Exporting and firm performance: Evidence from India

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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 1994 to 2014, 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 after entry. There is self-selection of more productive firms into exporting.

JEL Classification: F43, L1, D24

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

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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 the proposal of many export promoting 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 1994 to 2014. 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 8,275 firms, is that within it are a large number of firms with clean trajectories. We see 3510 firms which are sustained non-exporters: who do not export in any year of the sample. There are 473 firms who have two years of no export followed by three years of exporting. With matching techniques, we are able to compare export starters to non-exporters both before and after they commence exporting. This offers a unique quasi-experimental opportunity to examine the phenomena of interest.

As has been observed in the recent decade by numerous papers, we also find that export starters are bigger, younger, pay higher wages and are more productive, prior to exporting. There is no *conscious* effort to augment the productivity before entering export markets. Exporting has a positive impact upon size. But there is no evidence of learning by exporting.

Our results are consistent with the Melitz and HMY models in that firm productivity is immutable. Second order questions are now suggested, in understanding what drives productivity and whether there is heterogeneity in learning outcomes. 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.

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 measurement of key variables. Section 4 discusses the methodology we have used to study the pre-and post entry performance of exporters. 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 find 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. Hallward-Driemeier et al. (2002) find that the firms that explicitly target export markets make systematically different decisions and thus raise their productivity.

Four studies have analysed self-selection and LBE for Indian firms. Tabrizy and Trofimenko (2010) and Haidar (2012) find evidence for self-selection but not for learning by exporting. Mallick and Yang (2013) and 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.

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[1] since their exporting activity is easily distinguishable. CMIE Prowess currently has data for approximately 11,000 manufacturing firms since 1990, however, data is sometimes not available or are reported as missing[2]. After cleaning the data, we get 59,985 observations for 8,275 firms. Approximately 8 years of data is available for each firm. 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 [3].

[1]Manufacturing firms are defined as firms for which revenue from industrial sales is atleast 50 percent of the total sales.

[2]We exclude observations for which data on sales, total assets, gross fixed assets, wage bill, raw material expenses and power are missing. We also exclude observations where sales is less than Rs. 5 million.

[3]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.

Table 1 Summary statistics

All variables are in Rs. million. All nominal series have been converted to 2014 prices. While the maximum sales are Rs. 5042 billion, the mean sales is only Rs. 6653 million. The distribution for all variables is positively skewed. This indicates that there is a large number of small firms in the dataset.

Variable	Category	Mean	SD	Min	25th	Median	75th	Max	Observed
Sales (INR Million)	All firms	6653.96	78352.57	5.03	251.23	807.33	2574.23	5042782.72	59985
	Exporters	10995.21	106206.24	5.05	514.16	1502.40	4575.49	5042782.72	32307
	Non-Exporters	1586.67	9552.71	5.03	121.32	390.32	1083.58	553978.54	27678
Total assets (INR Million)	All firms	6331.90	55735.16	1.24	254.90	708.64	2411.44	3677440.00	59985
	Exporters	10403.06	75389.65	3.24	508.04	1403.46	4554.01	3677440.00	32307
	Non-Exporters	1579.87	7507.34	1.24	143.61	345.75	902.85	279186.04	27678
Gross fixed assets (INR Million)	All firms	3510.35	34382.44	0.17	136.58	390.87	1363.76	2855495.76	59985
	Exporters	5758.05	46593.40	0.20	255.68	748.47	2500.30	2855495.76	32307
	Non-Exporters	886.72	3904.51	0.17	80.90	203.77	541.11	120310.50	27678
Wage bill (INR Million)	All firms	231.04	1379.81	0.11	10.19	34.63	118.92	91115.44	59985
	Exporters	376.01	1854.40	0.11	25.50	73.70	226.60	91115.44	32307
	Non-Exporters	61.83	243.12	0.11	4.98	13.82	40.77	8542.75	27678
Age (Years)	All firms	24.47	66.08	-10930.00	13.00	20.00	30.00	134.00	59765
	Exporters	27.04	19.20	-15.00	14.00	22.00	35.00	134.00	32226
	Non-Exporters	21.47	95.02	-10930.00	11.00	18.00	26.00	123.00	27539
Raw material expenses (INR Million)	All firms	3198.57	39907.46	0.11	112.14	397.51	1297.11	3293130.00	59985
	Exporters	5166.66	53936.96	0.15	228.55	709.96	2187.61	3293130.00	32307
	Non-Exporters	901.33	6787.74	0.11	51.42	196.96	611.69	438182.10	27678
Power expenses (INR Million)	All firms	257.77	1610.31	0.00	7.47	28.67	107.47	101530.00	58725
	Exporters	394.49	2101.62	0.00	12.62	49.49	183.28	101530.00	31856
	Non-Exporters	95.68	618.53	0.00	4.28	16.10	54.24	25251.12	26869
TFP (LP) ()	All firms	1.81	0.88	-2.35	1.29	1.62	2.14	8.11	58642
	Exporters	1.89	0.92	-1.57	1.35	1.67	2.19	8.11	31809
	Non-Exporters	1.71	0.83	-2.35	1.20	1.56	2.08	7.04	26833
Labour productivity ()	All firms	0.00	0.81	-3.40	-0.51	-0.02	0.50	3.25	57483
	Exporters	-0.01	0.71	-3.05	-0.46	-0.04	0.41	3.10	31513
	Non-Exporters	0.02	0.90	-3.40	-0.60	0.01	0.62	3.25	25970
Capital productivity ()	All firms	-0.00	0.90	-4.11	-0.49	0.05	0.56	3.03	57483
	Exporters	0.04	0.79	-4.11	-0.41	0.07	0.53	3.03	31442
	Non-Exporters	-0.05	1.00	-4.05	-0.61	0.01	0.61	2.98	26041
Profit-sales ratio ()	All firms	-0.00	0.25	-2.47	0.01	0.05	0.09	0.48	58785
	Exporters	0.03	0.20	-2.47	0.02	0.06	0.10	0.48	31918
	Non-Exporters	-0.03	0.29	-2.46	-0.00	0.04	0.07	0.44	26867
Cobb-douglas residual ()	All firms	-0.00	0.33	-1.10	-0.20	-0.02	0.17	1.35	58589
	Exporters	0.00	0.30	-1.10	-0.18	-0.02	0.15	1.35	31871
	Non-Exporters	-0.01	0.38	-1.10	-0.24	-0.03	0.19	1.35	26718

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 8 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.

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 ordinary least squares regression since unobservable productivity shocks and input levels are correlated. We use a semi-parametric estimator for total factor productivity developed by Levinsohn and Petrin (2003) (TFP-LP henceforth). This measure uses intermediate inputs as a proxy, arguing that intermediaries may respond more smoothly to productivity shocks.

We estimate TFP-LP for each two-digit NIC industry separately and use raw material expenses deflated by Core Wholesale Price Index (WPI-Core) as the proxy[4]. Output is calculated as sales deflated by industry specific WPI series, and capital is calculated as gross fixed assets divided by WPI-Manufacturing. Labour is estimated by deflating total wage bill by Consumer Price Index for the Industrial Workers (CPI-IW). 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[5].

3.2 Defining export starter

We categorise firms in our dataset into one of the following sets.

- Constant exporters are firms that export continously in the sample period.

[4]Core WPI is measured at WPI-All commodities minus WPI-Food articles and WPI-Fuel

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

Table 2 Categorisation of firms based on exporting trajectory

Category	Percentage of firms
Constant exporter	22%
Constant non-exporter	32%
Entrants: One switch from non-exporter to exporter	6%
Quitters: One switch from exporter to non-exporter	3%
Flip-flop	7%
Missing data	29%

- Continous non-exporters do not export in any year of the sample period. This large set of firms allows us construct counterfactuals for export starters.
- Entrants are non-exporters, that shift status to become exporters, and remain exporters throughout the sample period. This set of firms also includes firms that have exported for only one or two years. Since we need sustained exporting to measure LBE, this set is not sufficient for our analysis.
- Quitters are exporters, who exit the export market and do not re-enter during the sample period.
- Flip-flops enter the export market more than once in the sample period.
- Missing data includes those firms for which we do not have a continous time series of export sales. We cannot categorise the into any of the above sets, but neglecting this set can lead to sample selection bias.

The entry and exit from exporting is an important source of difficulty for measuring pre and post entry productivity gains. To measure pre-entry productivity premium of exporters, the firm must remain a non-exporter for a couple of years before undertaking exporting. If learning by exporting has to be observed, the firm must undertake sustained exporting, through which there is a 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.

We define an export starter as any firm that does not export for two years, and then exports for the next three consecutive years. This definition gives us 486 export 'starters' or 'treatment' firms. Conversely, firms which make the transition into exporting need to be compared against firms which have uncontaminated trajectories of zero export. There are 3510 firms in our dataset which do not export in any year during the sample period.

Table 3 Are exporters different?

Outcome variable	Coefficient on export dummy
Log(Gross fixed assets)	1.47 (0.037) ***
Log(Wage bill)	1.63 (0.035) ***
Log(Sales)	1.55 (0.036) ***
Log(Total assets)	1.48 (0.035) ***
Total factor productivity (LP)	0.15 (0.011) ***

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

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 using the following specification.

$$y_{it} = \alpha + \beta EXP_{it} + \delta Time_t) + \lambda_k Ind_k \tag{1}$$

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. $Time_t$ are time fixed effects, and Ind_k are industry 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 are also more productive than the non-exporters. This is a simple correlation and has no causal implication of exporting on firm performance. In the following section we ask the following four questions to establish how exporting and firm performance are impact each other.

4 Results

4.1 Do more productive firms self-select to become exporters?

To study if better firms self-select themselves into exporting, we look at how firm characteristics in $t-1$ affect the probability to export for export starters. Here $START_{it}$ is the dependent variable. It is a dummy variable which is equal to 1 for firm i that *begins* to export in year t, and 0 for non-exporters. We use a logit model to study self-selection.

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

Table 4 Self-selection

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-19.74	-19.05	-18.25	-18.41	-17.84
	(1670.17)	(1640.28)	(1664.37)	(1692.41)	(1654.16)
$Log(Age)_{it-1}$	-0.24^{**}	-0.17^{*}	-0.33^{***}	-0.29^{***}	-0.36^{***}
	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)
$Log(WageBill)_{it-1}$	0.40^{***}	0.51^{***}	0.42^{***}	0.43^{***}	0.45^{***}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$TFP(LP)_{it-1}$	0.57^{***}				
	(0.10)				
$LabourProd_{it-1}$		0.53^{***}			
		(0.07)			
$CapitalProd_{it-1}$			0.26^{***}		
			(0.06)		
$OLS-Residual_{it-1}$				0.64^{***}	
				(0.15)	
$Log(PAT/Sales)_{it-1}$					0.35^{***}
					(0.07)
N	5687	5557	5592	5681	4908
AIC	3043.74	2956.69	3009.91	3073.90	2721.14
BIC	4160.25	4069.32	4123.60	4190.24	3812.90
$\log L$	-1353.87	-1310.34	-1336.96	-1368.95	-1192.57

All variables are 3 year averages

† significant at $p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

where $F(.)$ is the normal cumulative distribution function. The controls include three year averages of productivity, wage bill (as a proxy for skill of the labour force) and age of i 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 logit are shown in Table 4. We show the results with five different measures of productivity: Total factor productivity using Levinsohn Petrin methodolody, Labour productivity, Capital productivity, Cobb-douglas OLS residual, and log-value of the ratio of Profit after tax (PAT) to sales of a firm. The estimation of these measures is discussed in section 5. Our results indicate that the probability of starting to export is greater for more productive firms, across all measures of productivity. The probability is higher the higher the wage bill and younger the firm. This shows that better firms are more likely to *start* exporting.

4.2 Do firms learn to export?

The theory of self-selection suggests that firm productivity is immutable, and better firms become exporters. Lopez (2004) proposed that selection of firms into exporting may be a *conscious* process by which firms increase their productivity with the explicit purpose of becoming exporters. Thus the firms might be 'learning to export'. Firms that want to compete in global markets, especially those operating

Table 5 Match balance: Kolmogorov-Smirov test

p-values in brackets.

	Before Matching	After Matching
$TFP(LP)_{i,t-1}$	0.1098	0.093
	(0.0213)	(0.5047)
$Log(Size)_{i,t-1}$	0.1824	0.0697
	(0)	(0.838)
$Log(Salary)_{i,t-1}$	0.184	0.1014
	(0)	(0.391)
$Log(Age)_{it-1}$	0.0385	0.0601
	(0.939)	(0.938)

in developing countries, have to buy new technology and upgrade quality of their goods before they start exporting. This is likely to yield productivity gains for the firms ahead of time.

To analyse the hypothesis of 'learning to export', we study the productivity premium of export starters vis-a-vis non-exporters before they begin to export. To get a sharp estimate of productivity gains before exporting, we need to compare similar non-exporters and export starters. We use Mahalanobis distance matching to match an export starter with a non-exporter three years before the firm starts exporting. We match the firms on productivity, size, wage bill, and age. This gives us 210 matched pairs. We check for the match balance using Kolmogorov-Smirnov test. The results, reported in table 5, show that the null of no difference before matching is rejected, while after matching it cannot be rejected for various firm characteristics.

We calculate the productivity premium of export starters as follows:

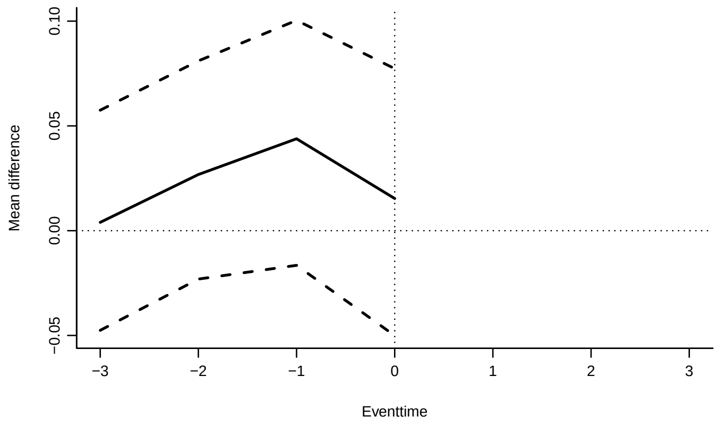
$$\frac{1}{N_s}\sum_i (Prod_{i,s} - Prod_{j,s}) \tag{3}$$

where $Prod_i$ is the TFP of export starter i and $Prod_j$ is the TFP of its matched non-exporter. We rescale time such that s=0 when an export starter exports for the first time. We look at the productivity premium at s=-1,-2,-3, that is, one, two, and three years before exporting[6]. Figure **??** shows the gain in productivity for exporters as compared to non-exporters.

The black line in figure 1 is the mean productivity difference of the 210 matched pairs. The dotted black lines represent the 95% confidence interval using bootstrapped standard errors. It can be seen that the productivity premium in s=-3 is not statistically different from zero. The producitivity premium of exporters does not increase significantly in the years before entry. In summary, the evidence does

[6]We have matched export starters and non-exporters in s=-3, and hence do not expect to see a significant difference in productivity

Figure 1 Learning to export: Productivity premium



not provide support for the idea that firms make conscious efforts to increase their productivity before they make an entry into export markets.

4.3 Do firms learn by exporting?

To study the causal impact of exporting on firm productivity, we need to evaluate the $w_{is}^1 - w_{is}^0$, where w is the firm productivity for firm i at time s, and the superscript is equal to 1 for an exporter and 0 when it is a non-exporter. But for an exporter, we do not observe w_{is}^0 i.e. the outcome had it not exported. Hence, we need to find a counterfactual to estimate the firm productivity of exporters had they not exported. Since exporters are *a priori* better than non-exporters (see table 4), 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 self-selection and construct a counterfactual for export starters[7].

The export starters as defined above form the treatment group and the non-exporters form the control group. We estimate the probability to export for firms in the treatment group and control group using a logit model. We control for productivity, size, wage bill, age, and industry group in the logit. We use the propensity score calculated from the logit to do nearest-neighbour matching without 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. We use a caliper matching method to ensure a region

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

Table 6 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 59, but we get matches for 42 firms only. This leads to loss in data, but we get a better match balance and can do a more robust analysis for the outcome variable.

Year	Number of controls	Number of treated	Matched pairs
2000	59	6	2
2001	112	13	10
2002	337	48	31
2003	379	37	27
2004	404	51	33
2005	515	49	35
2006	586	59	42
2007	723	76	55
2008	731	48	36
2009	568	40	28
2010	464	28	24
Total	5124	473	336

of common support, that is, if for a treated firm we do not find a close enough control unit, we drop the firm from subsequent analysis. We get 336 matched pairs using this technique. Table 6 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 7 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 0.75 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

$$\frac{1}{N_s}\sum_i (Prod_{i,s} - Prod_{j,s}) \tag{4}$$

where i is the treated firm, and j is the corresponding matched control firm. $s = 0, 1, 2, 3$ is the rescaled time where 0 is the time at which a treated firm starts exporting. $Prod$ is the productivity of the firm. We bootstrap[8] this statistic to

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

Table 7 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

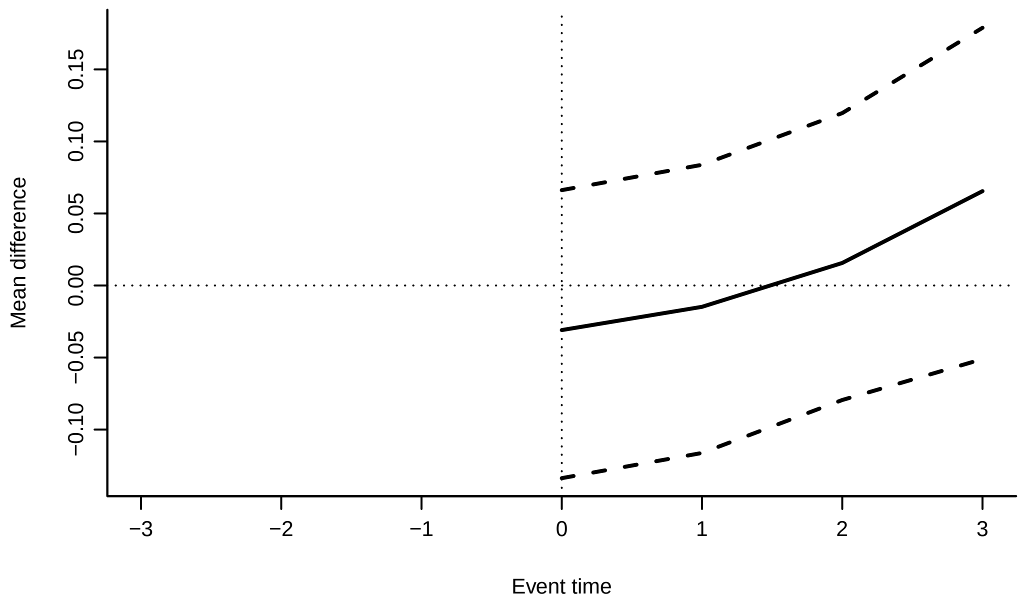
	Before Matching	After Matching
Propensity Score	0.75	-0.00
$TFP(LP)_{i,t-1}$	0.19	0.05
$Log(Size)_{i,t-1}$	0.68	0.01
$Log(Salary)_{i,t-1}$	0.63	-0.01
$Log(Age)_{it-1}$	-0.10	-0.05
$Log(Sales)_{it-1}$	0.66	0.01

Kolmogorov Smirnov test

	Before Matching	After Matching
Propensity Score	0.4667	0.0208
	(0)	(1)
$TFP(LP)_{i,t-1}$	0.1262	0.0565
	(0)	(0.6559)
$Log(Size)_{i,t-1}$	0.2707	0.0565
	(0)	(0.6559)
$Log(Salary)_{i,t-1}$	0.2823	0.0744
	(0)	(0.3102)
$Log(Age)_{it-1}$	0.0575	0.0357
	(0.1061)	(0.9829)
$Log(Sales)_{it-1}$	0.2483	0.0417
	(0)	(0.9324)

Figure 2 DID for productivity

The black line in the graph is the estimate of the statistic calculated using equation 4. 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.



obtain the standard errors.

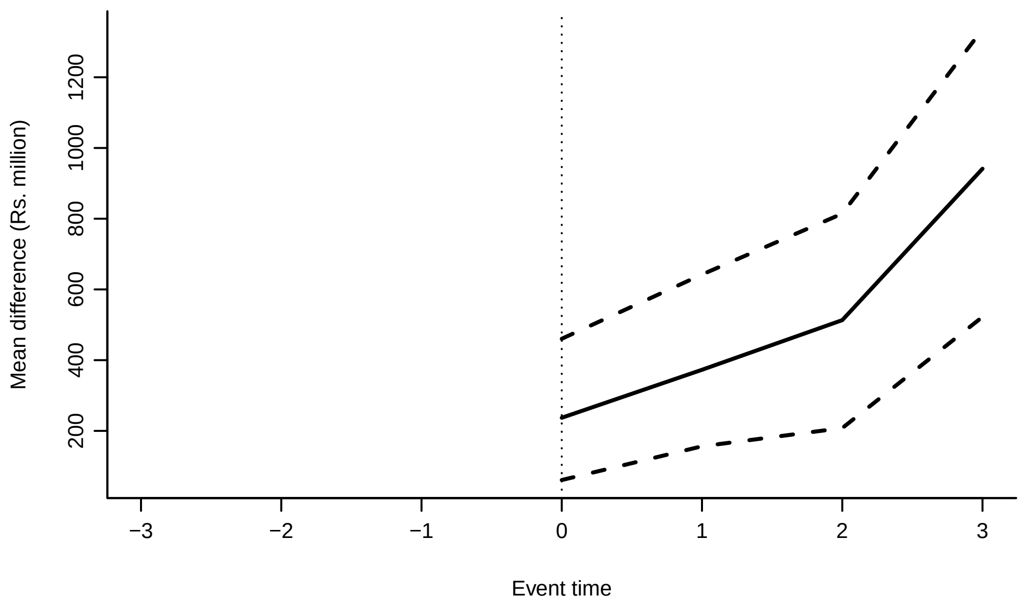
Figure 2 shows the impact of exporting on productivity premium of export starters from the time they start exporting to three years after it. The mean difference in productivity (solid black line in the figure) is not statistically different from zero at a horizon of one, two and three years after the firm starts exporting. This rejects the hypothesis of learning by exporting.

4.4 Do export starters grow significantly after export market entry?

$$\frac{1}{N_s}\sum_i (Size_{i,s} - Size_{j,s}) \tag{5}$$

Figure 3 plots the mean difference is size of the export starters and their matched

Figure 3 DID for size



counterfactuals at a horizon of one, two and three years after a firm starts exporting. Three years after entering export markets, the average size premium of an exporter is approximately Rs. 1 billion. This is a substantial gain for export starters and is likely to lead to reallocation of resources in the industry the export starter belongs to.

5 Robustness Tests

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

5.1 Change the definition of an export starter

In the sections above, we define an export starter as a firm that does not export for atleast two consecutive years, and then makes an entry and exports for the next two years. This definition of an export starter allows us to look at the impact of sustained exporting, and also gives us a large set of treatment firms. To check the robustness of our result to the definition of an export starter, we use both a smaller trajectory and a longer one to define an export starter.

Shorter trajectory

An export starter is a firm that does not export for atleast one year, and then enters the export market and remains an exporter for atleast the next one year. Using this definition and the methodology discussed above, we find evidence for self-selection of more productive firms into exporting, but not for learning to export. We do not find evidence for learning by exporting, but export starters grow at a higher rate compared to matched counterfactuals.

Longer trajectory

An export starter is a firm that does not export for atleast three years, and then enters the export market and remains an exporter for atleast the next three years. Using this definition and the methodology discussed above, we find evindence for self-selection of better firms into exporting, but not for learning to export. Exporters grow more than non-exporters after entry, but do not experience a rise in productivity as compared to the counterfactuals.

This confirms that our main results are not driven by the selection of a specific sample of firms based on a strict definition of an export starter.

5.2 Alternative measures of productivity

The main results of the paper were based on productivity estimates calculated using the Levinsohn Petrin methodology. We use two single-factor productivity ratios to assess the robustness of our results.

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. Labour productivity corresponds to value added per worker hour. CMIE Prowess does not report the number of employees, and hence we use wage bill as a proxy for labour input. We calculate labour productivity as follows:

$$log(VA_{it}) - log(L_{it}) \tag{6}$$

where VA_{it} is the firm-level value added, computed as total industrial sales plus change in stock minus power and fuel expenditures, and raw material expenses; and L_{it} is the total wage bill.

We find evidence for self-selection of firms as reported in table 4 but not for learning to export. There are no gains in labour productivity after the firm enters export markets, however they do show substantially higher growth rates than their matched counterfactuals.

Capital productivity

Capital productivity is value-added per unit of capital input. We calculate it as follows:

$$log(VA_{it}) - log(K_{it}) \tag{7}$$

where K_{it} is the gross fixed assets of the company, and other definitions are the same as in equation 6. Using this productivity measure, we find evidence for self-selection, and also for learning to export. There is no evidence for post-entry gains in productivity, however export starters grow at a significantly higher rate as compared to their matched counterfactuals.

We also check the results with two other productivity measures: Cobb-douglas OLS residuals and the profit to sales ratio. We do not find evidence for learning to export with these measures, although there is evidence for self-selection. Learning by exporting is rejected. Export starters grow at a high rate.

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 8275 Indian manufacturing firms from 1994 to 2014, 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 two 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, we do not find evidence for a *conscious* increase in productivity before export market entry. Firms experience large growth after they begin to export, but rise in scale does not translate into higher productivity. Firms do not learn by exporting. However, 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).

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Appendix

Table 8 Export Statistics by Year

	$EXPDUM = 1$	$EXPDUM = 0$
1989	52.27	47.73
1990	51.72	48.28
1991	45.95	54.05
1992	54.55	45.45
1993	50.46	49.54
1994	45.15	54.85
1995	51.61	48.39
1996	53.92	46.08
1997	48.88	51.12
1998	46.07	53.93
1999	41.92	58.08
2000	53.15	46.85
2001	53.86	46.14
2002	54.38	45.62
2003	54.11	45.89
2004	54.09	45.91
2005	52.30	47.70
2006	52.90	47.10
2007	53.46	46.54
2008	53.73	46.27
2009	52.94	47.06
2010	51.25	48.75
2011	54.31	45.69
2012	60.02	39.98
2013	67.77	32.23
2014	87.10	12.90