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Nexus between export, productivity, and competitiveness in the Indian manufacturing sector

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This article assesses the nexus between export, productivity, and competitiveness in the Indian manufacturing sector. To do this, we examine the “learning by exporting” and “self-selection” hypotheses using firm-level data relating to Indian manufacturing firms relating to period from 1994 to 2017. The empirical analysis supports the “learning by exporting” hypothesis, but does not support the “self-selection” hypothesis. We also investigate the impact of export on competitiveness, and the results indicate a positive relationship. These findings remain consistent when we segregate manufacturing firms based on industries, intensity use of labor and capital, and firm ownership. In the light of these findings, we recommend that policy focus on enhancing the export capacity of manufacturing firms to further strengthen the competitiveness of Indian manufacturing.

1. Introduction

Competitiveness is the willingness of a firm to manufacture reliable and innovative products that can satisfy the market’s needs. The competitiveness of firms includes their efficiency and productivity (Porter, 1990), which is directly linked to export performance. Thus, an increase in export activity could lead to better performance of firms and enhance their competitiveness. In general, we know that exports encouraged by international trade increase firm efficiency and productivity, which aids firm competitiveness and eventually contributes to economic growth (Balassa, 1988). As a result, exporting firms perform a vital role in the competitiveness of firms. The theoretical strategy of export-led growth propagated by Grossman and Helpman (1991), Krugman (1987), and Rodrik (1988) indicates that exposure to international markets through export activities helps firms become more productive and efficient. Similarly, exports also improve productivity through technology transfer (Barro & Sala-i-Martin, 1995; Parente & Prescott, 1994; Sharma, 2018) and innovation (Melitz, 2003; Rivera-Batiz & Romer, 1991; Wu, Wu, & Zhang, 2020).

In this article, we explore the nexus between export, productivity, and competitiveness in the Indian manufacturing sector. Our main goal is to see which of the following two hypotheses “learning by exporting” and “self-selection” is valid in the Indian manufacturing sector. The contribution of the Indian manufacturing sector to overall economic growth is significant, accounting for 17% (WDI, 2020). In recent years, especially following the global financial crisis, the government of India has constantly emphasized the importance of the Indian manufacturing sector through various programs such as the “Make in India” initiative and expects this sector to be crucial in terms of exports and competitiveness.

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A number of empirical studies have been conducted in India to analyze the performance of the manufacturing sector at both industry and firm levels (see, for instance, Basant & Fikkert, 1996; Bhattacharya & Rath, 2020; Bhaumik & Kumbhakar, 2008; Franco & Sasidharan, 2010; Hasan, 2002; Kathuria, 2002; Kumar & Aggarwal, 2005; Narayanan & Bhat, 2009; Mitra, Sharma, & Véganzonès-Varoudakis, 2014; Rath, 2018; Ray & Bhaduri, 2001; Raut, 1995; Sahoo & Rath, 2018; Sasidharan & Kathuria, 2011; Seenaiah & Rath, 2017, 2018; Sharma & Mishra, 2011; Behera, Dua, & Goldar, 2012; Sharma, 2012; Siddharthan & Narayanan, 2016). This study adds to existing literature by examining the "learning by exporting" and "self-selection" hypotheses. In India, the government has formulated export promotion policies to accompany the foreign trade policy to improve export activities. As such, India's foreign trade policy (2015–2021), with the aid of the "Make in India" initiative, affords a basis for increasing exports of "goods and services" to create mass employment and includes more value to the development of the economy (IBEF, 2021).

The export performance of a firm is linked to two hypotheses based on theoretical mechanisms, namely, "learning by exporting" and "self-selection". The "learning by exporting" hypothesis proposes that the productivity of firms increases once they enter the export market, whereas the "self-selection" hypothesis suggests that firms that are more productive enable themselves to enter the export market. Based on the importance of export participation, some recent studies have examined the association of "exports and productivity" based on firms' performances. In this context, the foundation of the "learning by exporting" hypothesis on a firm's productivity performance has been examined by Bernard and Jensen (1999, 2004), Bernard and Wagner (1997), Baldwin and Gu (2004), and Wagner (2007). At the same time, research by Roberts and Tybout (1997), Clerides, Lach, and Tybout (1998), Delgado, Farinas, and Ruano (2002), Gupta, Patnaik, and Shah (2018), Melitz (2003), Roberts and Tybout (1997), and Tybout (2003) on the "self-selection" hypothesis has confirmed that firms self-select themselves for the export market. Similarly, there are a few studies which support the existence of both the "self-selection" and "learning from exporting" hypotheses (see, for example, Bigsten & Gebreeysus, 2009; Demirhan, 2016; Fernandes & Isgut, 2005; Girma, Greenaway, & Kneller, 2004; Hahn, 2004; Kraay, 1999; Sharma & Mishra, 2011).

Our study adds to the established body of knowledge and is distinct from it in several ways. First, from the existing research, as we know, the "learning by exporting" and "self-selection" hypotheses have observed a link between export activities and productivity. In this study, we move one step further to see whether firms can learn from their export activities and become more competitive. For this, we first compute the competitiveness of firms through the composite Industrial Competitiveness Index (ICI) based on sales growth, labor productivity, and profitability. Second, most studies in published literature use dummy variables for export activities to analyze the relationship between productivity and export activities of firms. Using an absolute value of exports is more important than using binary variables. Thus, instead of using a placebo, we use a firm's export intensity, which is defined as the ratio of the firm's actual exports to sales. Third, there has been extensive research with regard to the measurement of total factor productivity (TFP) along with the merits and limitations of each approach. The most widely adopted approaches for estimating TFP at the firm level were developed by Levinsohn and Petrin (2003) and Olley and Pakes (1996). However, both approaches also have limitations owing to a functional dependence problem (Ackerberg, Caves, & Frazer, 2015) (hereafter, "ACF"). To resolve this challenge, we estimate firms' TFP with the production function approach designed by ACF. It has an extended version of the production function estimation approaches by Olley and Pakes (1996) (hereafter, "OP") and Levinsohn and Petrin (2003) (hereafter, "LP"), and offers more reliable estimators than early parametric and non-parametric techniques. Fourth, while previous studies tested the "learning by exporting" and "self-selection" hypotheses empirically, they largely ignored issues such as endogeneity and reverse causality. To address this, our study not only uses the dynamic panel generalized method of moments estimator approach, but also links the effect of exports on firms' competitiveness. Further, we examine both the hypotheses by separating the firms based on their ownership structure (foreign and domestic firms) and use of inputs (labor and capital intensive). Finally, we examine the effect of export on the competitiveness of key industries to confirm the existence of "learning by exporting" in the case of Indian manufacturing industries.

The remainder of this article is organized as follows. The review of literature is presented in Section 2, and the data and variables are explained in Section 3. Section 4 discusses the methodology used, and empirical findings are presented and discussed in Section 5. Section 6 concludes.

2. Review of literature

In this section, we examine the theoretical and analytical literature on the nexus between a firm's decision to export and its productivity and competitiveness. Conventional literature has primarily investigated two major hypotheses, "self-selection" and "learning by exporting", to determine the causal nexus between firms' exports and their productivity.

First, the "learning by exporting" theory claims that exporting to the international market boosts learning effects for firms, which results in increased productivity and competitiveness (Bernard & Wagner, 1997; Fernandes & Isgut, 2005; Kraay, 1999; Yousefi, Madanizadeh, & Sobhani, 2019). Some relevant studies that examine this hypothesis are Bernard and Jensen (1999, 2004), who studied firms in the United States; Girma et al. (2004), who researched firms in the United Kingdom; Wagner (2002), who studied German companies; Clerides et al. (1998), who studied companies in Colombia, Morocco, and Mexico; and Aw, Chung, and Roberts (2000), who researched companies in Taiwan, and Wang, Xu, and Dai (2021), who examined the case of Chinese firms. These studies find that firms that engage in exports are typically more productive than those that do not. Other studies also confirm the "learning by exporting" hypothesis, such as Sjoholm (1999), who studied Indonesian firms; Baldwin and Gu (2004), who examined Canadian firms; and Van Biesebroeck (2005), who studied low-income countries in Africa. Similarly, Atkin, Khandelwal, and Osman (2017) and Greenaway and Kneller (2007) investigated the export performance of firms in the United Kingdom and Egypt, respectively. These studies confirm the positive effect of exports on firms' productivity.

A few other studies also examine the role of exports on firms' output and productivity. Previous research on this topic has shown that the “learning by exporting” hypothesis is assessed in terms of total factor productivity, labor productivity, and output. According to Hansson and Lundin (2004), exports help firms increase their productivity by 2–3%, and studies by Blalock and Gertler (2004) reveal that “learning by exporting” has a higher impact in the case of Indonesian firms. Clerides et al. (1998) observe that a firm’s productivity increases because of higher exports. This is made possible by the elimination of inefficiency as a result of increased competitiveness, which is possible through export participation. Similarly, Cassey and Schmeiser (2013) and Koenig (2009) investigate the “learning by exporting” hypothesis using spillover from other exporting firms. Lopez (2005) supports the hypothesis and proposes that firms select themselves into the export market to increase their productivity and become bigger exporters. Likewise, Yasar, Nelson, and Rejesus (2006) and Yasar and Rejesus (2005) confirm that increase in the productivity of firms is attributable to their entry into export markets. Siba and Gebreeyesus (2016) examine both the “self-selecting” into the export market and “learning by exporting hypotheses” in the Ethiopian manufacturing sector for the period between 1996 and 2009. Their results support the “learning by exporting” hypothesis and show that firms engaged in export promotion activities are more profitable than other non-exporting firms. Thus, the overall outcome of studies indicates that exports have a sustainable effect on firms’ efficiency and competitiveness.

The second strand of literature focuses on the “self-selection” hypothesis. There is a plethora of research on the link between exporting firms and their productivity. Some studies have shown that exports play a critical role in firms’ improved efficiency and firms select themselves into the export market after becoming more productive and efficient (Gupta et al., 2018; Melitz, 2003; Sharma & Mishra, 2011; Wagner, 2007).

Melitz (2003) examines the link between exports and productivity through trade activities. He finds that more productive and profitable companies enter the export market. This encourages firms to “self-select into the export market”. Similarly, Greenway and Kneller (2007) observe that native firms become more competitive by entering the international market and pursue innovative activities that drive them into the export market. Schmeiser (2011) finds that firms that do export and are ready to take a loss, learn from it to increase productivity for future exports.

Sharma and Mishra (2011) study the role of export in manufacturing firms’ productivity in the case of India with the help of “self-selection” and “learning by exporting” methods for the period 1994–2006. Their study strongly supports the “self-selection” hypothesis instead of “learning by exporting” one, claiming that exporting firms reported decreasing productivity growth. Arnold and Hussinger (2005) explore the effect of export involvement on German manufacturing firms’ productivity. They point out that firms that are observed to be more productive “self-select” for involvement in exports, but they do not find evidence that existing export firms have pushed for increased productivity. Haidar (2012) discovers that learning through exporting has an adverse effect on a firm’s productivity. It means that “entering the export market” has a negative impact on the growth of productivity. He concludes that learning through exporting is not a viable strategy for the expansion of India’s manufacturing sector. Gupta et al. (2018) find in favor of the “self-selection” hypothesis, by demonstrating that the large firms export to the global market, whereas small firms do not. There is no evidence, however, that companies became more productive when they reach, and export to, foreign markets.

In a nutshell, several studies have examined the link between export activities and productivity at the firm level through emphasis on the “learning through exporting” or “self-selection” hypotheses. However, linking competitiveness to export and productivity remains largely unexplored. The study in this article fills this research gap using Indian manufacturing firms as a case.

3. Data and variables

We collected data relating to 650 Indian manufacturing firms in 11 industries for the period from 1994 to 2017. The annual data were collected from the Centre for Monitoring Indian Economy (CMIE) Prowess-IQ (version-1.95) database. These industries can broadly be categorized under the two-digit National Industrial Classification (NIC) code. The 650 firms were chosen based on the availability of data for an extensive period in respect of all variables used in the study. First, we created a multidimensional industrial competitiveness index (ICI) comprising the sales growth index (SGI), labor productivity index (LPI), and firm profitability index (PTI) as a measure of the competitiveness of Indian manufacturing firms. Sales growth is measured as a percentage change in a firm’s growth over two consecutive periods. Labor productivity is the ratio of a firm’s gross sales to employment and profitability is the share of a firm’s profit to gross sales. Next, for TFP estimation, we collected data on the total sales of firms as an output variable, with labor, capital, and raw material use taken as input variables. Both sets of variables were deflated using the acceptable price deflator with the base year of 2004–05 and expressed in real terms. Data on employees are available only with respect to a few firms in the Prowess database, but it contains complete information on the wages and salaries of firms. Thus, to construct the labor variable, we followed three steps. First, we calculated the average wage by measuring the ratio of “wages and salary” to the total number employees of those firms that provide data on both wages and employees in the Prowess database. Second, we calculated the “average wage” of each industry by taking the average wage of all firms within that industry, which was obtained from the first step. Third, we computed the number of employees for all firms in our sample by dividing the “total wages and salaries” of a firm by the “average wage” of each industry that was obtained in the second step. For the capital series data, the stock of total fixed capital series was calculated using the “perpetual inventory method” (PIM) as a capital stock indicator. Appendix 1 contains details of the estimation of capital stock variables. Export constitutes an important factor in firms’ productivity and competitiveness, and to understand the role of export on competitiveness, we use export intensity as an independent variable along with import intensity, technology transfer intensity, and research and development (R&D) intensity as the control variables. Export intensity is measured through the total foreign exchange earnings of firms with respect to their sales ratio, and similarly, import intensity is computed through the ratio of total foreign exchange spending divided by gross sales of the firms. Technology transfer intensity is measured as the ratio of expenditure on royalties and technology know-how fees to the total gross sales of the firms. R&D intensity is calculated as the ratio of total R&D expenditure of firms to their total gross sales.

4. Methodology

To measure the values of the three individual indices, first, we used a standard process that transforms the absolute measure value into a scale value ranging from "0" to "100". We used the actual (A_k), minimum (m_k), and maximum (M_k) values to calculate the individual variables' competitiveness over the year. Thus, the lower value noted across firms "i" within an industry "j" over time "t" is considered less competitive; else, if the score increases, the highest overall value recorded is considered more competitive. The formula for the individual competitiveness index score of industry "j" at the firm-level is (I_k^{it}) and it is calculated as follows:

$$I_k^{ijt} = [(A_k^{ijt} - m_k)/(M_k - m_k)] \quad *100 \tag{1}$$

where the individual dimensions for competitiveness are $k = 1$(SGI), 2(LPI), and 3(PTI); for the firm "i" and industry "j" with time "t".

In the next stage, we combined the individual indices into ICI by calculating the arithmetic mean of three indices ($SGI + LPI + PTI$). We thus followed the study by Fischer and Schornberg (2007) and assigned equal weight to all the indices for the competitiveness measure.

Next, we used the method of production function approach developed by ACF to estimate the TFP of manufacturing firms.

4.1. ACF production function approach

It is challenging for researchers and policymakers to estimate firm-level productivity in economics science. Many econometric challenges plague efficiency predictions, including preference bias, measuring errors, and endogeneity issues (Bournakis & Mallick, 2018; Kim, Petrin, & Song, 2016; Van Biesebroeck, 2007). Fundamental issues emerge, as inputs are associated with unobserved productivity, resulting in inconsistency in production function estimation. In recent times, many studies have extensively used the OP and LP approaches for production function estimation. The OP and LP approaches propose solutions for the problem of production function estimation by introducing intermediate inputs—investment as a proxy variable and capital as a state variable. These are the semi-parametric production function and controls the unobserved firm productivity. However, the OP and LP approaches have a functional dependency problem of input variables in the first stage of the estimation and misread labor as a free variable. This functional dependency is considered a non-identification problem (Bournakis & Mallick, 2018; Singh & Sharma, 2019).

The newly developed ACF method suggests a two-stage estimation of the production function approach. In the first stage, the estimation captures the functional dependency problems and non-parametric function of input variables. The demand function of input, which is dependent on state variables and also requires "labor input", as well as detailed simulation support for the estimation process is also suggested in the ACF method. The ACF production function can be described as follows:

$$y_{it} = \alpha_0 + \beta_k k_{it} + \beta_l l_{it} + \mu_{it} + \vartheta_{it} \tag{2}$$

where, y_{it} refers to the output function of firm "i" at time "t". α_0 is known as the constant, and l_{it} and k_{it} denote the labor and capital inputs respectively with β_l and β_k being their respective coefficients. μ_{it} denotes the unobserved state variable, which is also considered an input variable for the production decision, and ϑ_{it} represents the *iid* random variable shocks in the production function. In this study, μ_{it} represents raw material inputs used by the firms. As we know, l_{it} and k_{it} are potentially endogenous in nature and they are dependent on the μ_{it} set of input variables. To solve the issue of endogeneity, OP and LP proposed certain proxy measures. Where, OP use investment as a proxy measure (as small firms have zero investment cost) and LP use intermediate inputs as a proxy for endogeneity. In the OP and LP models, while proxy variables require the use of timing assumption of labor inputs, ACF makes it more flexible for labor inputs by considering labor as less viable than materials.

The "intermediate input demand function" of ACF is expressed as:

$$m_{it} = f_t \quad (l_{it}, k_{it,} \quad \mu_{it}) \tag{3}$$

The above function is strictly monotonic in μ_{it} for ($l_{it}, k_{it,}$), and we can express the reverse function as:

$$\mu_{it} = h_t \quad (\quad l_{it}, k_{it,} \quad m_{it}) \tag{4}$$

This intermediate function considers labor input l_{it} to be determined before the other intermediate variables, i.e., $k_{it,} m_{it}$. The production function can be written by substituting Eq. (4) for Eq. (2) as follows and the new production function is expressed as follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + h_t \quad (l_{it}, k_{it,} \quad m_{it}) + \vartheta_{it} = \quad \varphi_t \quad (l_{it}, k_{it,} \quad m_{it}) \quad + \quad \vartheta_{it} \tag{5}$$

We estimate φ ($l_{it}, k_{it,} m_{it}$), in the first stage of ACF, by minimizing the objective function of sample correspondence.

$$[E] = [(\quad y_{it} \quad - \varphi_t \quad (l_{it}, k_{it,} \quad m_{it}) \tag{6}$$

The first stage function is estimated using the regression model, with the help of parametric function control variables.

Next, the second stage of ACF is estimated using the approximate control function φ_t and first-order Markov method related to productivity.

$$\mu_{it} = E[\mu_{it}|\mu_{it-1}] + \xi_{it} = g(\mu_{it-1}) + \quad \xi_{it} \tag{7}$$

To control and solve endogeneity inputs, the model uses an innovation term (ξ_{it}), with conditional moments.

$$E[\xi_{it}+\vartheta_{it}|I_{it-1}]=E[y_{it}-\beta_0-\beta_k k_{it}+\beta_l l_{it}-g\quad(\varphi_{t-1}\quad(l_{it-1},k_{it-1},\quad m_{it-1})-\quad\beta_0-\beta_k k_{it-1}-\beta_l l_{it-1})\mid\quad I_{it-1}]\quad=\quad 0 \tag{8}$$

where, I_{it-1} signifies the lag period [*(t-1)* information] of the firm, and instruments are used depending on how easily input decisions are supposed to be made on the timing expectations. For instance, $Z_{it}=\left[1,k_{it},l_{it-1},\varphi_{t-1}\left(l_{it-1},k_{it-1},m_{it-1}\right)\right]$ is for the labor input chosen after *(t-1)* period, but we can also use the *(t-1)* period with the function: $Z_{it}=[1,k_{it},l_{it},l_{it-1},\varphi_{t-1}(l_{it-1},k_{it-1},m_{it-1})]$. In the Markov method, the mean function, which is conditional on other functions, is usually parameterized as $g(\mu_{it-1};\beta_\mu)$. For instance, researchers and industry experts might use a sample autoregressive model as follows:

$\mu_{it}=\rho\mu_{it-1}+\xi_{it,}$ let $w_{it}=[(y_{it,}l_{it})\cup Z_{it}]$ and the moment condition as $E[r(w_{it};\Theta_0)]=0]$,

$$\text{where} r(w_{it};\Theta_0)=Z_{it}\times[y_{it}-\beta_0-\beta_k k_{it}+\beta_l l_{it}-g\quad(\varphi_{t-1}\quad(k_{it-1},\quad l_{it-1},m_{it-1})-\quad\beta_0-\beta_k k_{it-1}-\beta_l l_{it-1;}\quad\beta_\mu)],\tag{9}$$

where, $\Theta=\beta_0,\beta_k,\beta_l$ and Θ_0 indicates the true parameter to be estimated.

When the first stage estimation of moment condition is observed, it shows the estimated production function to be a "nonlinear optimization problem" since the production parameters $(\beta_0,\beta_k,\beta_l)$ follow both the "production function" and $g(.)$.

In this study, we follow ACF's Monte Carlo setting with μ_{it} as an autoregressive process. Hence, the moment condition can be simplified into the following equation:

$$E[r(w_{it};\Theta_0)\quad=\quad E\quad[\quad Z_{it}\times\left(y_{it}-\beta_0-\beta_k k_{it}+\beta_l l_{it}-\rho.\quad(\varphi_{t-1}\quad(l_{it-1},k_{it-1},\quad m_{it-1})-\quad\beta_0-\beta_k k_{it-1}-\beta_l l_{it-1;}\quad))\right)=0 \tag{10}$$

Here, ACF proposed to concentrate on two parameters, $\beta_0 and \rho$, for the reduction of the dimension of the overhead nonlinear search. For parameters β_l and β_k, ACF first constructed an estimate for $\beta_0+\mu_{it}$, which is as follows:

$$\beta_0+\mu_{it}(\widehat{\beta_l,\quad\beta_k})=\widehat{\varphi_{it}}(k_{it},\quad l_{it},\quad\mu_{it}\quad)-\beta_k k_{it}-\beta_l l_{it}\tag{11}$$

where, $\widehat{\varphi_{it}}(l_{it},k_{it,}\mu_{it})$ is derived from the regression of the initial stage. Now, ACF assessed the AR(1) method by regressing $\beta_0+\mu_{it}(\widehat{\beta_l,\quad\beta_k})$ on its lagged variable $\beta_0+\mu_{it-1}(\widehat{\beta_l,\quad\beta_k})$ to find the residual of the model $\xi_{it}(\beta_k,\beta_l)$. Finally, ACF estimated β_k,β_l using the concentrated moment condition, as $E[\quad\xi_{it}(\beta_k,\beta_l)\times(k_{it,}l_{it-1})]=0$.

After obtaining β_k,β_l, we estimated the associate TFP indices of firms using the omega prediction (Rovigatti & Mollisi, 2018). Next, the effect of export on firm productivity and competitiveness is measured with the help of the dynamic system generalized method of moments (GMM) model.

4.2. System GMM model

After estimating the TFP, in the next stage, we examined the effect of export intensity on the TFP of Indian manufacturing firms and vice versa. Here, we used the panel system GMM model proposed by Blundell and Bond (1998) for the estimation process by employing Eq. (12). Next, after confirming the effect of exports on TFP, we measured the impact of exports on firms' competitiveness using Eq. (12). For the following two factors, the dynamic panel model was selected. First, the fixed effects definition overcomes the excluded variable bias that occurs in the case of cross-firm variability, where the GMM model includes the full set up collection of firm-specific effects among the explanatory variables. Second, the dynamic model considers the endogeneity problems that occur as a result of the explanatory variables. The model overcomes these issues by choosing the lagged dependent variable and producing a reliable estimate of the model. The dynamic model can be expressed as follows:

$$Y_{it}=\alpha_{it}+\beta_1(Y)_{it-1}\quad+\beta_2(X)_{it}+\beta_3(Z)_{it}+\mu_i+\lambda_t+u_{it}\tag{12}$$

where "α" and "βs" are the unknown parameters that are essential to be estimated. "λ_t" indicates the time-specific effect, "μ_i" denotes the firm-specific effect, and "u_{it}" represents the error term. The model also assumes a homoscedasticity error term, where the serial

Table 1
Production function estimates using ACF.

Variable	ACF coefficient
lnL	0.616*** (0.000)
lnK	0.359*** (0.000)
Wald test *p-value*	2.08(0.149)
Observation (Firm)	14,950(650)

Notes: Authors' calculations. *** indicates 1% significance level and standard errors are given in the parentheses. Wald test p-value shows the constant returns to scale. Gross value added is used as output variable, Labor(L) and Capital(K) are used as input variables, and raw materials expenses are used as proxy variables.

correlations are checked among the variables. The model uses past values of the dependent variables to tackle the endogeneity issues identified by Arellano and Bover (1995). All our estimates are accompanied by Sargan and Hansen test statistics to determine the validity of the overidentifying restrictions. The second-order autocorrelation test AR (2) statistics are also used to check the autocorrelation of the error variances (Arellano & Bond, 1991).

5. Empirical results

5.1. ACF production function results

We start our empirical analysis by presenting the results of TFP measured through the ACF method. Table 1 shows the coefficient of production function computed through the ACF approach. We follow the value-added method for the estimation of TFP. The TFP of firms is estimated using the log of value-added as output and the log of labor, capital, and raw materials (intermediate inputs) as input variables. The labor (L) and capital (K) coefficients are significant at the 1% level. We employed the ACF method over LP method and the superiority of ACF method is explained in Appendix 2. The estimated TFP is also used for the purpose of further empirical analysis of the “self-selection” and “learning by exporting” hypotheses.

5.2. Self-selection hypothesis

After estimating the TFP for all firms, we examine the linkages between “TFP and export intensity” of firms. Export intensity, as defined earlier, is measured as the ratio of total foreign earnings to gross sales of the firm. The following model, expressed in Eq. (13), clearly explains the “self-selection” hypothesis.

$$Exp\_int_{it} = \alpha_{it} + \beta_1(Exp\_int)_{it-1} + \beta_2(TFP)_{it} + \beta_3(Imp\_int)_{it} + \beta_4(Tech\_int)_{it} + \beta_5(R\&D\_int)_{it} + u_{it} \tag{13}$$

Here, *TFP* and *Exp_int* of the firm are considered the TFP and “export intensity” of a firm (*i*) at time (*t*). We include import intensity, R&D intensity, and technology intensity as a control variables and check their impact on firms’ export activities.

Table 2 sets out the impact of productivity on the export activities of firms. The results show that for the manufacturing sector as a whole, TFP does not significantly affect firms’ export intensity but significantly reduces the export activities of foreign firms. On the other hand, the lag effect of export intensity has a positive and significant impact on export. Import intensity also has a significant and positive impact on manufacturing firms’ export activity and technology has a negative effect on export activities. The results further reveal that there is no support for the “self-selection” hypothesis. This finding is supported by the results of previous studies by Atkin et al. (2017), Greenaway and Kneller (2007), and Thomas and Narayanan (2012), showing the absence of any kind of relationship between productivity and export activities. We also check the same hypothesis for firms that belong to labor- and capital-intensive sectors as well as foreign firms and domestic firms. The results again do not support the hypothesis in segregated sectoral level data; rather, in the case of foreign firms, TFP significantly reduces the export activities of firms. The results of our analysis do not provide any substantial evidence in support of the “self-selection” hypothesis at this point.

Table 2
Impact of productivity on export intensity.

Export-intensity (Dependent)	All manufacturing	Labor intensive	Capital intensive	Domestic firms	Foreign firms
L.Exp_int	0.637***	0.542***	0.694***	0.583***	0.885***
	(0.027)	(0.022)	(0.038)	(0.026)	(0.031)
TFP	-0.475	-0.440	-0.381	-0.299	-0.660***
	(0.320)	(0.408)	(0.428)	(0.360)	(0.142)
Imp_int	0.117***	0.124***	0.091**	0.134***	0.064***
	(0.031)	(0.031)	(0.041)	(0.030)	(0.018)
Tech_int	-0.172**	-0.061	0.646	-0.159	-0.012
	(0.079)	(0.104)	(1.25)	(0.132)	(0.270)
R&D_int	2.48***	0.496	2.187***	1.822***	0.317***
	(0.342)	(0.850)	(0.404)	(0.343)	(0.067)
Constant	2.768***	4.567***	1.574**	3.819***	0.435**
	(0.478)	(0.567)	(0.644)	(0.538)	(0.178)
AR(1) *p-value*	-1.84(0.066)	-1.27(0.205)	-2.24(0.000)	-1.78(0.074)	56.91(0.034)
AR(2) *p-value*	0.81(0.710)	0.98(0.329)	1.49(0.137)	1.79(0.073)	0.89(0.372)
Sargan *p-value*	0.000	0.000	0.000	0.000	0.000
Hansen *p-value*	0.150	0.022	0.876	0.225	0.180
Instruments	27	27	27	27	27
Industry dummy	Yes	Yes	Yes	No	No
Observations(Firm)	14,300 (650)	8734(397)	5566(253)	11,748 (534)	2552(116)

Note: Authors’ calculations. *** and ** indicates statistical significance at 1% and 5% levels, respectively. Standard errors are given in parentheses. Export intensity (Exp_int) is the dependent variable. Total factor productivity (TFP), Import intensity (Imp_int), Technology transfer intensity (Tech_int), and Research and Development intensity (R&D) are the explanatory variables. L refers to the lag of the variables. The estimators are obtained using the system GMM method, where Hansen and Sargan tests are used to check the over-identifying restrictions. AR(1) and AR(2) are considered the Arellano-Bond test for the model’s first and second-order autocorrelation.

5.3. Learning by exporting hypothesis

Next, we examine the "learning by exporting" hypothesis for Indian manufacturing firms. Here the empirical model for the hypothesis is expressed as follows.

$$TFP_{it} = \alpha_{it} + \beta_1(TFP)_{it-1} \quad + \beta_2(Exp\_int)_{it} + \beta_3(Imp\_int)_{it} + \beta_4(Tech\_int)_{it} + \beta_5(R\&D\_int)_{it} + u_{it} \tag{14}$$

The results reported in Table 3 demonstrate that exports are significant and positively related to manufacturing firms' productivity in the case of India. This shows that an increase of 1 unit of export activities leads to a 0.012-unit increment of its productivity. At the same time, we see that import intensity and R&D intensity have a substantial effect on the productivity of firms. We also observe that in the case of labor- and capital-intensive sectors, there is a progressive effect of export on the productivity of firms. However, export intensity has a higher effect on capital-intensive firms than on labor-intensive firms. Similarly, for domestic and foreign firms, the measurement of export intensity is significant and positively affects their productivity. As with the analysis of "manufacturing as a whole" and in most sub-sectors, we see that exports boost a firm's productivity. Hence, export helps improve the firm's performances in the international market. However, the findings only confirm limited backing for "the learning by exporting hypothesis" in the Indian manufacturing sector.

Thus far, we have examined the "learning by exporting" hypothesis in the case of firms' export activities and productivity. In this part, we determine whether the same premise holds good in the case of firms' exports and their competitiveness. For this, we first calculate the ICI for Indian manufacturing firms as a combination of sales growth, labor productivity, and profitability. It is a composite index value for all manufacturing firms. Next, we apply export intensity on a firm's competitiveness. In this case, our standard empirical model for "learning by exporting" can be extended from exports to competitiveness as follows:

$$ICI_{it} = \alpha_{it} + \beta_1(ICI)_{it-1} \quad + \beta_2(Exp\_Int)_{it} + \beta_3(Imp\_Int)_{it} + \beta_4(Tech\_int)_{it} + \beta_5(R\&D\_int)_{it} + u_{it} \tag{15}$$

The results in Table 4 reveal that in the case of "manufacturing as a whole", export intensity has a significant effect on the competitiveness of firms. We note that 1 unit of improvement in firms' exports helps them improve their competitiveness by 0.020 units. Export intensity is also significant and has a positive effect on competitiveness in all firms segregated by labor- and capital-intensive sectors. At the same time, however, export is only significant in case of domestic firms, and not in case of foreign firms. In comparison, results show that the measure of export coefficients is higher in the case of capital-intensive firms than labor-intensive firms. Similarly, the coefficient of export intensity is elevated in the case of domestic firms. It may be argued that capital-intensive and domestic firms' export activities help them become more competitive. We also see that manufacturing firms' import activities significantly affect their competitiveness, but technology and R&D do not have a significant effect on their competitiveness. Similarly, in the case of sectoral division, we noticed that technology and R&D have a positive but not significant impact on the competitiveness of domestic and foreign firms. R&D is also positively significant in the case of labor-intensive sectors. The results also show that the effects of competitiveness from previous years also help to improve the competitiveness in current years, as the lag effect of ICI has a significant positive impact on firm competitiveness. Here, the result shows that in all cases of sub-sectoral and overall manufacturing, export intensity has a positive effect on firms' competitiveness. This indicates that firms become more competitive when they are primarily involved in the export market. It may be said that when domestic exporting firms encounter international exporting firms and their innovative products and note the quality of their products, they learn from the market and apply these learnings to their firms and initiate more experiments in innovation. Thus, it helps such firms become more competitive in the market through export activities. The results show that manufacturing firms that enter the export market are able to improve their productivity and competitiveness. These findings are consistent with those of Siba and Gebreeyesus (2016) and Yousefi et al. (2019), in which they confirmed the "learning by exporting" hypothesis with regard to the impact of firms' exports on productivity in the case of Iranian and Ethiopian manufacturing firms respectively. Although our findings support the "learning by exporting" hypothesis, we still checked the reverse hypothesis, i.e., "self-selection," in order to check the link in our analysis from competitiveness to export. In the reverse case, we do not find any link between competitiveness and export participation. Results for the impact of competitiveness on export are reported in Appendix 3.

Next, for a more robust analysis, we examine the "learning by exporting" behavior through export and competitiveness of individual industries in the Indian manufacturing sector. Our study considers ten major industries, which are food products, textile, basic metals, non-metallic products, rubber, machinery and equipment, chemical, pharmaceutical, electrical, and automobile and transport equipment of Indian manufacturing sector.[1] The results reported in Table 5 show that export has a strong positive significant effect on the competitiveness of all industries except the non-metallic products industry. Apart from export, other control variables such as import, technology, and R&D intensity also have significant positive effect on the majority of industries. Thus, the overall result supports the "learning by exporting" hypothesis in the case of Indian manufacturing.

To test the consistency of GMM estimates, we also check the over-identifying restriction through Sargan and Hansen tests and serial autocorrelation tests of AR(1) and AR(2) statistics, proposed by Arellano and Bond (1991). The results based on the level of sub-sectors and individual industries show that although the Sargan test statistic is significant, the Hansen test fails to reject the null hypothesis. Thus, it is proved that the instruments in our model are valid. This also implies that instrument variables are jointly valid and helps

[1] We have not included the paper industry because data are available only with respect to a few firms. The other reason is to avoid the instrumental problem in the GMM model.

Table 3
Impact of export intensity on productivity.

TFP (Dependent)	All manufacturing	Labor intensive	Capital intensive	Domestic firms	Foreign firms
L.TFP	0.411***(0.018)	0.365***	0.071***	0.395***	0.488***
		(0.020)	(0.022)	(0.020)	(0.026)
Exp_int	0.012**	0.021***	0.060***	0.019***	0.012**
	(0.005)	(0.006)	(0.012)	(0.006)	(0.004)
Imp_int	0.006**	0.005***	0.005***	0.007***	0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Tech_int	-0.003	0.023**	-0.010	0.001	-0.002***
	(0.005)	(0.007)	(0.008)	(0.007)	(0.006)
R&D_int	0.065***	0.047	0.060**	0.070***	0.019
	(0.013)	(0.044)	(0.026)	(0.012)	(0.014)
Constant	0.161***(0.034)	-0.141***	-0.417***	0.189***	-0.064***
		(0.039)	(0.047)	(0.041)	(0.031)
AR(1) *p-value*	-3.84(0.000)	-2.59(0.000)	-2.44(0.015)	-2.62(0.009)	-7.40(0.000)
AR(2) *p-value*	0.24(0.811)	0.55(0.581)	1.46(0.145)	1.11(0.265)	-3.88(0.006)
Sargan *p-value*	0.000	0.000	0.000	0.000	0.046
Hansen *p-value*	0.140	0.300	0.004	0.110	0.063
Instruments	27	27	27	27	27
Industry dummy	Yes	Yes	Yes	No	No
Observation (Firm)	14,300 (650)	8734(397)	5566 (253)	11,748(534)	2552(116)

Note: Authors' calculations. *** and ** indicates statistical significance at 1%, and 5% levels, respectively. Standard errors are given in parentheses. Total factor productivity (TFP) is the dependent variable. Export intensity (Exp_int), Import intensity (Imp_int), Technology transfer intensity (Tech_int), and Research and Development intensity (R&D) are the explanatory variables. L refers to the lag of the variables. The estimators are obtained using the system GMM method, where Hansen and Sargan tests are used to check the over-identifying restrictions. AR(1) and AR(2) are considered the Arellano-Bond test for the model's first and second-order autocorrelation.

Table 4
Impact of exports on competitiveness.

ICI (Dependent)	All manufacturing	Labor intensive	Capital intensive	Domestic firms	Foreign firms
L.(ICI)	0.325***	0.311***	0.361***	0.326**	0.320**
	(0.013)	(0.016)	(0.021)	(0.050)	(0.028)
Exp_int	0.020**	0.024**	0.027**	0.015**	0.010
	(0.009)	(0.014)	(0.014)	(0.008)	(0.019)
Imp_int	0.091***	0.117***	-0.062***	0.075***	0.165***
	(0.013)	(0.019)	(0.016)	(0.013)	(0.026)
Tech_int	0.015	0.062	-0.030	-0.050	0.108
	(0.136)	(0.183)	(0.184)	(0.145)	(0.280)
R&D_int	0.232	0.885**	-0.143	0.046	-1.103
	(0.273)	(0.454)	(0.218)	(0.243)	(1.352)
Constant	27.80****	28.27***	26.34***	27.09***	26.88***
	(0.136)	(0.000)	(0.978)	(0.691)	(1.354)
AR(1) p-value	-22.52(0.000)	-17.80(0.000)	-13.64(0.000)	-20.5(0.000)	-9.11(0.001)
AR(2) p-value	1.55(0.120)	1.09(0.278)	1.21(0.206)	1.59(0.113)	0.31(0.756)
Sargan *p*-value	0.000	0.000	0.000	0.000	0.000
Hansen *p*-value	0.177	0.050	0.743	0.239	0.551
Instruments	27	27	27	27	27
Industry dummy	Yes	Yes	Yes	No	No
Observation (Firm)	14,300 (650)	8734(397)	5566 (253)	11,748(534)	2552 (116)

Note: Authors' calculations. *** and ** indicates statistical significance at 1% and 5% levels, respectively. Standard errors are given in parentheses. The Industrial Competitiveness Index (ICI) is the dependent variable. Export intensity (Exp_int), Import intensity (Imp_int), Technology transfer intensity (Tech_int), and Research and Development intensity (R&D) are the explanatory variables. L refers to the lag of the variables. The estimators are obtained using the system GMM method, where Hansen and Sargan tests are used to check the over-identifying restrictions. AR(1) and AR(2) are considered the Arellano-Bond test for the model's first and second-order autocorrelation.

predict our true model. There are a reasonable number of studies in literature in support of our model, such as, Khanna and Sharma (2018) and Mitra, Sharma, and Véganzonès-Varoudakis (2016), which also report significant values of Sargan and Hansen test statistics, and related studies by Fan, Zhang, and Liu (2016), which find the results of the Sargan statistic significant, but not the Hansen statistic. Similarly, the AR(1) test rejects the null hypothesis of "absence of first-order serial correlation", whereas the AR(2) test accepts the null hypothesis that there is an absence of serial autocorrelation throughout the model. The model also controls the instruments in our analysis, using the instrumental collapse option, suggested by Roodman (2009).

Table 5
Impact of exports on competitiveness by industry.

ICI (Dependent)	Food	Textile	Basic metal	Non metallic	Rubber and plastic	Machinery and equipment	Chemical	Pharmaceutical	Electrical	Automobile and transport
L.(ICI)	0.292***	0.304***	0.235***	0.289**	0.423***	0.533***	0.358**	0.240***	0.441***	0.049
	(0.033)	(0.027)	(0.034)	(0.038)	(0.028)	(0.030)	(0.030)	(0.035)	(0.028)	(0.035)
Exp_int	0.516**	0.116**	0.065**	0.012	0.028**	0.074**	0.056**	0.060***	0.051**	0.781**
	(0.219)	(0.046)	(0.023)	(0.014)	(0.015)	(0.034)	(0.022)	(0.021)	(0.022)	(0.259)
Imp_int	0.140*	-0.089**	0.024	0.206***	0.092**	0.218***	0.137***	0.041**	-0.040	0.206**
	(0.050)	(0.037)	(0.024)	(0.050)	(0.027)	(0.038)	(0.024)	(0.016)	(0.029)	(0.080)
Tech_int	0.163	-0.741	0.798***	1.330***	-0.080**	0.386	2.664***	-0.515	-0.160***	-1.887**
	(0.158)	(1.043)	(0.242)	(0.349)	(0.016)	(0.239)	(0.378)	(1.644)	(0.041)	(0.669)
R&D_int	5.433**	0.412***	0.863	0.896	0.984**	0.783	8.688	-0.557**	-0.193	-0.563
	(2.400)	(1.302)	(0.778)	(2.355)	(0.401)	(0.694)	(1.125)	(0.109)	(0.275)	(1.560)
Constant	27.87***	27.19***	32.82***	26.94***	21.65***	18.61***	23.26***	32.42***	24.34**	47.98***
	(1.617)	(1.775)	(1.649)	(1.517)	(1.267)	(1.341)	(1.263)	(1.605)	(1.291)	(2.111)
AR(1) *p*-value	0.000	0.000	0.000	0.00	0.000	0.000	0.000	0.001	0.000	0.018
AR(2) *p*-value	0.439	0.395	0.012	0.989	0.324	0.585	0.675	0.369	0.141	0.642
Sargan *p*-value	0.002	0.000	0.033	0.001	0.000	0.000	0.000	0.100	0.000	0.010
Hansen *p*-value	0.733	0.294	0.915	0.315	0.704	0.828	0.796	0.205	0.517	0.786
Instruments	27	27	27	27	27	27	27	27	27	27
Observation (firm)	1276(58)	1958(89)	1254(57)	1012(46)	1276(58)	1622(73)	2552(116)	682(31)	1298(59)	987(47)

Note: Authors' calculations. ***, ** and * indicates statistical significance at 1%, 5%, and 10% levels, respectively. Standard errors are given in parentheses. Industrial Competitiveness Index (ICI) is the dependent variable. Export intensity (Exp_int), Import intensity (Imp_int), Technology transfer intensity (Tech_int), and Research and Development intensity (R&D) are the explanatory variables. L refers to the lag of the variables. The estimators are obtained using the system GMM method, where Hansen and Sargan tests are used to check the over-identifying restrictions. AR(1) and AR(2) are considered the Arellano-Bond test for the model's first and second-order autocorrelation.

5.4. Discussion of results

Findings from the above analysis of the "learning by exporting" and "self-selection" hypotheses in case of Indian manufacturing firms do not support the "self-selection" into the export market hypothesis; instead, we have evidence for the "learning by exporting" hypothesis in all industries in the Indian manufacturing sector. On the other hand, the results of our study show that firms' export activities have played a significant role in the improvement of their productivity and competitiveness. This finding also supports the results of several international studies, such as those by Harris and Li (2009) and Siba and Gebreeyesus (2016), in which they noted that export by firms has a significant and positive effect on their productivity. Our findings also support the growth theory proposed by Barro and Sala-i-Martin (1995) and Obstfeld and Rogoff (1996). They contended that countries are better able to capture new ideas from other countries with trade openness, which aids development. Although some Indian studies, by Gupta et al. (2018), Haidar (2012), and Sharma and Mishra (2011), claim the existence of the "self-selection" hypothesis, our finding differs from theirs and are consistent with the results published by Mallick and Yang (2013) and Ranjan and Raychaudhuri (2011). These authors argue that firms learn from their experiences and implement these ideas for future productivity. To become more competitive in the industry, exporters learn how to boost product quality, product innovation, competitiveness, and performance from the international markets and from their competitors.

6. Conclusion and suggestions for policymaking

In the present study, to understand the links between export, competitiveness, and productivity, we empirically examined the hypotheses of "learning through exporting" and the "self-selection" in the case of Indian manufacturing firms. The analysis was based on data from 650 firms in the Indian manufacturing sector for the period from 1994 to 2017. First, the study examined both the hypotheses and while the results do not support the "self-selection" hypothesis, they do provide evidence in favor of the "learning by exporting" hypothesis. Second, the study explored whether exports help the firms' competitiveness. For this, we examined the firms' competitiveness through the multidimensional ICI of sales growth, labor productivity, and profitability, and tried to establish its link to export intensity. The results show that export has a positive relationship with firms' competitiveness. Third, we extended the study to labor- and capital-intensive firms and firms that are foreign-owned and domestic. The results further support the "learning by exporting" hypothesis, indicating that exports significantly influence competitiveness in the Indian manufacturing sector. Individual industries also support the hypothesis by demonstrating that export helps improve the competitiveness of manufacturing industries. Other variables, such as import, R&D, and technology also have a significant positive effect on productivity. Similarly, R&D and technology are not significant to competitiveness in the case of manufacturing as a whole, but having a significant positive effect in the majority of disaggregated industry levels.

Overall, the findings suggest that exports have a significant impact on the competitiveness of manufacturing firms. From a policy perspective, it is important for the government to increase the pace of export promotion policies to boost productivity and competitiveness of the Indian manufacturing sector. At the same time, competitiveness of individual industries is also influenced by R&D activities and technology transfer. Hence, industries should focus on enhancing in-house innovation activities and transfer of technology.

In this study, we have only considered the "learning by exporting" activities of export-oriented firms in the Indian manufacturing sector. Future research can include different sub-samples based on both exporting and non-exporting firms.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix 1. Perpetual inventory method

The physical capital stock of Indian manufacturing industries is not available. Thus, we use the perpetual inventory method (PIM) to compute the series of capital stocks (Easterly & Levine, 2001; Sharma & Mishra, 2011). Here, initial fixed capital is considered the net book value of the benchmark year. In our estimation, the year 1994 is considered the benchmark year. Once we estimate the initial fixed capital, we measure the gross fixed capital series using the equation given below:

$$K_{it} = (1 - \delta)K_{it-1} + I_{it}$$

Here,K_{it} = Real gross capital stock for firm "i" at period "t"I_{it} = Real gross investment rate for firm "i" at period "t"δ = Annual rate of depreciation or discard capital.

In this study, we use discard capital at 7%, following Ghosh (2009) and Mitra et al. (2014). The gross real investment of firm I_{it} is computed using the following formula:

$$I_{it} = (B_{it} - B_{it-1} + D_{it})/P_{it}$$

where B_{it} is the book value of the fixed capital of firm "*i*" at time "*t*", D_{it} refers to the depreciation rate of firm "*i*" at year "*t*", and P_{it} is the price index of "machinery and machine tools" of firms with the same year "*t*" in the base year of 2004–05, which was collected from the *Handbook of Statistics of Indian Economy*, published by Reserve Bank of India (RBI).

Appendix 2. Production function estimates (LP and ACF)

Variable	LP coefficient	ACF coefficient
lnL	0.294***(0.000)	0.616*** (0.000)
lnK	0.625***(0.000)	0.359*** (0.000)
Wald test *p-value*	10.09***(0.01)	2.08(0.149)
Observation (Firm)	15,600(650)	14,950(650)

Notes: Authors' calculations. *** indicates 1% significance level and standard errors are given in the parentheses. Wald test *p*-value shows the null of constant returns to scale. Gross value added is used as output variable, Labor(L) and Capital(K) are used as input variables, and raw materials expenses are used as proxy variables.

The correct estimation of production function estimates is a challenging task for researchers. However, studies by Ackerberg et al. (2015), Bournakis and Mallick (2018), and Singh and Sharma (2019) argue that Levensohn and Patrin (2003) underestimates the contribution of labor, because there is no variance in labor inputs remaining after the first stage of the estimation process to identify second-stage estimation. On the other hand, the ACF estimate is considered the best alternative among the other traditional non-parametric production estimates. It considers labor to be a dynamic input and is treated as a freer variable in the second stage estimation of the ACF process (Bournakis & Mallick, 2018). In this regard, we compared the results between our two estimates, LP (2003) and Ackerberg et al. (2015). As we know, labor is freer in the ACF method, and in our estimation process, we also discovered that the labor coefficient in the ACF method (0.616) is greater than that in the LP method (0.294). The real contribution of labor to output growth can be well captured through ACF estimation. The joint contribution of labor and capital coefficient in the ACF (0.975) method is also higher than the LP (0.919) method. We also observed that in the studies by Sharma and Mishra (2011), the coefficient of labor in Indian manufacturing industries varies from 0.28 to 0.61 depending on the industry. However, based on the Monte Carlo experiment in Ackerberg et al. (2015) and Rovigatti and Mollisi (2018), ACF is found to be superior (mean square errors are small) to LP. Hence, in our estimation process, we preferred the ACF production function estimates to the LP method.

Appendix 3. Impact of competitiveness on exports

Export-intensity (Dependent)	All manufacturing	Labor intensive	Capital intensive	Domestic firms	Foreign firms
L.(Exp_int)	0.641***	0.538***	0.707***	0.578***	0.891***
	(0.199)	(0.022)	(0.034)	(0.026)	(0.032)
ICI	0.007	0.014	0.006	0.005	0.005
	(0.011)	(0.012)	(0.013)	(0.011)	(0.006)
Imp_int	0.119**	0.120***	0.089**	0.135***	0.058***
	(0.030)	(0.031)	(0.038)	(0.030)	(0.017)
Tech_int	-0.166	-0.075*	-0.199	-0.156	-0.028
	(0.127)	(0.094)	(0.177)	(0.130)	(0.027)
R&D_int	1.290**	0.172	1.310***	1.82***	0.325***
	(0.690)	(0.472)	(0.341)	(0.342)	(0.065)
Constant	2.622***	4.097***	1.664**	3.654***	0.075
	(1.738)	(0.740)	(0.717)	(0.706)	(0.226)
AR(1) p-value	-1.71(0.087)	-1.26(0.206)	-2.19(0.028)	-1.78(0.075)	-2.11(0.034)
AR(2) p-value	1.24(0.110)	0.97(0.330)	1.47(0.142)	1.79(0.273)	0.90(0.370)
Sargan *p*-value	0.000	0.000	0.000	0.000	0.000
Hansen *p*-value	0.188	0.087	0.886	0.303	0.147
Instruments	27	27	27	27	27
Industry dummy	Yes	Yes	Yes	No	No
Observation (Firm)	14,300 (650)	8337(397)	5566 (253)	11,748(534)	2552 (116)

Note: Authors' calculations. *** and ** indicates statistical significance at 1%, and 5% levels, respectively. Standard errors are given in parentheses. Export intensity (Exp_int) is the dependent variable. Industrial Competitiveness Index (ICI), Import intensity (Imp_int), Technology transfer intensity (Tech_int), and Research and Development intensity (R&D) are the explanatory variables. L refers to the lag of the variables. The estimators are obtained using the system GMM method, where Hansen and Sargan tests are used to check the over-identifying restrictions. AR(1) and AR(2) are considered the Arellano-Bond test for the model's first and second-order autocorrelation.

References

Ackerberg, D. A., Caves, K., & Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica, 83*, 2411–2451.

Arellano, M., & Bond, S. R. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*(2), 277–297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68*(1), 29–51.

Arnold, J. M., & Hussinger, K. (2005). Export behavior and firm productivity in German manufacturing. A firm-level analysis. *Review of World Economics, 141*, 219–243.

Atkin, D., Khandelwal, A. K., & Osman, A. (2017). Exporting and firm performance: Evidence from a randomized experiment. *The Quarterly Journal of Economics, 132*(2), 551–615.

Aw, B. Y., Chung, S., & Roberts, M. J. (2000). Productivity and turnover in the export market: Micro evidence from Taiwan and South Korea. *World Bank Economic Review, 14*, 65–90.

Balassa, B. (1988). Outward orientation. In H. Chenery, & T. N. Srinivasan (Eds.), *Handbook of development economics* (2 ed., pp. 1645–1689). Amsterdam: North-Holland.

Baldwin, J. R., & Gu, W. (2004). Export-market participation and productivity performance in Canadian manufacturing. *Canadian Journal of Economics, 36*, 634–657.

Barro, R. J., & Sala-i-Martin, X. (1995). *Economic growth*. New York: McGraw-Hill.

Basant, R., & Fikkert, B. (1996). The effects of R&D, foreign technology purchase, and domestic and international spillovers on productivity in Indian firms. *Review of Economics and Statistics, 78*, 187–199.

Behera, S., Dua, P., & Goldar, B. N. (2012). Foreign direct investment and technology spillover: Evidence across Indian manufacturing industries. *Singapore Economic Review, 57*(2), Article 1250011.

Bernard, A. B., & Jensen, J. B. (1999). Exceptional exporter performance: Cause, effect, or both? *Journal of International Economics, 47*(1), 1–25.

Bernard, A. B., & Jensen, J. B. (2004). Exporting and productivity in the USA. *Oxford Review of Economic Policy, 20*(3), 343–357.

Bernard, A. B., & Wagner, J. (1997). Exports and success in German manufacturing. *Review of World Economics, 133*(1), 134–157.

Bhattacharya, P., & Rath, B. N. (2020). Innovation and firm-level labour productivity: A comparison of Chinese and Indian manufacturing based on enterprise surveys. *Science, Technology and Society, 25*(3), 465–481.

Bhaumik, S. C., & Kumbhakar, S. C. (2008). Is the post-reform growth of the Indian manufacturing sector efficiency driven? Empirical evidence from plant-level data. *Journal of Asian Economics, 21*, 219–232.

Van Biesebroeck, J. (2005). Exporting raises productivity in sub-Saharan African manufacturing firms. *Journal of International Economics, 67*, 373–391.

Van Biesebroeck, J. (2007). Robustness of productivity estimates. *Journal of Industrial Economics, 55*(3), 529–569. https://doi.org/10.1111/j.1467-6451.2007.0032

Bigsten, A., & Gebreeysus, M. (2009). Firm productivity and exports: Evidence from Ethiopian manufacturing. *Journal of Development Studies, 45*(10), 1594–1614.

Blalock, G., & Gertler, P. J. (2004). Learning from exporting revisited in a less developed setting. *Journal of Development Economics, 75*, 397–416.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115–143.

Bournakis, I., & Mallick, S. (2018). TFP estimation at firm level: The fiscal aspect of productivity convergence in the UK. *Economic Modelling, 70*(C), 579–590.

Cassey, A., & Schmeiser, K. (2013). Multilateral export decompositions. *Open Economies Review, 24*, 901–918.

Clerides, S., Lach, S., & Tybout, J. (1998). Is learning-by-exporting important? Micro-dynamic evidence from Colombia, Mexico, and Morocco. *Quarterly Journal of Economics, 113*(3), 903–947.

Delgado, M., Farinas, J., & Ruano, S. (2002). Firm productivity and export markets: A nonparametric approach. *Journal of International Economics, 57*(2), 397–422.

Demirhan, A. A. (2016). Export behavior of the Turkish manufacturing firms. *Emerging Markets Finance and Trade, 52*(11), 2646–2668.

Easterly, W., & Levine, R. (2001). *It's not factor accumulation: Stylized facts and growth models*. Washington, DC: World Bank. Retrieved from ⟨https://openknowledge.worldbank.org/handle/10986/17440⟩.

Fan, Z., Zhang, R., & Liu, X. (2016). Income inequality, entrepreneur formation, and the economic development: Evidence from China. *Journal of the Asia Pacific Economy, 21*(3), 444–464.

Fernandes, A. M., & Isgut. A. E. (2005). *Learning-by-doing, learning-by-exporting, and productivity: Evidence from Colombia*. Working Paper 3544, Washington, DC: World Bank.

Fischer, C., & Schornberg, S. (2007). Assessing the competitiveness situation of EU food and drink manufacturing industries: An index-based approach. *Agribusiness, 23*(4), 473–495.

Franco, C., & Sasidharan, S. (2010). MNEs, technological efforts and channels of export spillover: An analysis of Indian manufacturing industries. *Economic System, 34*(3), 270–288.

Ghosh, S. (2009). Do productivity and ownership really matter for growth? Firm-level evidence. *Economic Modelling, 26*, 1403–1413.

Girma, S., Greenaway, D., & Kneller, R. (2004). Does exporting increase productivity? A microeconometric analysis of matched firms. *Review of International Economics, 12*(5), 855–866.

Greenaway, D., & Kneller, R. (2007). Firm heterogeneity, exporting and foreign direct investment. *The Economic Journal, 117*(517), 134–161.

Grossman, G. M., & Helpman, E. (1991). *Innovation and growth in the global economy*. Cambridge, MA: MIT Press.

Gupta, A., Patnaik, I., & Shah, A. (2018). Exporting and firm performance: Evidence from India. *Indian Growth and Development Review, 12*(1), 83–104.

Hahn, C. (2004). *Exporting and performance of plants: Evidence from Korean Manufacturing*. Working Paper 10208, Cambridge MA: National Bureau of Economic Research.

Haidar, J. I. (2012). Trade and productivity: Self-selection or learning-by-exporting in India. *Economic Modelling, 29*, 1766–1773.

Hansson, P., & Lundin, N. N. (2004). Exports as an indicator on or promoter of successful Swedish manufacturing firms in the 1990s. *Review of World Economics, 140*(3), 415–445.

Harris, R., & Li, Q. C. (2009). Exporting, R&D, and absorptive capacity in UK establishments. *Oxford Economic Papers, 61*, 74–103.

Hasan, R. (2002). The impact of imported and domestic technologies on the productivity of firms: Panel data evidence from Indian manufacturing firms. *Journal of Development Economics, 69*, 23–49.

IBEF, (2021). *Foreign trade policy of India*. Retrieved from: ⟨https://www.ibef.org/economy/trade-and-external-sector⟩.

Kathuria, V. (2002). Liberalisation, FDI and productivity spillovers an analysis of Indian manufacturing firms. *Oxford Economic Papers, 54*, 688–718.

Khanna, R., & Sharma, C. (2018). Testing the effect of investments in IT and R&D on labour productivity: New method and evidence for Indian firms. *Economics Letters, 173*, 30–34. https://doi.org/10.1016/j.econlet.2018.09.003

Kim, K., Petrin, A., & Song, S. (2016). Estimating production functions with control functions when capital is measured with error. *Journal of Econometrics, 190*(2), 267–279.

Koenig, P. (2009). Agglomeration and the export decisions of French firms. *Journal of Urban Economics*, 186–195.

Kraay, A. (1999). Exportations et performances economiques: Etude d'un panel d'entreprises chinoises'. *Revue d'Economie Délután Developpement, 7*(1–2), 183–207.

Krugman, P. (1987). The narrow moving bank, the Dutch Disease and the competitive consequences of Mrs. Thatcher: Notes on trade in the presence of dynamic scale economies. *Journal of Development Economics, 27*, 41–55.

Kumar, N., & Aggarwal, A. (2005). Liberalisation, outward orientation and in-house R&D activity of multinational and local firms. *Research Policy, 34*, 441–460.

Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies, 70*, 317–341.

Lopez, R. A. (2005). Trade and growth: Reconciling the macroeconomic and microeconomic evidence. *Journal of Economic Surveys, 19*(4), 623–648.

Mallick, S., & Yang, Y. (2013). Productivity performance of export market entry and exit: Evidence from Indian firms. *Review of International Economics, 21*(4), 809–824.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica, 71*(6), 1695–1725.

Mitra, A., Sharma, C., & Véganzonès-Varoudakis, M. A. (2014). Trade liberalization, technology transfer, and firms' productive performance: The case of Indian manufacturing. *Journal of Asian Economics, 33*, 1–15.
Mitra, A., Sharma, C., & Véganzonès-Varoudakis, M. A. (2016). Infrastructure, information and communication technology and firms' productive performance of the Indian manufacturing. *Journal of Policy Modeling, 38*(2), 353–371.
Narayanan, K., & Bhat, S. (2009). Technology sourcing and its determinants: A study of basic chemical industry in India. *Technovation, 29*(8), 562–573.
Obstfeld, M., & Rogoff, K. S. (1996). *Foundations of international macroeconomics*. MIT Press Books, The MIT Press, edition 1, vol. 1, number 0262150476.
Olley, G. S., & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica, 64*, 1263–1297.
Parente, S., & Prescott, E. C. (1994). Barriers to technology adaptation and development. *Journal of Political Economy, 102*, 298–321.
Porter, M. E. (1990). *Competitive advantage of nation*. New York: The Free Press.
Ranjan, P., & Raychaudhuri, J. (2011). Self-selection vs learning: Evidence from Indian exporting firms. *Indian Growth and Development Review, 4*(1), 22–37.
Rath, B. N. (2018). Productivity growth and efficiency change: Comparing manufacturing and service based firms in India. *Economic Modelling, 70*(c), 447–457.
Raut, L. K. (1995). R&D spillover and productivity growth: Evidence from Indian private firms. *Journal of Development Economics, 48*, 1–23.
Ray, A. S., & Bhaduri, S. (2001). R&D and technological learning in Indian industry: Econometric estimation of the research production function. *Oxford Development Studies, 29*, 156–171.
Rivera-Batiz, L. A., & Romer, P. M. (1991). Economic integration and endogenous growth. *Quarterly Journal of Economics, 106*, 531–555.
Roberts, M., & Tybout, J. (1997). The decision to export in Colombia: An empirical model of entry with sunk costs. *American Economic Review, 87*(4), 545–564.
Rodrik, D. (1988). Imperfect competition, scale economies and trade policy in developing countries. In R. E. Baldwin (Ed.), *Trade policy issues and empirical analysis*. Chicago: University of Chicago Press.
Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics, 71*(1), 135–158.
Rovigatti, G., & Mollisi, V. (2018). Theory and practice of total-factor productivity estimation: The control function approach using Stata. *The Stata Journal, 18*(3), 618–662.
Sahoo, P. K., & Rath, B. N. (2018). Productivity growth, efficiency change and source of inefficiency: Evidence from the Indian automobile industry. *International Journal of Automotive Technology and Management, 18*(1), 59–74.
Sasidharan, S., & Kathuria, V. (2011). Foreign direct investment and R&D: Substitutes or complements, a case of Indian manufacturing after 1991 reforms. *World Development, 39*, 1226–1239.
Schmeiser, K. (2011). Learning to export: Export growth and the destination decision of firms. *Journal of International Economics, 87*, 89–97.
Seenaiah, K., & Rath, B. N. (2017). Obstacles to innovation in selected Indian manufacturing firms. *International Journal of Technological Learning, Innovation and Development, 9*(4), 379–398.
Seenaiah, K., & Rath, B. N. (2018). Determinants of innovation in selected manufacturing firms: Role of R&D and exports. *Science, Technology and Society, 23*(1), 65–84.
Sharma, C. (2012). R&D and firm performance: Evidence from the Indian pharmaceutical industry. *Journal of the Asia Pacific Economy, 17*(2), 332–342.
Sharma, C. (2018). Exporting, access of foreign technology, and firms' performance: Searching the link in Indian manufacturing. *The Quarterly Review of Economics and Finance, 68*(C), 46–62.
Sharma, C., & Mishra, R. K. (2011). Does export and productivity growth linkage exist? Evidence from the Indian manufacturing industry. *International Review of Applied Economics, 11*(6), 633–652.
Siba, E., & Gebreeyesus, M. (2016). Learning to export and learning from exporting: The case of Ethiopian manufacturing. *Journal of African Economies, 26*(1), 1–23.
Siddharthan, N. S., & Narayanan, K. (2016). *Technology: Corporate and social dimensions*. Springer.
Singh, A. P., & Sharma, C. (2019). Does selection of productivity estimation techniques matter? Comparative analysis of advanced productivity estimation techniques. *Indian Growth and Development Review, 13*(1), 125–154.
Sjoholm, H. (1999). Technology gap, competition and spillovers from direct foreign investment: Evidence from establishment data. *The Journal of Development Studies, 36*(1), 53–73.
Tybout, J. R. (2003). Plant- and firm-level evidence on "new" trade theories. *Handbook of International Trade*, 388–415. https://doi.org/10.1002/9780470756461.ch13
Wagner, J. (2002). The causal effects of exports on firm size and labor productivity: First evidence from a matching approach. *Economics Letters, 77*(2), 287–292.
Wagner, J. (2007). Exports and productivity: A survey of the evidence from firm level data. *The World Economy, 30*(1), 60–82.
Wang, F., Xu, Z., & Dai, X. (2021). Is learning by exporting technology specific? Evidence from Chinese firms. *Economics of Innovation and New Technology*, 1–30. https://doi.org/10.1080/10438599.2021.1910031
WDI (2020). *World development indicators database*. The World Bank. Retrieved from: ⟨https://databank.worldbank.org/source/world-development-indicators⟩.
Wu, F., Wu, H., & Zhang, X. (2020). How does innovation activity affect firm export behavior? Evidence from China. *Emerging Markets Finance and Trade, 56*(8), 1730–1751.
Yasar, M., Nelson, C. H., & Rejesus, R. (2006). Productivity and exporting status of manufacturing firms: Evidence from quantile regressions. *Review of World Economics, 142*(4), 675–694.
Yasar, M., & Rejesus, R. M. (2005). Exporting status and firm performance: Evidence from a matched sample. *Economics Letters, 88*(3), 397–402.
Yousefi, K., Madanizadeh, S. A., & Sobhani, F. Z. (2019). Growth through export: Evidence from Iran's manufacturing plants. *Journal of Economic Studies, 47*(1), 111–131.