms to exit. This reallocation of resources towards more productive firms should propel growth in the economy (Melitz, 2003). Moreover, lack of evidence in favour of learning by exporting suggests that trade missions and trade liberalisation cannot solely lead to growth in productivity of firms. Thus, the focus of policy should be to push for a more conducive environment for business, reduce costs of operation, and hence promote firm productivity. This would increase global competitiveness and lead to overall growth of the economy.

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Appendix

Table 7 Export Statistics by Year

	Percent exporters	Mean Export-sales (Percent)
1990	52.51	9.38
1991	50.58	11.35
1992	53.17	12.85
1993	52.41	16.03
1994	52.63	19.17
1995	52.59	20.97
1996	54.48	22.28
1997	55.09	22.34
1998	53.78	22.50
1999	51.20	23.36
2000	49.83	23.02
2001	50.73	24.58
2002	49.90	23.93
2003	49.27	25.31
2004	49.37	24.67
2005	47.86	25.37
2006	48.68	24.57
2007	49.78	25.22
2008	50.91	24.93
2009	51.32	26.18
2010	51.46	23.63
2011	60.79	22.18

Figure 6 Age

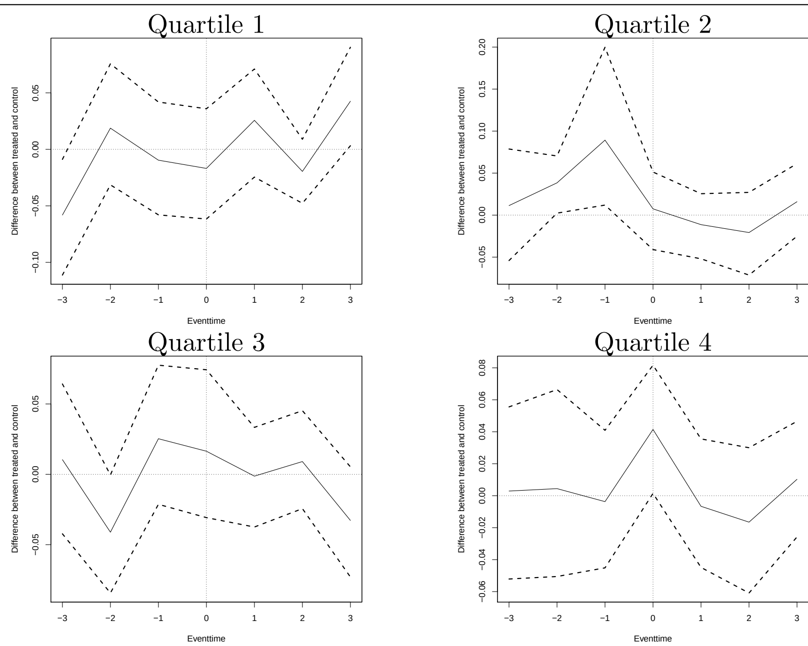

Figure 7 Size

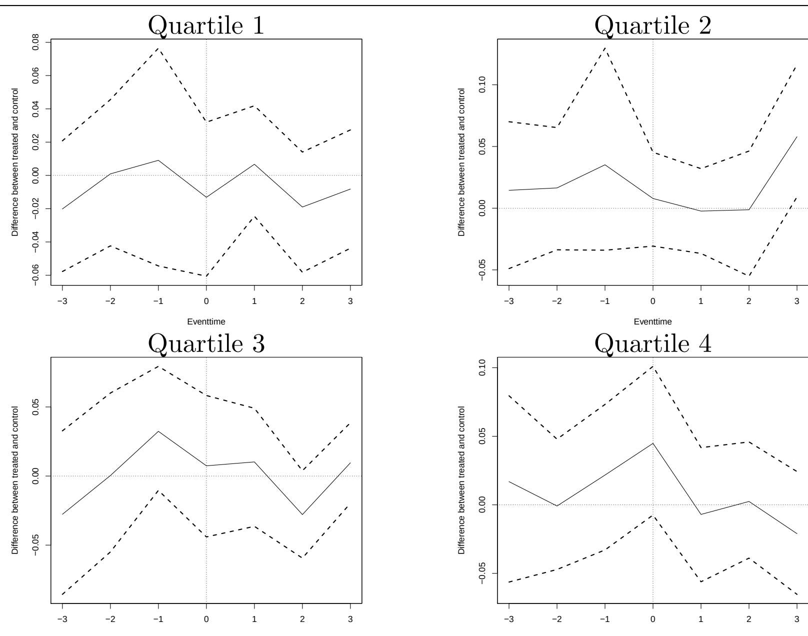

Figure 8 Productivity