Working Paper No. 02-2023

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Self-Selection versus Destination based Learning-by-Exporting: Firm Level Evidence from Pakistan

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Abstract: *This study examines the self-selection and the learning-by-exporting hypotheses to determine the direction of causality between firm's productivity and its export status for the textile manufacturers in Punjab, Pakistan. Using disaggregated product level data from the years 2000-2010, productivity is estimated based on the methodology by De Loecker et al. (2016). The study employes the Propensity Score Matching (PSM) and the Multivariate Distance Matching (MDM) techniques based on multiple matching algorithms. In line with the prediction of recent heterogeneous firm models of international trade, the main finding of the paper is that more productive firms become exporters, i.e., there is clear evidence of self-selection. This is mainly due to the large sunk costs associated with the liability of foreignness and a bigger risk cushion needed against uncertainties within the international market. However, the evidence for the learning-by-exporting hypothesis is less conclusive, indicating that exporting activities may not enhance productivity, unless the products are exported to high income economies. We also find evidence that firms exporting to high-income economies indulge in export sophistication as, in addition to the productivity enhancement, they improve on output quality, which is accompanied by capital accumulation and increased labor usage.*

Keywords: Self-selection, learning by exporting, export destination, firm productivity.

JEL Classification: B17, D22, F13, F14, O24.

First Printing: January, 2023

Funding: There is no funding for this research.

Compliance with ethical standards: The authors have complied with ethical standards.

Conflict of interest: The authors declare no conflict of interest.

Data availability statement: The data is available on request.

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1. Introduction

It is a well-documented fact that exporters outperform non-exporters. The exporting firms are more productive, larger in scale, more capital-intensive, and pay higher wages than non-exporting firms (De Loecker, 2007; Fernandes & Isgut, 2015; Wagner, 2016; Jamil et al., 2022). However, the direction of causality- productivity increases exports or exports enhance productivity- is still debatable within the trade-firm-productivity literature. The two hypotheses: *self-selection* versus *learning-by-exporting* are alternatives, but not mutually exclusive hypotheses on why exporters perform better than non-exporters.

According to the self-selection (SS) hypothesis, the more productive firms self-select into exporting, i.e., productivity leads to exports. Selling in international markets comes with additional costs. These additional costs usually involve transportation costs, distribution or marketing costs, hiring of employees with management skills to manage foreign networks, and the cost of production in modifying domestic products to meet the needs of the foreign market. These costs act as entry barriers which less successful firms cannot overcome (Haider, 2012). There are sunk costs[1] associated with exporting in the international markets. Only highly productive firms can afford to cover these costs and engage in foreign trade (Roberts & Tybout, 1997; Pisu, 2008; Hong, 2023). Furthermore, firms may face intense competition in foreign markets, where only the most productive firms can compete (Melitz, 2003).

Under the learning-by-exporting (LBE) hypothesis, export starters improve firm performance after export entry, i.e., exports lead to productivity gains. Knowledge flows from international buyers and competitors helps these new exporters improve their performance (Haider, 2012). Exporting provides relatively easy and quick access to technology and better

[1] Sunk costs may include, for example, acquiring information about the export market, identifying a sales agent, or establishing a distribution channel. These costs are significant and may only be borne by more productive and established firms (Roberts & Tybout, (1997); Melitz, (2003)).

management practices that are not yet available at home, allowing exporting firms to increase productivity (Pisu, 2008). Exporters can benefit from economies of scale and gain knowledge from greater exposure to foreign markets, which encourages learning (Farias & Martín-Marcos, 2007). Furthermore, exporting exposes these firms to more intense competition in foreign markets, forcing them to improve faster than non-exporters. As a result, exporting enhances firms' productivity. According to Verhoogen (2008), better quality standards and intense competition in the foreign market may encourage exporting firms to innovate, upgrade their production technology, and shift the skill composition of the workforce towards highly educated workers.

Thus, the former hypothesis means that "more efficient firms become exporters" while the latter concept states that "exporters become more efficient firms" (Wagner, 2007). According to the literature, the self-selection (SS) hypothesis appears to be more robust, especially for developing countries (Wagner, 2007; Gupta et al., 2019; Camino-Mogroa et al., 2023). However, for the learning-by-exporting (LBE) hypothesis, there is still lack of conclusive evidence.

LBE effects are important, not only from an academic perspective, but also from a policy standpoint. If LBE exists, then the government's aid for encouraging firms to engage in export activities should be justified by productivity gains in those firms and, eventually, other positive externalities generated by higher productivity growth[2] (Silva et al., 2012). If these effects do not exist, then the use of public funds becomes less viable[3].

One potential reason for the limited evidence of the LBE hypothesis could be the methodological way in which the export status has been treated, which is not adequate to conclude the causal effect of exporting on productivity. It was not until De Loecker (2007, 2013) and later De Loecker

[2] This is the economic logic behind the government spending millions of dollars in R&D subsidies and tax breaks. Many free trade agreements prohibit direct export subsidies. Nowadays, export state aid takes more subtle forms, such as making it easier to finance market research and participation in trade fairs, providing information about the export market and foreign customers, and so on (Pisu, 2008).

[3] This is not to suggest that this policy intervention will be completely unjustified. Exporters may generate positive externalities associated with factors other than high productivity growth, such as increased employment or innovation contributing to quality improvements rather than productivity improvements.

et al. (2016) argued that the past export status of the firm impacts its future productivity. Thus, the productivity law of motion is endogenous.

Furthermore, the most common method for examining the LBE effect has been to compare the performance of mutually exclusive groups, such as exporters and non-exporters. The problem is that not all exporters have the same level of international market engagement; while some devote significant resources to export activities, others only marginally export, with little opportunity for learning. The presence of marginally exporting firms in a group of exporters is likely to produce a downward bias in the effect of LBE. Additionally, learning has sharply diminishing returns, so well-established exporters are unlikely to learn from exporting activities. As a result, their inclusion in a group of exporters is likely to produce a downward bias in the LBE effect (Fernandes & Isgut, 2005).

Another possible explanation for the lack of evidence for the LBE hypothesis is that much of the literature has ignored the export market characteristics when examining the impact of exporting on firm performance. Export productivity gains, if they exist, are determined by the characteristics of the export destination. Export market selection is critical in influencing firms' productive capacity (Esaku, 2022).

In this study, we examine both the SS and LBE hypotheses for firms in Punjab, Pakistan. We specifically focus on the firms within the textile sector, which is Pakistan's largest export sector. The analysis is based on firm level panel dataset from the years 2000 to 2010. This data set is rich since it provides detailed information on output and prices that is disaggregated not only at the firm level but also at the product level. As a result, we have variation at the product, firm, and time level[4].

This paper aims to address the concerns regarding the LBE hypothesis. We address the methodological concern by estimating productivity based on the methodology developed by De Loecker et al. (2016). Their methodology considers the impact of the firm's export status and endogenizes the law of motion for productivity i.e., it allows for the law of motion to incorporate the impact of a firm’s past export status on its future productivity. Moreover, their methodology helps address other biases that are hardly accounted for in productivity literature. While

[4] Using product-level data allows us to completely eliminate the *omitted price bias*. As a result, we do not need to use sectoral deflators to deflate firm revenue.

disaggregated data allows them to correct for the *omitted output price bias*, their methodology also corrects for *unobserved input price bias* and *unobserved input allocation bias*. Additionally, their estimation of the production function is flexible since it makes no assumptions about the level of competition, consumer demand, or market structure.

We also address the limitation raised by Fernandes and Isgut (2005), by comparing new exporters to non-exporters in examining the LBE effects. Omitting the well-established exporters in the LBE analysis helps us omit the downward bias due to the existence of diminishing returns from exports. Furthermore, this study investigates the LBE effects based on export destination. According to the World Bank's classification, export destination countries are divided into four categories for this analysis: low-income economies, lower-middle income economies, upper-middle income economies, and high-income economies. We examine how the LBE may change based on which of the four categories of export destinations.

To examine the direction of causality between export status and productivity, we start by presenting the results from the fixed effects analysis, based on time, segment and segment-time fixed effects. As the main technique, the study uses the multivariate Mahalanobis Distance Matching approach along with the Propensity Score Matching approach based on kernel matching and nearest-neighbor matching between exporters and non-exporters. Additionally, we focus on additional firm-level outcomes besides productivity, including output quality and input usage. We estimate output quality based on the nested logit demand system model developed by Khandelwal (2010).

The rest of the paper is as follows. Section II provides a brief background of Pakistan's textile sector and Section III describes the empirical methodology. Section IV describes the data. Section V presents the main results from the SS and LBE hypotheses. Section VII concludes.

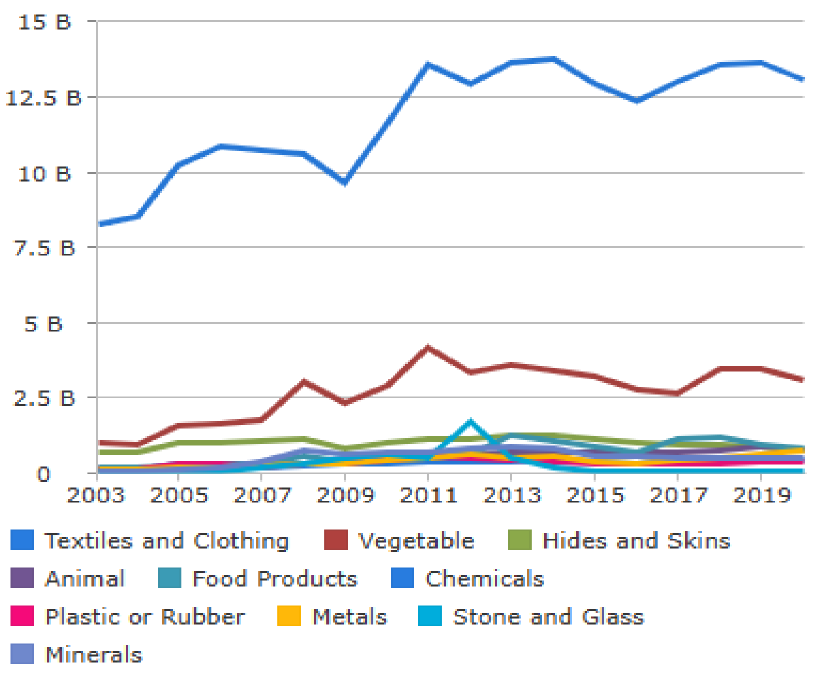
2. Pakistan's Textile Sector

The textile sector is the largest exporting sector of Pakistan. It accounts for roughly 46% of total output, or 8.5% of the country's GDP as of 2020. Pakistan is Asia's sixth largest exporter of textile products, employing 45% of the country's workforce. Cotton-based textiles account for approximately 60% of total exports and 46% of overall manufacturing.

The availability of cheap labor and basic cotton as a raw material for the textile industry has played a significant role in the expansion of Pakistan's Cotton Textile Industry (Kiron, 2022).

Figure 1 below shows Pakistan's top major exports for the year 2003-2020. Clearly, textile and clothing are the dominant export sector for Pakistan. Table 1 below shows that as of 2021, Pakistan is amongst the top 10 textile exporting countries of the world.

Figure 1: Pakistan's Top Export Sectors between 2003-2020 (US $000)



Data Source: World Integrated Trade Solution (WITS)- Country Profile

Table 1: Top Textile Exporters of the World as in 2021

Rank	*Exporter*	*Value of Export ($ Billions)*	*Growth Rate (2020-2021)*	*Market Share*
1	China	145.6	-5.5%	41.1%
2	European Union	73.6	13.7%	20.8%
3	India	22.2	47.8%	6.3%
4	Turkey	15.2	29.6%	4.3%
5	USA	13.1	15.3%	3.7%
6	Vietnam	11.5	17.1%	3.2%
7	Pakistan	9.2	29.2%	2.6%
8	South Korea	8.7	12.1%	2.5%
9	Taiwan	8.6	21.3%	2.4%
10	Japan	6.2	10.6%	1.8%

Data Source: World Trade Organization (WTO) as in Lu (2022)

Table 2 below shows the top major export destinations for textile exports for Pakistan for the year 2017-2018. With a market share of 2.4%, the United States is Pakistan's biggest destination for textile exports. Moreover, textile exports to the UK exceed $1 billion, with Pakistan having the largest market share in the UK as compared to other export destinations.

Table 2: Top 5 Textile Export Markets for Pakistan

Export Destination	*Export (Millions $)*	*Pakistan's Market Share*
USA	3,071	2.4%
UK	1,422	4%
Germany	1,094	1.9%
China	963	2.9%
Spain	803	3.2%

Data Source:Pakistan Bureau of Statistics

Despite being one of the world's top export textile countries, Pakistan's textile sector confronts major challenges. While the United States and Europe are Pakistan's primary customers, it faces strong competition from China, Bangladesh, and Vietnam in these regions. Bangladesh's Everything But Arms (EBA) status, for example, grants it zero-tariff access to the EU with no quotas. Furthermore, the textile sector in Pakistan is primarily reliant on cotton. It raises the risk because if the crop fails due to bad weather, the textile sector's productivity declines. Due to high tariffs, Pakistan also lacks access to higher-quality intermediate inputs such as man-made fiber. As a result, Pakistan is frequently unable to supply many of the high-demand products on the international market. Finally, Pakistan places less emphasis on value-added products, resulting in low earnings in international markets. In 2018, Pakistan exported more than $3 billion in raw cotton. Pakistan could have generated a lot more money by converting this cotton into readymade garments. Pakistani readymade garment's poor quality makes it less appealing to outside consumers, particularly in Europe and America (Mazhar, 2022). Given these challenges and potential opportunities, it is important to fully understand the performance of the textile exporters in the international market.

3. Empirical Methodology

We start this section by reviewing the methodology for the firm level productivity based on De Loecker et al. (2016) and output quality estimation by Khandelwal (2010) used in this analysis. We then discuss the estimation of the self-selection and learning-by-exporting hypothesis using the fixed effects approach. Next, we discuss the estimation of the self-selection and learning-by-exporting hypothesis based on the matching techniques.

3.1 Firm Level Productivity and Product Quality Estimation

3.1.1 Firm Level Productivity based on De Loecker et al. (2016)

We begin by estimating firm level productivity based on the methodology developed by De Loecker et al. (2016). This methodology works well when price and physical quantity information is available at the product level for multi-product firms, as it is with our data. One of the major contributions of this methodology is that, unlike traditional production function estimation approaches, it estimates the production function at the product level rather than the firm level. Additionally, this methodology has the advantage of estimating productivity without considering any parametric assumptions about consumer demand, market structure, or the nature of competition. As a result, this methodology enables the analysis to be conducted using product-level data without the requirement to explicitly assume a market demand function to aggregate output and prices at the firm level.

Using disaggregated price and physical output data at the product level, the estimation of the quantity-based production function helps control for any omitted output price bias that typically arises when the analysis relies on sectoral deflators. In this methodology, since disaggregated price and physical output data is used (as is available in our data set), there is no need for sectoral deflators. Additionally, this methodology addresses a number of other biases, typically ignored in literature. These biases include the *omitted input price bias* (mainly arising due to different variety/quality of inputs used by firms) and the *unobserved allocation of inputs* across multi-product firms (mainly arising due to data limitations where typically input expenditures are available at firm level rather than at the product level).

Based on De Loecker et al. (2016), we start by writing the production function for firm *f* producing product *j* at time *t* as:

$$Q_{fjt} = F_{jt}\left(V_{fjt}, K_{fjt}\right)\Omega_{ft} \tag{1}$$

where Q is the physical output, V is a vector of variables inputs which adjust freely and K is a vector of fixed inputs facing some adjustment cost. Ω_{ft} is the firm specific productivity.

Taking logs of the production function as in equation (1) gives:

$$q_{fjt} = f_j\,(\chi_{fjt}\,;\,\beta) + \omega_{ft} + \varepsilon_{fjt} \tag{2}$$

where $q_{fjt}$is the log of output which is a function of the vector χ_{fjt} which includes the log of physical inputs $\{V_{fjt}, K_{fjt}\}$. *β* represents the respective coefficients while ω_{ft} is the log of productivity. ε_{fjt} is the with idiosyncratic error. Denoting $\widetilde{\chi_{ft}}$ as the observed vector of price index-deflated input expenditures, the product-level input quantities $\chi_{fjt}$for each input are then given as:

$$\chi_{fjt} = \rho_{fjt} + \widetilde{\chi_{ft}} - w_{fjt}^{x} \tag{3}$$

where ρ_{fjt} is the share of firm input expenditures (in logs) allocated to product *j* at time *t*. w_{fjt}^{x} is the deviation of the unobserved firm-specific input prices from the industry-wide input price index (in logs). Substituting this expression of physical inputs (3) into equation (2) and denoting w_{fjt} as a vector of log firm product specific input price gives:

$$(q_{fjt} = f_j\widetilde{\chi_{ft}};\,\beta) + A(\,\rho_{fjt}, \widetilde{\chi_{ft}}, \beta) + B\left(w_{fjt}, \rho_{fjt}, \widetilde{\chi_{ft}}, \beta\right) + \omega_{ft} + \varepsilon_{fjt} \tag{4}$$

Comparing equation (2) to equation (4), there are now two additional unobserved terms:

A(.) represents the *input allocation bias* which is due to the presence of the unobserved product-level input allocation ρ_{fjt}, while *B(.)* represents the *input price bias* which arises from unobserved firm-specific input prices w_{fjt} .

De Loecker et al. (2016) relies on the data from the single product firms to estimate the product-level production function. Using single product firms means that the term $A(.)= 0$ as $\rho_{fjt} = 1$ by definition. The model by De Loecker et al. (2016) assumes that if the *physical* relation between input-output is the same for both the single and multi-product firms which produce the same product, and that the technology used in the manufacturing of product *j* is independent of other products produced by the firm, in that case the input-output relationship from single-product firms can help in approximating the input allocations for multi-product firms.[5]

Using single-product firms only (with $A(.)=0$), equation (4) then can be re-written as:

$$q_{fjt} = f_j\,(\widetilde{\chi_{ft}};\,\beta) + B\left(w_{fjt}, \rho_{fjt}, \widetilde{\chi_{ft}}, \beta\right) + \omega_{ft} + \varepsilon_{fjt} \tag{5}$$

In order to solve the problem from the omitted input price bias in *B(.)* as in equation (5), this methodology uses information from the product level output data as proxy for input prices. The main idea is that high quality inputs are needed to manufacture high quality output. Therefore, output prices reflect the quality of inputs and thus, contain information regarding input prices. Assuming that input prices increasing monotonically in input quality, this methodology uses output prices, market share and product dummies to proxy for input prices. Therefore, input prices w_{fjt}^{x} are written as a function of output quality v_{ft} and firm location G_f as:

$$w_{fjt}^{x} = w_t\,(v_{ft}, G_f) \tag{6}$$

[5] To illustrate this with an example, this methodology assumes that a firm which only produces motorcycles will use the same technology as a firm which produces both motorcycles and cars.

where output quality v_{ft} is estimated based on output price of the firm p_{ft}, vector of market share ms_{ft}, vector of product dummies $D_{f,}$, and export status of the firm EXP_{ft}. Hence equation (6) can be written as:

$$w_{fjt}^{x} = w_t\,(p_{ft}, ms_{ft}, D_{f,} EXP_{ft}, G_f) \tag{7}$$

As a next step, the GMM estimation procedure is applied to solve for the production function estimates. Once these estimates are obtained, they are used to solve for the input allocation across multi-product firms by simultaneously solving a system of $J_{ft} + 1$ equations for each multi-product firm (where J_{ft} is the number of products produced by firm *f* in time *t*). This then helps to back out firm level productivity.

Additionally, this methodology also applies a selection-correction procedure, since firms self-select into being a multi-product firms based on their productivity and input set. This introduces a self-selection bias in the sample, which is corrected by a correction procedure. The correction procedure is based on a probability estimation of the firm being a multi-product firm, based its own productivity threshold and information set.

3.1.2 Output Quality based on Khandelwal (2010)

We use the methodology by Khandelwal (2010) to estimate output quality. This methodology is based on nested logit demand system which allows for both preferences of both horizontal and vertical attributes. The methodology assumes that the quality is a vertical component of the model which represent the mean value a typical consumer attaches to the product. Therefore, it is essential to incorporate product differences at the horizontal level, as expensive imported products may co-exist in the market at the same time with cheap rivals, where price might not be an appropriate proxy for quality.

In the model, a typical consumer *n*'s preferences are based on assuming that she purchases that variety of the product *ch* within product *h* at time *t* to maximize her utility. Therefore, the demand curve of a typical consumer can be represented as:

$$ln(s_{cht}) - ln\,(s_{ot}) = \lambda_{1,ch} + \lambda_{2,t} + \alpha p_{cht} + \sigma ln\,(ns_{cht}) + \lambda_{3,cht} \tag{8}$$

where $\ln(s_{cht})$ is the log of variety *ch's* overall market share and $ns_{cht}$is its market share within product *h* (nest share). ln (s_{ot}) is the log of the outside option's market share. p_{cht} is the price of the variety *ch* at time *t*.

Quality is defined as $\lambda_{1,ch} + \lambda_{2,t} + \lambda_{3,cht}$ which reflects a valuation of variety *ch* common across all consumers[6]. Thus, the quality term is decomposed into three main elements: $\lambda_{1,ch}$ the time invariant valuations that the consumer attaches to variety *ch* reflecting variety fixed-effects; $\lambda_{2,t}$ captures time trends across all varieties represented by the time fixed-effects; and $\lambda_{3,cht}$ a variety-time deviation observed by the consumer (and not by the econometrician) that plays the role of the estimation error. The quality of variety *ch* is then computed as[7]:

$$\lambda_{cht} = \hat{\lambda}_{1,ch} + \hat{\lambda}_{2,t} + \hat{\lambda}_{3,cht} \tag{9}$$

3.2 Fixed Effects Approach

For the first set of results, for both the self-selection (SS) and learning-by-exporting (LBE) hypothesis, we present the results using the fixed effects estimation described below.

For the self- selection (SS) hypothesis, we estimate the impact of exporting on firm level outcomes for firm *i* at time *t* as shown in equation (10):

$$Y_{it} = \beta_0 + \beta_1 Exp_{it} + \beta_z X_{it} + \alpha_t + \alpha_s + \alpha_{st} + \varepsilon_{it} \tag{10}$$

Y_{it} includes the log of firm level outcomes like productivity, product quality and input usage for firm *i* at time *t*[8]. Exp_{it} is a dummy variable which takes a value of 1 if firm *i* exports at time *t* and 0 otherwise. X_{it} are firm level controls including product dummies, number of products and missing year dummies. *β's* are the regression parameters. α_t are the time fixed effects, α_s are the segment fixed effects and α_{st} are the segment-time fixed effects. We divide the textile sector into five segments (clothing,

[6] There is no subscript *n* in these terms since it represents common valuation across all consumers.
[7] For our study, we aggregate the quality at the firm level by using product revenue shares as weights.
[8] Firm productivity and quality are measured as described in section 2.1, while the inputs are directly observed from the data set.

interior, spinning, technical and finishing) based on De Loecker (2011). ε_{it} is the error term.

For the learning by exporting (LBE) hypothesis, only the new-export entrants and the non-exporters are considered as done in literature (Pisu ,2008; Yang & Mallick, 2010). Therefore, for the LBE hypothesis we need to observe the same firm for at least 2 time periods. We modify equation (10) in order to estimate the fixed effects equation (11) for the LBE hypothesis as:

$$Y_{it} = \beta_0 + \beta_1 NewExp_{it} + \beta_z X_{it} + \alpha_t + \alpha_s + \alpha_{st} + \varepsilon_{it} \qquad (11)$$

where instead of Exp_{it}, the variable of interest is now $NewExp_{it}$, which is a dummy which takes a value of 1 if firm *i* is a new entrant in the export market at time *t* and is 0 if it remains a non-exporter.

In order to further study the impact of the LBE according to export destination, we modify equation (11) based on the export destination of the new export entrant. Therefore, we rewrite equation (11) as:

$$Y_{it} = \beta_0 + \beta_1 Low_{it} + \beta_2 LowMiddle_{it} + \beta_3 UpperMiddle_{it} + \beta_4 High_{it} + \beta_z X_{it} + \alpha_t + \alpha_s + \alpha_{st} + \varepsilon_{it} \qquad (12)$$

where Low_{it} is a dummy which takes a value of 1 if firm *i* is a new entrant in the export market classified as a low-income country by the World Bank at time *t* and is 0 otherwise. $LowMiddle_{it}$ is a dummy which takes a value of 1 if firm *i* is a new entrant in the export market classified as a low-middle income country by the World Bank at time *t* and is 0 otherwise. $UpperMiddle_{it}$ is a dummy which takes a value of 1 if firm *i* is a new entrant in the export market classified as a upper-middle income country by the World Bank at time *t* and is 0 otherwise. $High_{it}$ is a dummy which takes a value of 1 if firm *i* is a new entrant in the export market classified as a high-income country by the World Bank at time *t* and is 0 otherwise.

3.3 Matching Approach

In addition to the fixed effects approach, the study uses matching techniques to examine the SS and LBE hypothesis. The matching techniques are based on matching the treatment group with the control group "conditional on X_{it}". The basic idea behind matching is that for each observation in the treated group, a "statistical twin" is found in the control group with similar X_{it} covariates. Next, the Y_{it} values of these matching observations are used to compute a counterfactual outcome without treatment for the observation in hand. Finally, an estimate for the average treatment effect on treated (ATT) can be estimated as the mean difference between the observed values and the "imputed" counterfactual values over all observations.

Based on the matching, we then test for the SS hypothesis by estimating the Average Treatment on the Treated (ATT). The treatment group in this case is defined by the export status. For the treated group $T = 1$ which implies $Exp_{it} = 1$, where T is the treatment variable. For the control group, $T = 0$ which implies $Exp_{it} = 0$. More formally, the average treatment effect on treated (ATT) is given as:

$$\widehat{ATT} = \frac{1}{N^{T=1}} \sum_{i|T=1} [Y_{it} - \widehat{Y_{it}^0}] \quad \text{where } \widehat{Y_{it}^0} = \sum_{j|T=0} w_{ijt} Y_{jt} \tag{13}$$

where T is the treatment variable (Exp_{it} status of firm in our case which can take a value of 0 or 1). Y_{it} as before are the firm level outcomes for firm i at time t while Y_{it}^0 are the potential firm outcome without the treatment.

For the LBE hypothesis, we report the Average Treatment on the Treated (ATT) as in equation (13) but in this case our treatment is 1 if the firm begins exporting i.e., is a new exporter. Thus, in this case for the treated group $T = 1$ which implies $NewExp_{it} = 1$, where T is the treatment variable. For the control group, $T = 0$ which implies $NewExp_{it} = 0$.

Similarly, for the LBE based on export destination, equation (13) is run four times for each export destination. For firms exporting to low-income countries, treatment group $T = 1$ implies $Low_{it} = 1$. For the control group, $T = 0$ which implies $Low_{it} = 0$. For firms exporting to low-middle income countries, treatment group $T = 1$ implies $LowMiddle_{it} = 1$. For the control group, $T = 0$ which implies $LowMiddle_{it} = 0$. For firms exporting to upper-middle income countries, treatment group $T = 1$ implies $UpperMiddle_{it} = 1$. For the control group, $T = 0$ which implies $UpperMiddle_{it} = 0$. Similarly, for firms exporting to high income countries, treatment group $T = 1$ implies $High_{it} = 1$. For the control group, $T = 0$ which implies $High_{it} = 0$.

The exact matching is based on:

$$w_{ijt} = \begin{cases} 1/k_{it} & if \quad X_{it} = X_{jt} \\ 0 & Else \end{cases}$$

k_{it} are the number of observations for which matching takes place for firm *i* at time t with firm *j* at the t i.e., when $X_{it} = X_{jt}$. The result of this matching is equivalent to "sub-classification" or "perfect stratification" [9].

3.3.1 Matching Techniques

We use two matching techniques in this study, the Propensity Score Matching (PSM) and the Multivariate Distance Matching (MDM). We discuss both of these techniques below.

- *Propensity Score Matching (PSM)*

Rosenbaum and Rubin (1983) proposed the Propensity Score Matching (PSM) technique, which matches treated and non-treated firms solely based on their propensity scores. The PSM technique is based on the following:

$(Y_{it}^0, Y_{it}^1) \perp\!\!\!\perp T \mid X_{it}$ which implies $(Y_{it}^0, Y_{it}^1) \perp\!\!\!\perp T \mid \pi(X_{it})$

Defining $\pi(X_{it})$ as the propensity score (treatment probability conditional on the covariates X_{it}), the PSM technique assumes that individuals or firms with the same value of $\pi(X_{it})$ will also have the same distribution of covariates X_{it}. Hence, as a result of the matching on propensity scores, the distribution of covariates X_{it} in the treated and control groups will be balanced, where Y_{it}^1 are the potential firm outcome with the treatment while Y_{it}^0 are the potential firm outcome without the treatment. The PSM simplifies the task as the matching is done on a single-dimensional $\pi(X_{it})$ instead of multi-dimensional X_{it}.

The PSM technique has two main steps. In the first step the propensity score $\pi(X_{it})$ is estimated for each observation using for example the logit model conditional on covariates X_{it} . In the second step a matching

[9] Refer to Cochran (1968).

algorithm is applied to match the observations using the difference in the propensity scores, $|\ \hat{\pi}(X_{it}) - \ \hat{\pi}\ (X_{jt})|$ instead of multivariate distances.

The PSM technique, however, has some drawbacks. Firstly, exact matching is unlikely, and secondly, the functional form of $\pi(X_{it})$ is rarely known[10].

- *Multivariate Distance Matching (MDM)*

Due to the limitations of the PSM, we also employ the alternate approach based on the Multivariate Distance Matching (MDM). In this approach, the matching is based on a distance metrics that measures the proximity between the observations in the multivariate space of X_{it}. This implies using observations which are close to each other, but not necessarily equal as matches.

The common approach uses the following as a distance metrics:

$$MD\big(X_{it}, X_{jt}\big) = \sqrt{(X_{it} - X_{jt})'\Sigma^{-1}(X_{it} - X_{jt})}$$

where $\mathbf{\Sigma}$ is an appropriate scaling matrix. In our cases, using the Mahalanobis matching, $\mathbf{\Sigma}$ is a covariance matrix of X_{it}. The Mahalanobis matching is equivalent to Euclidean matching based on standardized and orthogonalized *X*.

- *Matching Algorithms for PSM and MDM*

There are various matching algorithms which can be used to find the potential matches based on $\pi(X_{it})$ or MD and to determine the matching weights w_{ijt}. We use the following:

- *Kernel Matching: Similar to radius matching (which all controls with a distance smaller than some threshold c), but employs a kernel function, like the Epanechnikov kernel, to give controls with shorter distances more weight.*

[10] Wanger (2002) was the first to use the PSM technique in the context of a firm. This technique is used in the study to investigate the causal effect of a firm's export status on its size and labor productivity.

- *Nearest-Neighbors matching (with replacement): Find the k closest observations from the control group for each observation in the treatment group. A control can be applied more than once. Use all ties as matches in the event of a tie. The researcher sets k. In our study, we set k=1 and k=5, respectively.*

- *Pair matching (one-to-one matching with replacement): For each observation in the treatment group find the closest observation in the control group. Each control can be used more than once.*

We present the results from the Kernel Matching as our main matching results using both the PSM and MD approach. Results from nearest-neighbor matching (based on 1 and 5 neighbors respectively) and pair matching with replacement using the MD approach are also presented. Additionally, we also present results based on different cross validation criteria for bandwidth selection under the MD approach.

- *Comparison of the MD and PSM matching technique*

According to King and Nielsen (2019), the Propensity Score Matching (PSM), while being an extremely popular technique for preparing data for causal inference, frequently does the opposite of what it sets out to do, leading to an increase in bias, model dependency, imbalance, and inefficiency. In experimental language, the inadequacy of PSM stems from its attempts to approximate based on complete randomization as opposed to a more effective fully blocked randomised experiment as done by other matching techniques including the Multivariate Distance (MD) approach. A fully blocked design is more efficient, as it leads to fewer data imbalances and less model dependence. Therefore, according to King and Nielsen (2019), the MD approach dominates the PSM approach.

4. Data Set

4.1 Census of Manufacturing Industries (CMI) Punjab, Pakistan

We use the Census of Manufacturing Industries (CMI), a firm-level census undertaken by the Punjab Bureau of Statistics, Pakistan. It is a detailed firm level survey conducted every five years. The survey includes detailed modules regarding the firm's revenues, sales, and input usage, including various capital stock measures, labor expenses, and energy utilization. Using three waves of the CMI for the years 2000, 2005 and 2010 for firms in Punjab, Pakistan, we developed an unbalanced panel data set. This data set, unlike most of the micro data sets, has an advantage of reporting disaggregated output price and quantity information, not only at the firm level but also at the product level. This means, that for every product *j* produced by firm *f* at time *t*, we have information regarding the output price and quantity. Therefore, this gives us three variations in the data set; at the product, firm and time level. This improves our estimation since observing the actual product level quantity, as opposed to relying on sectoral deflators, helps our analysis be free from omitted output price bias.

Since our focus is on the textile sector within Pakistan, we present the firm level stats for textile manufacturers for the three waves of the CMI (years 2000, 2005 and 2010) in table 3[11]. We can clearly see that the exporters are much bigger in terms of inputs (a proxy for firm size) as compared to the non-exporters in all years.

Table 3: Textile Firm Summary Stats based on CMI

	Capital (PKR)		*Labor*		*Materials (PKR)*		*Number of Firms*	
CMI Year	**Exporters**	**Non-Exporters**	**Exporters**	**Non-Exporters**	**Exporters**	**Non-Exporters**	**Exporters**	**Non-Exporters**
2000	362,840	217,971	445	161	364,714	155,008	90	433
2005	506,279	276,705	456	252	413,323	180,341	108	366
2010	654,148	325,222	475	266	1,410,323	193,270	147	378

4.2 Export Transactions Database

We use the export transaction database to identify the export status of each firm (including if the firm is an export entrant), along with the export destinations. This data set contains detailed information on each textile firm's export shipments from Pakistan from 2000 to 2011. It includes information about the export destination, shipping date, shipment product code, and shipment value for each export transaction. We merge this database with the CMI to identify the export status of each firm, which is then use to categories them into exporters and non-exporters, as presented in table 3.

For testing the self-selection (SS) hypothesis, we take the entire CMI sample for the analysis. However, as mentioned earlier, we only use the

[11] Capital and Materials are reported in Pakistani Rupee (PKR). 1 PKR equals to approximately $0.0035 as in the year 2023. Labor represents the number of workers hired by the firm.

new-export entrants and non-exporters for the learning-by-exporting (LBE) hypothesis. For this, we need to observe the firms for at least two time periods, so we focus on the CMI waves for the year 2005 and 2010 only, where the new-export entrants are identified using the Export Transaction Database[12]. This narrows down the sample for the LBE hypothesis as presented in table 4.

Table 4: Number of Firms Identified for the LBE hypothesis

CMI year	***2005***	***2010***
Total Firms (new exporters plus non-exporters)	305	253
New Exporters	44	26

Finally, in order to study the LBE hypothesis based on the export destination, we identify the export destination for new exporters using the Export Transaction database. The export destinations are categorized as low-income, low-middle income, upper-middle income, and high-income countries as identified by the World Bank. Table 5 below reports the export destination of these new export entrants.

Table 5: % of New Exporters according to export destination

CMI year	***2005***	***2010***
Low	27.2%	15.4%
Lower-Middle	36.4%	61.5%
Upper-Middle	66%	50.1%
High	53%	19.2%

5. Results and Discussion

5.1 Self- Selection (SS) Hypothesis

We start examining the SS hypothesis by discussing our results from the fixed effects specification as in equation (10). Table 6 shows the results for this specification. We examine the impact of the export status Exp_{it} on firm productivity, output quality and input usage. These specifications control for time, segment, and segment-time fixed effects.

[12] Since the Export Transaction data set starts from the year 2000, we cannot identify which firms are new exporters versus established exporters for the CMI year 2000. Hence, we exclude the year 2000 from our LBE analysis.

Table 6: Self Selection Hypothesis (Fixed Effects Approach)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	***Quality***	***Capital***	***Material***	***Labor***
Exp_{it}	0.0927***	0.0669***	1.073***	1.077***	0.827***
	(0.0274)	(0.0081)	(0.1333)	(0.1146)	(0.0952)

N = 1177
Robust Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Controls: product dummies, time FE, segment FE, segment-time FE, missing base dummies, number of products.
Since the dependent variable in all specifications is in log form, the effect is estimated as e^{β}-1.

Results show clear evidence of self-selection. Exporters tend to have a 10 percent higher productivity than non-exporters. Additionally, exporters tend to have a 7 percent higher output quality as compared to non-exporters. The input usage amongst the exporters is also higher and significant as compared to the non-exporters. This suggests that the exporting firms are much bigger in size as compared to the non-exporting firms.

We next examine the results from the matching approach. For this, as the initial step, we start by analyzing the quality of our matching. It is critical for the purpose of this study to establish that the treatment and control groups share substantial overlapping firm characteristics. This assures that a matching based on vector X results in an adequate "like-for-like" comparison. One simple way to evaluate the strength of our matching is to look for overlap in the propensity scores of firms in the treatment and control groups. This allows us to determine the magnitude of the differences between these two groups after conditioning on the propensity scores. A good match will be apparent when the equality of the defined firm characteristics is not significantly different, and the treated and control groups have similar characteristics. Figure 2 shows the visual representation of our matching. The first figure shows the matching as a distribution, whereas the second figure shows the matching as a boxplot. We can clearly see substantial overlapping in the treatment and control group propensity scores after matching. This depicts that most covariates between the treated and the control group after kernel matching are similar.

Results from the matching are presented in table 7. Panel A of table 7 presents the results from the Mahalanobis-Distance Kernel Matching, while panel B presents the results from the Propensity Score Kernel Matching.

Table 7: Self Selection Hypothesis (Matching Techniques)

Panel A: Mahalanobis-Distance Kernel Matching					
	(1)	***(2)***	***(3)***	***(4)***	***(5)***
	Productivity	***Quality***	***Capital***	***Material***	***Labor***
Exp_{it}	0.0961***	0.0912***	1.259***	1.167***	0.938***
	(0.0303)	(0.0103)	(0.126)	(0.126)	(0.103)
Panel B: Propensity Score Kernel Matching					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
Exp_{it}	0.0866***	0.0812***	1.219***	1.159***	0.915***
	(0.0238)	(0.00920)	(0.133)	(0.129)	(0.0790)

The results represent the Average Treatment Effect on Treated (ATT). Treatment is equal to 1 if the firm is an exporter.
N = 1177
Standard errors (computed through bootstrapping) in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01
Controls: product dummies, time FE, segment FE, segment-time FE, missing base dummies, number of products.
Since the dependent variable in all specifications is in log form, the effect is estimated as e^β-1 .

Our results from the matching technique are in line with the results from the fixed effects approach. Exporting firms are around 10 percent more productive as compared to non-exporters. Similarly, exporters manufacture better quality output as compared to the non-exporters and are much larger in size (as measured by the input usage). Additionally, in table 8, we try different matching algorithms within the Mahalanobis-Distance Kernel Matching approach to check the robustness of our results. Irrespective of whichever algorithm we use, we find evidence of bigger, more productive, and better output quality manufacturing firms self-selecting into exporting.

There are various reasons why more productive and larger firms self-select to export, as in our case. Roberts and Tybout (1997), who are the pioneers in the work on analyzing the *pre-entry* performance of firms in the export market, suggest that exporting is costly and hence, firms must pay the sunk costs in addition to other variable production costs. These sunk costs may be related to the establishment of distribution channels, market demand and customer preferences research, and upgrading product quality to international standards, amongst other things. These costs are significant and may not be recovered even if the firm decides not to enter export markets; as such, they can only be borne by large and productive firms.

Ahn and Mcquoid (2012) suggest that exporters can respond to market demand shocks and lessen aggregate output volatility due to their financial and physical capacity. Accessing and providing services for export markets is complicated and expensive. The expenses associated with entering foreign markets include learning about the local market and identifying target markets, customizing products and services, adhering to regulations, transportation, local distribution, managing the credit risks associated with international trade (trade debt risks and higher working capital requirements), and managing the uncertainty surrounding realizable profit margins due to exchange rate fluctuations and potential payment delays (Wilson et al., 2022). These expenses, demand shocks and the capacity to adhere to market and financial uncertainty can only be borne by larger firms, which then self-select into exporting, as in our case.

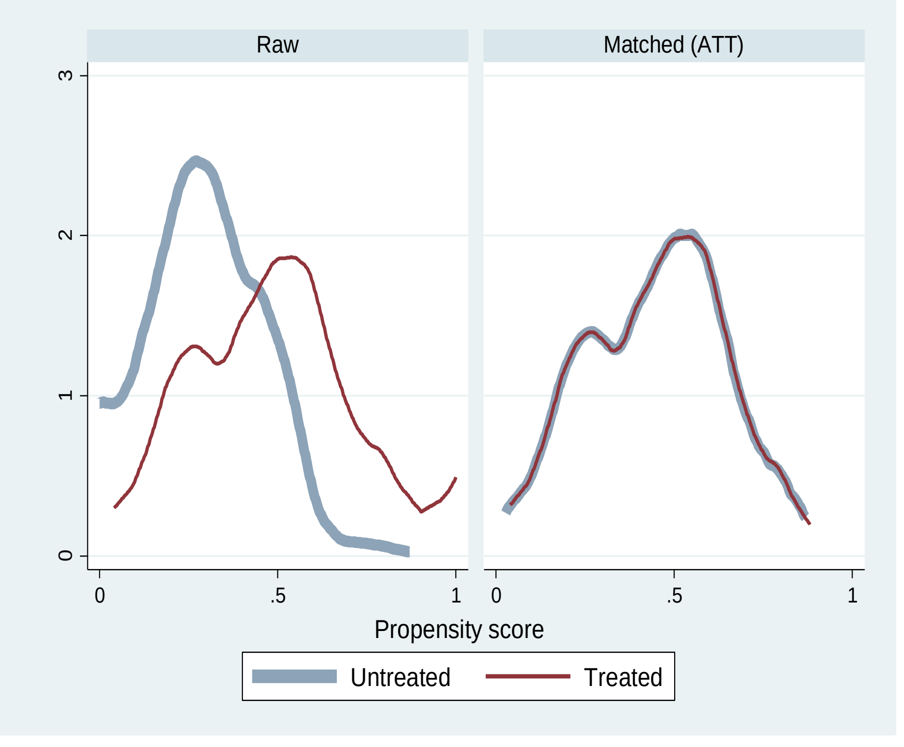


Figure 2: Visual representation of the propensity scores of matched firms (treatment and control group) in the ATT analysis for self-selection hypothesis.

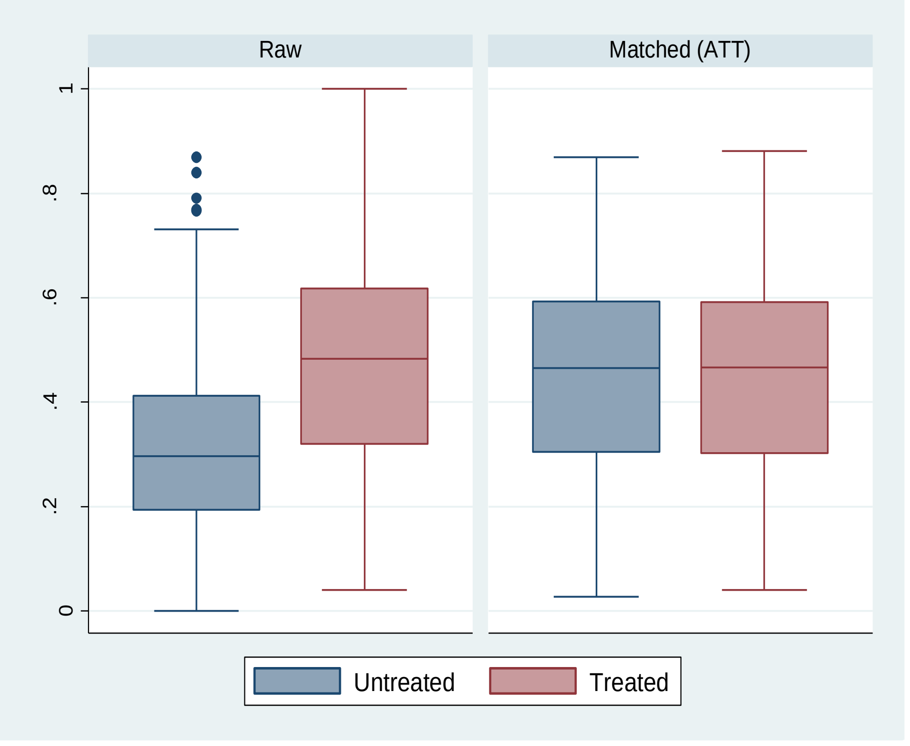


Table 8: Self-Selection Hypothesis: Mahalanobis-Distance Kernel Matching based on different matching techniques

Panel A: Nearest Neighbor Matching (1 Neighbor)					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
Exp_{it}	0.1458***	0.0697***	1.0702***	1.1278***	0.8276***
	(0.0343)	(0.0086)	(0.1430)	(0.1438)	(0.1083)
Panel B: Nearest Neighbor Matching (5 Neighbor)					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
Exp_{it}	0.1228***	0.0755***	1.1003***	1.0773***	0.8675***
	(0.0352)	(0.0094)	(0.1305)	(0.1421)	(0.1246)
Panel C: Pair Matching with replacement (Huber et al. 2013, 2015)					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
Exp_{it}	0.0961***	0.0912***	1.2588***	1.1668***	0.9378***
	(0.0278)	(0.0103)	(0.1564)	(0.1324)	(0.1154)
Panel D: Cross Validation with respect to the mean of X					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
Exp_{it}	0.0999***	0.0923***	1.2247***	1.1247***	0.9197***
	(0.0339)	(0.0104)	(0.1577)	(0.1297)	(0.0995)
Panel E: Cross Validation with respect to Y (Frolich, 2004, 2005)					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
Exp_{it}	0.1001***	0.0911***	0.9976***	1.1779***	0.7761***
	(0.0293)	(0.0096)	(0.1600)	(0.1423)	(0.0991)
Panel F: Weighted Cross Validation with respect to Y (Galdo et al., 2008)					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
Exp_{it}	0.0722**	0.0910***	1.2633***	1.1692***	0.9301***
	(0.0333)	(0.0099)	(0.1505)	(0.1066)	(0.1285)

The results represent the Average Treatment on Treated (ATT) effect.
N = 1177
Standard errors (computed through bootstrapping) in parentheses.
* p<0.10, ** p<0.05, *** p<0.01
Controls: product dummies, time FE, segment FE, segment-time FE, missing base dummies, number of products.
Since the dependent variable in all specifications is in log form, the effect is estimated as e^{β}-1.

Exporting firms face greater challenges and uncertainty, which is summarized in the phrase “liability of foreignness” (Eden & Miller, 2004). Firms must have sufficient resources to develop relevant competencies to achieve international sales and face the liability of foreignness in order to deal with these challenges. Tseng et al. (2007) argue that foreign expansion necessarily requires more resources to cushion the costs and risks associated with the required managerial complexity and liability of foreignness. Therefore, only those firms that can bear these costs and have the capacity to serve the global market are likely to enter export markets.

This holds true in our context as well. The textile sector is the biggest exporting sector in Pakistan. Yet, many firms, even within this sector, do not export. Our analysis supports the idea that the bigger firms (with more inputs) tend to self-select into exporting, as they are “big” enough to incur these sunk costs of entering the export market. Our results suggest that since these firms have higher inputs as compared to non-exporters, they are in a better position to bear these sunk costs as well as encounter the challenges that come with the liability of foreignness. Since these firms are larger and more productive, they have more resources to provide a cushion associated with the risk of exporting. Our result is in line with the work of Rho and Rodrigue (2016), who suggest large firms export, since they have sufficient firm-level investments in physical capital which can help reduce their exposure to demand disturbances across markets as they have sufficient capacity to respond to these demand shocks.

Our results are also in line with the standard models of modern trade theory, including the work by Melitz (2003) and Helpman et al. (2004) who suggest that firms are heterogeneous and that the most productive ones self-select to export. Melitz and Redding (2015) support the result that the change in the overall productivity is due to firm selection. Caldera (2009) building on the work by Melitz (2003), concludes that innovative firms have the ability to charge a lower price due to a lower marginal cost of production. The study implies that exporting firms are more productive, have lower production costs, and are thus more competitive in foreign markets. They argue that firms increase productivity through process innovation while remaining competitive and increasing market share through the introduction of new or significantly improved products. This encourages them to export. Our results support the work by Caldera (2009), as our results suggest that more productive firms enter the export market. Additionally, in one of our companion papers, we show that textile firms exporting to China indulge in "dynamic pricing" in order to compete with other countries and to increase their market share within the Chinese market. These firms are able to charge lower prices since these firms are productive and have a lower marginal cost (in addition to being big in size). Therefore, the exporting firms are in a better position to compete in the foreign market and to offer lower prices (Jamil et al., 2023).

Moreover, our results suggest, that more productive firms are in a better position to compete in the international market, not just due to their higher productivity and bigger size, but also due to their ability to produce significantly better-quality products. In another companion paper of ours, we show that for these textile firms, productivity and output quality are complements. In simple words, more productive exporters tend to manufacture better quality products (Jamil et al., 2022). Therefore, this enables these firms to compete in the foreign market to gain market share, not just through price competition but also through quality competition.

5.2 Learning by Exporting (LBE) Hypothesis

We examine the LBE hypothesis by estimating the learning effects on new exporters as compared to non-exporters. Table 9 presents the results from the fixed effects equation as in (11).

Table 9: Learning by Exporting Hypothesis (Fixed Effects Approach)

	(1)	***(2)***	***(3)***	***(4)***	***(5)***
	Productivity	***Quality***	***Capital***	***Material***	***Labor***
$NewExp_{it}$	0.1152	0.0129	0.0301	0.3688**	-0.1176
	(0.0795)	(0.0098)	(0.1527)	(0.1493)	(0.1069)

N = 558
Robust Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Controls: product dummies, time FE, segment FE, segment-time FE, missing base dummies, number of products.
Since the dependent variable in all specifications is in log form, the effect is given as e^{β}-1.

Using the fixed effects analysis, we can clearly see that there is no evidence of learning by exporting (LBE). We do not find evidence of new exporters improving their productivity or output quality as they enter into the international market. We do not find any significant investment in capital or labor. However, according to the fixed effects analysis, we find evidence that the new exporters are using more martials as they enter the global market.

Next, we examine the LBE hypothesis using the matching technique. Figure 3 shows the matching between the treatment and the control group. The first figure depicts the matching as a distribution, while the second depicts it as a box plot. After matching, we can clearly see overlapping in the treatment and control group propensity scores. This shows that after kernel matching, most covariates in the treated and control groups are similar.

Table 10 represents the results from the equation (13) based on the matching technique, where now the treatment is equal to 1 if the firm begins exporting i.e., is a new exporter. Thus, in this case for the treated group $T = 1$ which implies $NewExp_{it} = 1$, where T is the treatment variable. For the control group, $T = 0$ which implies $NewExp_{it} = 0$. Panel A of table 10 presents the results from the Mahalanobis-Distance Kernel Matching, while panel B presents the results from the Propensity Score Kernel Matching.

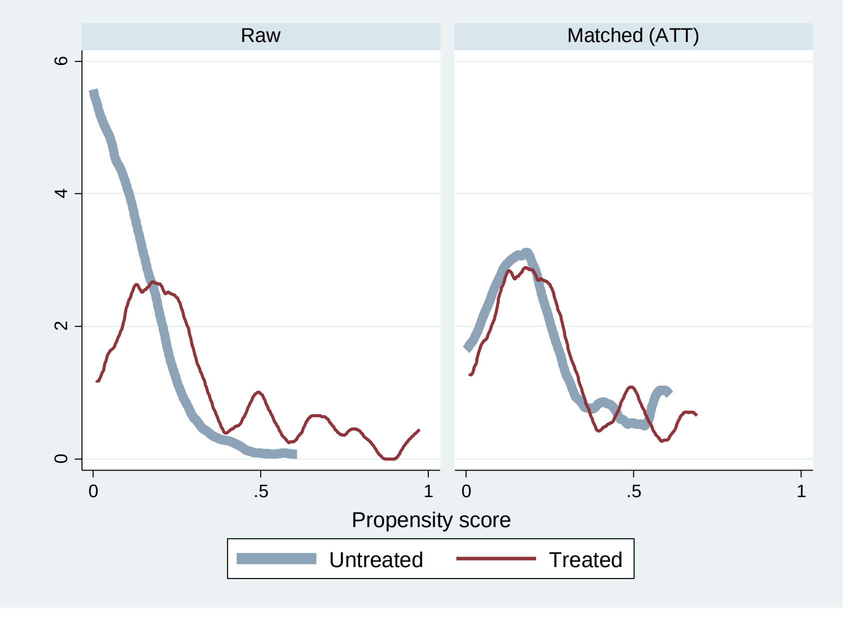
Table 10: Learning-by-Exporting Hypothesis (Matching Techniques)

Panel A: Mahalanobis-Distance Kernel Matching					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
	0.1044	0.0180	0.0900	0.3301	-0.0780
$NewExp_{it}$	(0.0904)	(0.0154)	(0.2586)	(0.2799)	(0.1974)
Panel B: Propensity Score Kernel Matching					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
$NewExp_{it}$	0.0972	0.0046	0.1947	0.5209*	0.0334
	(0.0793)	(0.0095)	(0.325`)	(0.2676)	(0.2102)

The results represent the Average Treatment on Treated (ATT) effect
N=558
Standard errors (computed through bootstrapping) in parentheses.
* p<0.10, ** p<0.05, *** p<0.01
Controls: product dummies, time FE, segment FE, segment-time FE, missing base dummies, number of products.
Since the dependent variable in all specifications is in log form, the effect is given as e^{β}-1.

Based on the matching approach, we find that new exporters do not have significant efficiency gains via any changes in productivity and quality once they enter the international market. We do, however, find evidence that these new firms use more material (only significant in the propensity score matching) as compared to the non-exporters. We do not find any evidence of new exporters investing more in capital intensive inputs or in labor. In table 11, based on Mahalanobis-Distance Kernel Matching, we various matching algorithms to confirm our results. Irrespective of whichever matching technique we use, the results are consistent throughout the analysis.

Figure 3: Visual representation of the propensity scores of matched firms (treatment and control group) in the ATT analysis for the learning by exporting (LBE) hypothesis.



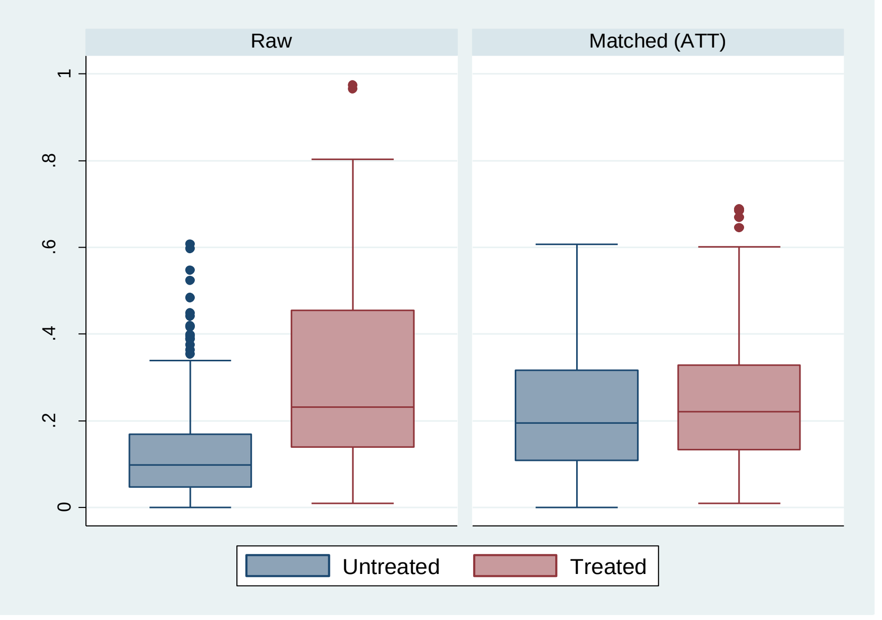


Table 11: Learning by Exporting Hypothesis: Mahalanobis-Distance Kernel Matching based on different matching techniques

Panel A: Nearest Neighbor Matching (1 Neighbor)					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
$NewExp_{it}$	0.0754	0.0084	0.3357	0.5073*	0.1190
	(0.0711)	(0.0145)	(0.3069)	(0.2916)	(0.2565)
Panel B: Nearest Neighbor Matching (5 Neighbor)					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
$NewExp_{it}$	0.0917	0.0219	0.2557	0.5535*	0.0813
	(0.0684)	(0.0157)	(0.2828)	(0.3054)	(0.2062)
Panel C: Pair Matching with replacement (Huber et al. 2013, 2015)					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
$NewExp_{it}$	0.1012	0.0251	0.2668	0.4909**	0.0939
	(0.0695)	(0.0157)	(0.2578)	(0.2394)	(0.2412)
Panel D: Cross Validation with respect to the mean of X					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
$NewExp_{it}$	0.0726	0.0210	0.3845	0.6936**	0.2744
	(0.0829)	(0.0137)	(0.2448)	(0.3207)	(0.1857)

Panel E: Cross Validation with respect to Y (Frolich, 2004, 2005)					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
$NewExp_{it}$	0.0761	0.0205	0.4998	0.5481	0.3223
	(0.0702)	(0.0143)	(0.3216)	(0.3527)	(0.2273)
Panel F: Weighted Cross Validation with respect to Y (Galdo et al., 2008)					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Material*	*Labor*
$NewExp_{it}$	0.1067	0.0182	0.2470	0.6939**	0.0793
	(0.0673)	(0.0132)	(0.3265)	(0.3160)	(0.1881)

The results represent the Average Treatment on Treated (ATT) effect.
N=558
Standard errors (computed through bootstrapping) in parentheses.
* p<0.10, ** p<0.05, *** p<0.01
Controls: product dummies, time FE, segment FE, segment-time FE, missing base dummies, number of products.
Since the dependent variable in all specifications is in log form, the effect is estimated as e^{β}-1.

Learning-by-exporting (LBE) suggests that once a firm enters an export market, its export intensity increases through a variety of channels, including increased access to new knowledge and technology through increased contact with foreign customers, suppliers, and competitors. Economies of scale may result from serving larger international markets with fixed amounts of R&D investment (Wilson et al., 2022). Entering a foreign market places a firm in a more competitive and creative environment, affecting the quality of its products, marketing strategies, knowledge transfers, and efficiency parameters (Greenaway & Kneller, 2007). Salomon and Shaver (2005) suggest that exporting firms may gain access to diverse knowledge and information not available in the domestic market, fostering increased innovation. Thus, exporting, in general, provides access to foreign knowledge, which can improve exporters' productivity performance (Van Biesebroeck, 2005).

In our analysis, the evidence for the LBE hypothesis is less conclusive. We do not find productivity or quality improvements after the firms start exporting. Similarly, there is no evidence of firms investing more in capital. Our findings are consistent with those of Ciarli et al. (2023), who examined self-selection and learning-by-exporting hypotheses in Chilean firms. Using a structural vector autoregressive analysis on firm level data from the years 2001 to 2007, they find evidence of the SS hypothesis but no evidence of the LBE hypothesis. Thus, increased productivity leads to increased export growth but not vice versa. Therefore, they suggest that Chilean exporting firms must enhance their productivity and increase in size, among other factors, in order to increase the amount of goods/services they export. Their findings imply that growing sales in foreign markets does not assist exporting firms, at least in the short run.

Our results are opposite to those found for India by Sahoo et al. (2022). They investigate LBE hypothesis in Indian manufacturing firms from 1994 to 2017. Their findings suggest that exporting activities have a significant impact on competitiveness in the Indian manufacturing sector, lending support to the LBE concept. Their results remain robust to various manufacturing industries with varying degree of labor and capital usage. Our findings also contradict with those of Manjon et al. (2013), who found evidence of LBE for Spanish firms. Based on De Loecker's (2007) criticism of determining the LBE hypothesis, they estimate that exporting results in an average productivity gain of roughly 3% for exporters at least four years. They also find evidence that if the new exporters had remained non-exporters, they would have suffered a 1.3% productivity loss.

LBE traces back to Krugman's model (1979) where exporting firms are more likely to be innovative than non-exporting firms with a higher level of innovation novelty. Innovation can take the form of creating an entirely new product (new to the market or perhaps the world) or improving an existing product. Increased levels of product novelty may make firms more competitive in global markets (Ramadani et al., 2019; Nathan & Rosso, 2022). Similarly, Lim et al. (2018) propose a model in which customers want a differentiated product in various grades ranging from low to high quality. Firms can invest in R&D activities to achieve the next grade of product, which is similar to product innovation. However, in our case we do not find evidence of firms investing in capital or improving product quality acting in a more competitive way in the foreign markets.

Learning by Exporting (LBE) Hypothesis: Destination Wise

Many studies have found a link between the LBE and export destinations. De Loecker (2007) confirmed this conclusion for a sample of Slovenian manufacturing firms operating between 1994 and 2000, concluding that export entrants become more productive once they begin exporting. However, the productivity gains of exporting firms varied according to the destination markets, with higher productivity gains for firms exporting to high-income regions. Similarly, Lim et al. (2018) in their model suggest that the nature of the learning effects may be affected by the export destination. Entering larger markets, as well as entering export markets with less established competition, should have a greater positive impact on the firm's performance.

To test the LBE hypothesis based on the export destination, we classify the export destination of each firm based on the categorization of the World Bank as low-income, lower-middle income, upper-middle income, and high-income countries. We estimate the fixed effects as in equation (12).

Table 12 shows the results from the fixed effects analysis. Disaggregating the new exporters, based on their export destination, we find clear evidence of the LBE for firms exporting to high income countries. For such firms, we find that their productivity and quality increase by up to 33 percent and 9 percent respectively. We also find evidence of new exporters, exporting to high-income countries, investing heavily in their inputs, especially in capital and materials. Therefore, exports to high income countries are backed by capital accumulation.

Table 12: Learning by Exporting Hypothesis: Fixed Effects Analysis (different export destinations)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	***Quality***	***Capital***	***Material***	***Labor***
Low	-0.0882	0.00195	-0.239	0.0950	-0.128
	(0.149)	(0.0309)	(0.589)	(0.596)	(0.380)
Lower-middle	-0.00197	0.0130	-0.137	-0.147	-0.251
	(0.102)	(0.0171)	(0.327)	(0.340)	(0.267)
Upper-middle	0.0650	-0.00550	0.0152	0.133	0.146
	(0.0895)	(0.0250)	(0.423)	(0.463)	(0.357)
High	0.292**	0.0842***	1.300***	1.342**	0.731*
	(0.143)	(0.0271)	(0.501)	(0.521)	(0.399)

N=558

Robust Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Controls: product dummies, time FE, segment FE, segment-time FE, missing base dummies, number of products

Since the dependent variable in all specifications is in log form, the effect is estimated as e^β-1.

Next, we check our results based on the matching techniques. Table 13 summarizes the results for the matching techniques. Panel A represents the results based on Mahalanobis-Distance Kernel Matching while Panel B represents the results based on Propensity Score Kernel Matching. Based on an export destination analysis, we clearly find evidence of LBE for firms exporting to high-income countries. We see that firms exporting to high income countries gain in productivity and quality. We also find evidence that firms exporting to high income countries increase their use of capital, material, and labor inputs. For firms exporting to destinations other than high-income countries, we do not find any evidence of LBE. Table 14 presents the results based on Mahalanobis-Distance Kernel Matching using different matching algorithms. Irrespective of whichever matching technique we use, the results are consistent throughout the analysis.

Our results are similar to those of Girma and Görg (2022) who investigate China's export-incentive policy. Their findings suggest that there are advantages of engaging in export processing at the firm level through learning-by-exporting. They suggest that encouraging export processing may result in gains, particularly for those entering industrialized economies through exporting. As a result, firms that join global value chains through export processing can later improve their performance. They also discover that export processors benefit more when firms enter the industrialized economies of the North rather than the South. Similarly, Oliveira et al. (2021) find evidence for firms in Vietnam entering the global value chains as experiencing process innovation post export entry conditional on their export to advanced economies. Firms exporting to emerging economies do not innovate their processes or products.

Our results also suggest that firms exporting to high income countries indulge in product quality upgradation, indicating “export sophistication”. According to Baliamoune-Lutz (2019), exporting to high-income economies leads to export sophistication via labor skill upgradation, which can be explained by two possible mechanisms. The first mechanism is explained by models developed by Verhoogen (2008) and Brambilla et al. (2015), in which developed economies require quality improvements which are skill-intensive. Exporting to developed countries encourages firms to enhance skills (thereby increasing sophistication), which ultimately results in higher wages. This has been empirically tested by Brambilla et al. (2015), who use data from Argentine firms to find a skill bias in export destinations. Similarly, Rankin and Schöer (2013) using South African firm data find evidence that firms that export outside the region earn more than workers in domestic markets. They highlight that the premium paid for skills by different types of exporters can explain wage differences, and they their findings support the theory that "export destination is related to product quality which in turn is related to worker quality and therefore wages". The second mechanism works through export-related services and activities (logistics, advertising, networking, etc.) that require a high level of skilled labor (Matsuyama, 2007; Arkolakis, 2010). We would anticipate a positive relationship between exporting to developed nations and export sophistication if developed countries' markets required more of these skill-intensive services, while the products exported are also skill-intensive. While we do not explore the channel of product sophistication in our analysis, we do find evidence of firms increasing their capital intensity along with labor usage, indicating a possibility of skill improvement, since capital accumulation compliments skilled labor.

Our results are also in like with the work by Deng and Lu (2021), who suggest that the transfer of technology and sales knowledge helps emerging economies overcome major entry barriers, such as distance from global science and a lack of access to advanced consumer knowledge in advanced international markets due to greater learning effects. According to Pisu (2008), exporting to developed countries may provide more learning opportunities due to advanced technological practices in such countries. This is clearly evident from the fact that in our analysis, firms exporting to high-income countries are indulging in capital accumulation. In one of our companion papers, we find evidence that firms exporting to China (upper-income country) had limited productivity and quality gains, partly because these exports were not backed by capital investments (Jamil et al., 2022). Wadho and Chaudhry (2018) further support this by finding evidence that amongst the Pakistani textile producers, innovation activities were primarily concentrated among exporters to high-income countries in Europe and the United States.

Table 13: Learning by Exporting Hypothesis: Destination Wise

Panel A: Mahalanobis-Distance Kernel Matching					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Materials*	*Labor*
Lower	-0.0373	0.0188	-0.1746	0.3059	-0.1917
	(0.1417)	(0.0412)	(0.6393)	(0.7651)	(0.3931)
Lower-middle	-0.0011	0.0160	-0.3393	-0.2064	-0.3177
	(0.091)	(0.0236)	(0.2786)	(0.3815)	(0.2501)
Upper-middle	0.1097	0.0229	0.4747	0.5104	0.2337
	(0.0705)	(0.0176)	(0.3901)	(0.4244)	(0.2573)
High	0.3492**	0.0901***	1.4654***	1.5415***	0.9202***
	(0.1043)	(0.0177)	(0.4297)	(0.4015)	(0.3367)
Panel B: Propensity Score Kernel Matching					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Productivity	*Quality*	*Capital*	*Materials*	*Labor*
Lower	-0.0374	0.0187	-0.1746	0.3059	-0.1917
	(0.1743)	(0.0372)	(0.3665)	(0.6998)	(0.1853)
Lower-middle	0.0334	0.0046	-0.5111	-0.4361	-0.4466
	(0.1474)	(0.0172)	(0.3103)	(0.3875)	(0.2959)
Upper-middle	0.0809	0.0272	0.1517	0.1827	0.0069
	(0.0850)	(0.0209)	(0.3742)	(0.4488)	(0.2799)
High	0.3728**	0.0768***	1.3255***	1.4097***	0.8385**
	(0.1868)	(0.0174)	(0.4110)	(0.3978)	(0.2848)

The results represent the Average Treatment on Treated (ATT) effect.
N=558
Standard errors (computed through bootstrapping) in parentheses.
* p<0.10, ** p<0.05, *** p<0.01
Controls: product dummies, time FE, segment FE, time-segment FE, missing base dummies, number of products.
Since the dependent variable in all specifications is in log form, the effect is given as e^β-1..

Table 14: Learning by Exporting Hypothesis: Destination Wise

			Productivity			
	Nearest Neighbor Matching (1 Neighbor)	*Nearest Neighbor Matching (5 Neighbor)*	*Pair Matching with replacement (Huber et al. 2013, 2015)*	*Cross Validation with respect to the mean of X*	*Cross Validation with respect to Y (Frolich, 2004, 2005)*	*Weighted Cross Validation with respect to Y (Galdo et al., 2008*
Lower	-0.0373	-0.0253	-0.0373	-0.0373	-0.0373	-0.0373
	(0.1299)	(0.1356)	(0.1330)	(0.1606)	(0.1274)	(0.1475)
Lower-middle	0.0102	-0.0027	-0.0012	0.0061	0.0080	0.0012
	(0.1019)	(0.0946)	(0.0872)	(0.0998)	(0.1114)	(0.0954)
Upper-middle	0.1060	0.0908	0.1097	0.0845	0.0895	0.1166
	(0.0836)	(0.0844)	(0.0903)	(0.0818)	(0.0607)	(0.0779)
High	0.3754**	0.3441**	0.3492**	0.3598**	0.3400***	0.3492***
	(0.1230)	(0.1281)	(0.1289)	(0.1260)	(0.1016)	(0.1076)
			Quality			
	Nearest Neighbor Matching (1 Neighbor)	*Nearest Neighbor Matching (5 Neighbor)*	*Pair Matching with replacement (Huber et al. 2013, 2015)*	*Cross Validation with respect to the mean of X*	*Cross Validation with respect to Y (Frolich, 2004, 2005)*	*Weighted Cross Validation with respect to Y (Galdo et al., 2008*
Lower	0.0188	-0.0077	0.0188	0.0188	0.0188	0.0188
	(0.0390)	(0.0321)	(0.0332)	(0.0313)	(0.0354)	(0.0345)
Lower-middle	0.0009	0.0026	0.0160	0.0122	0.0147	0.0122
	(0.0189)	(0.0149)	(0.0173)	(0.0154)	(0.0207)	(0.0160)
Upper-middle	0.0167	0.0303	0.0228	0.0202	0.0279	0.0259
	(0.0241)	(0.0272)	(0.0178)	(0.0200)	(0.0189)	(0.0183)
High	0.0760***	0.0805***	0.0900***	0.0901***	0.0929***	0.0900***
	(0.0171)	(0.0241)	(0.0143)	(0.0163)	(0.0176)	(0.0189)
			Capital			
	Nearest Neighbor Matching (1 Neighbor)	*Nearest Neighbor Matching (5 Neighbor)*	*Pair Matching with replacement (Huber et al. 2013, 2015)*	*Cross Validation with respect to the mean of X*	*Cross Validation with respect to Y (Frolich, 2004, 2005)*	*Weighted Cross Validation with respect to Y (Galdo et al., 2008*
Lower	-0.1746	-0.7148	-0.1746	-0.1746	-0.1746	-0.1746
	(0.7859)	(0.7411)	(0.7076)	(0.7008)	(0.6168)	(0.7868)
Lower-middle	-0.2987	-0.4289	-0.3393	-0.2381	-0.1528	-0.3852
	(0.2902)	(0.2700)	(0.2897)	(0.2496)	(0.2908)	(0.2874)
Upper-middle	0.5199	0.5595	0.4747	0.5384	0.6694	0.5689
	(0.4252)	(0.3495)	(0.3792)	(0.3609)	(0.4126)	(0.4017)
High	1.2467**	1.3839***	1.4654***	1.4324***	1.7263***	1.6612***
	(0.5031)	(0.5254)	(0.3645)	(0.4413)	(0.4145)	(0.5190)
			Materials			

	Nearest Neighbor Matching (1 Neighbor)	*Nearest Neighbor Matching (5 Neighbor)*	*Pair Matching with replacement (Huber et al. 2013, 2015)*	*Cross Validation with respect to the mean of X*	*Cross Validation with respect to Y (Frolich, 2004, 2005)*	*Weighted Cross Validation with respect to Y (Galdo et al., 2008*
Lower	0.3059	-0.2773	0.3059	0.3059	0.3059	0.3059
	(0.6932)	(0.8979)	(0.8035)	(0.8201)	(0.8702)	(0.6630)
Lower-middle	-0.2225	-0.2110	-0.2064	-0.2418	-0.2393	-0.2456
	(0.4151)	(0.3774)	(0.2467)	(0.3282)	(0.3628)	(0.3551)
Upper-middle	0.3936	0.6386	0.5105	0.4395	0.7256	0.5709
	(0.4456)	(0.5571)	(0.3996)	(0.5126)	(0.4895)	(0.4348)
High	1.2678**	1.5103***	1.5415***	1.5069***	1.8106***	1.7199***
	(0.4982)	(0.4203)	(0.3763)	(0.4037)	(0.3491)	(0.3414)
Labor						
	Nearest Neighbor Matching (1 Neighbor)	*Nearest Neighbor Matching (5 Neighbor)*	*Pair Matching with replacement (Huber et al. 2013, 2015)*	*Cross Validation with respect to the mean of X*	*Cross Validation with respect to Y (Frolich, 2004, 2005)*	*Weighted Cross Validation with respect to Y (Galdo et al., 2008*
Lower	-0.192	-0.5663	-0.1917	-0.1917	-0.1917	-0.1917
	(0.4639)	(0.3913)	(0.4208)	(0.4107)	(0.4156)	(0.4309)
Lower-middle	-0.3683	-0.4449	-0.3177	-0.2830	-0.2081	-0.3059
	(0.2786)	(0.2880)	(0.2590)	(0.1966)	(0.2781)	(0.2384)
Upper-middle	0.3500	0.3408	0.2336	0.3899	0.4043	0.4043
	(0.3309)	(0.3463)	(0.2548)	(0.3525)	(0.3108)	(0.3325)
High	0.7143**	0.8647***	0.9202***	0.9005***	1.1431***	1.0813***
	(0.3373)	(0.2632)	(0.2500)	(0.2802)	(0.2420)	(0.3325)

The results represent the Average Treatment on Treated (ATT) effect.
N = 558
Standard errors (computed through bootstrapping) in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Controls: product dummies, time FE, segment FE, time-segment FE, missing base dummies, number of products.
Since the dependent variable in all specifications is in log form, the effect is estimated as given by (e^β-1) *100.

6. Conclusion

Policy makers often debate on how trade openness boosts productivity and ultimately leads to economic growth. They view participation in export markets as a requirement for a developing country's economic success. However, neither theoretical nor empirical studies have reached a consensus on the direction of causality between firms' productivity and its export status. This study examines whether Pakistani exporting firms are more productive and whether they learn from exporting. Our paper investigates the hypotheses of self-selection and learning-by-exporting using panel data set for Pakistani firms from 2000 to 2010. The study has the advantage of using a rich data set that has disaggregated output and price information, not just at the firm level but also at the product level. Hence, there is time, firm and product level variation in our data set. This allows us to estimate firm productivity based on the methodology by De Loecker et al. (2016). This methodology allows us to endogenize the law of motion for productivity along with addressing newly debated biases in literature. We also estimate output product quality using a nested logit model developed by Khandelwal (2010).

We use the Propensity Score Matching (PSM) and the Multivariate Distance Matching (MDM) techniques to study the direction of causality between a firm's productivity and export status. We use kernel matching, nearest-neighbor matching, and pair matching algorithms, while our benchmark results are based on kernel matching using the Multivariate Distance Matching (MDM) technique. Robust to various matching algorithms, we find evidence of more productive and bigger sized firms with more capital, self-selecting in exporting. However, once the firm enters the export market, the learning from exports is limited unless the firm exports to high-income countries. Therefore, the learning-by-exporting effect is conditional on the export destination.

This study shows that on a trade and economic policy level, targeting less productive firms (via export subsidies or through other channels) may not lead to trade openness. The learning effects, once these firms enter the export market, are limited in terms of productivity. This does not mean that the government's justification of spending millions of dollars on subsize firms' entry into the export market is useless, since there can be other gains beyond the scope of this paper, like increases in sales, employment creation and increase in profit margins. However, trade policies specifically targeting entry into high-income economies are needed for the learning-by-exporting effects to be realized due to high technological advancements in these countries.

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