Import Competition, Productivity and Product Mix*

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Abstract

When faced with tougher import competition, firms can improve the productivity of their existing products (intensive margin) or reallocate their output towards more efficiently produced products (extensive margin). What is the contribution of each channel to aggregate productivity growth? To answer this question, I use a rich firm-product-level panel of Indian manufacturers between 1994 and 2008 to estimate product-specific productivity over time. The surge of Chinese exports to India allows me to estimate the causal effect of trade on both margins of productivity growth. I reach two main conclusions. First, greater Chinese import competition increased the productivity of existing products. Second, there was no causal effect on reallocation across products. My results suggest the intensive margin response to rising import competition accounts for 20-30 percent of the overall productivity growth in the manufacturing sector. These productivity gains have important policy implications because moving from low- to middle-income requires rising productivity, and my results provide evidence that greater import competition accelerates that process.

Keywords: import competition, productivity, multi-product firms

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1 Introduction

Trade affects productivity. While it is well known that the reallocation towards high-productivity firms improves aggregate productivity in response to trade shocks (Melitz, 2003; Pavcnik, 2002), less is known about the within-firm productivity effect and the *channels* generating it. Trade can (i) directly affect the productivity of existing products (intensive margin), and (ii) reallocate production across products in multi-product firms (extensive margin). These effects matter. Multi-product firms dominate international trade flows and domestic production, and their importance has been emphasized in recent trade theories (Eckel and Neary, 2010; Bernard, Redding and Schott, 2011; Mayer, Melitz and Ottaviano, 2014, 2016).[1] To date, however, no empirical study has *directly* estimated the impact of trade on each of these margins and their relative contribution to firm-level and aggregate productivity growth. I fill this gap by exploiting the rapid growth of China's exports to India, combined with rich Indian manufacturing data that allows me to estimate product-specific productivity.

China's export shock to the Indian economy has been considerable. While China was not even among the top-ten exporters to India in 1994, it became the leading exporter by 2008. Within this time frame (i.e. 1994–2008), the value of exports from China to India increased fortyfold—from 0.76 billion USD to 31.6 billion USD. Given the technological similarity of Chinese and Indian firms, the dramatic surge in Chinese exports to India led to a substantial rise in product-market competition for Indian firms.[2] How did this sizable increase in import competition affect productivity? The answer to this question is crucial as the ability of India to move from low- to middle-income depends on its productivity growth. Understanding whether greater Chinese import competition accelerates economic development, therefore, has important policy implications.

Theoretically, the mechanisms through which import competition, or competition generally, affects firm productivity are unclear. On one hand, economists have argued that competition increases productivity by placing downward pressure on costs, reducing pre-innovation rents, and spurring innovation (Arrow, 1972). This is known as the "escape competition effect." On the other hand, another influential literature following Schumpeter (1943) argues that intensified competition can adversely affect innovation (or productivity) by reducing post-innovation rents. This is known as the "Schumpeterian effect." Later, Aghion et al. (2005) showed in a model that the balance between these two effects generates an inverted-U relationship between competition and productivity. Therefore, the exact relationship between import competition and productivity remains an applied

[1]Several studies have emphasized the dominance of firms producing more than one product. For example, Bernard, Redding and Schott (2010) report that multi-product firms in the United States account for 87 percent of output in 1997. In my Indian data, more than three-quarters of output is produced by multi-product firms. Arkolakis, Ganapati and Muendler (2019) find multi-product firms produce more than 90 percent of all exports in Brazil.

[2]Di Giovanni, Levchenko and Zhang (2014) show that India is the most technological similar country to China across the world.

question. This paper empirically examines this relationship in the context of a developing economy: India.

A key contribution of this paper is to construct an unbiased productivity measure at the firm-product level and test how it is affected by import competition. My method to recover productivity builds on De Loecker et al. (2016), who use the price and quantity of output for the sample of single-product firms to estimate the production function. While successful in correcting various sources of bias, their procedure is insufficient to recover *product-specific* productivity for multi-product firms. The main challenge is that input allocations across products are unknown for multi-product firms. I overcome this challenge by exploiting rich data on energy use for each of the firm's products.[3] This information enables me to use observed data to allocate inputs across products rather than imperfectly estimating input allocations. Hence, it considerably reduces the number of unknowns and allows me to estimate productivity at the firm-product level.[4] I then link the firm-product-level panel of Indian manufacturers to product-level bilateral trade data in order to assess the impact of Chinese import competition.

There are two main concerns in attempting to capture the causal effect on productivity. First, countries import more if domestic firms are less productive in producing specific products. This simultaneity bias would lead to an underestimation of the effect of Chinese import competition. Second, unobserved demand shocks in India may drive growth both in imports and productivity. This omitted variable bias would lead to overestimating the effect of Chinese import competition. As the two sources of bias go in opposite directions, the overall sign and size of bias is ambiguous. To alleviate these concerns, I use an instrumental variable strategy based on Autor, Dorn and Hanson (2013). In particular, I use Chinese import penetration to other low-income economies as an instrument for Chinese import penetration in India. The identification assumption is that the demand shocks are uncorrelated across low-income countries and the rise in Chinese imports stems solely from supply shocks in China.[5]

My analysis begins by examining the response of firm-product-level productivity to the surge in Chinese imports. I find a positive relationship between Chinese import competition and productivity. In particular, I find that a 10 percentage point increase in Chinese import penetration increases productivity by 6.75 percent. Are these effects large or small? To interpret the magnitude of the results, I evaluate the contribution of the impact of Chinese imports in aggregate productivity growth.

[3]Energy data is collected by the Indian government as part of the Indian Companies Act of 1956.

[4]The estimation procedure is similar to Garcia-Marin and Voigtländer (2019) with one important difference. I allocate inputs to products using a quantity measure of input (energy), whereas they allocate inputs according to the variable cost of inputs. Moreover, I consider a more flexible functional form (translog specification) when estimating production function.

[5]Zhu (2012) emphasizes that productivity growth has been the main driver of China's rapid growth in the past three decades.

Back-of-the-envelope calculations show that productivity gains are sizable and account for 20-30 percent of the overall productivity growth in the Indian manufacturing sector.

Next, I explore reallocation responses across products. To do so, I use a standard decomposition of revenue-weighted productivity at the firm level. While, reassuringly, my results confirm the positive effect of Chinese import competition on firm-level productivity, I find no evidence that reallocation across products drives firm-level productivity. Thus, improvements in the productivity of individual products remain as the main explanation for the impact of greater import competition on firm-level productivity.[6] These results are consistent with the previous studies examining multi-product firms in India. For example, Goldberg et al. (2010) find no link between product reallocation and trade liberalization in India.

I also examine the heterogeneous effects of Chinese import competition in two dimensions. First, I explore whether productivity responses are an increasing function of competition or whether they follow an inverted-U curve. To do so, I split the sample by the change in Chinese import competition. My results indicate that the increase in productivity is larger for products that face more competition from China. Second, I explore the heterogeneous response of products based on their initial productivity levels. Hence, I split the sample into low-, moderate-, and high-productivity products. Interestingly, I find most of the efficiency gains come from increases in the productivity of initially low- and high-productivity products. This suggests firms in India are mainly investing in products at the two tails of the productivity distribution when faced with rising import competition.

This paper speaks to several strands of literature. I contribute to a growing literature examining the effect of Chinese import competition on innovation and productivity.[7] In this context, Autor et al. (2016) and Hombert and Matray (2018) find a negative relationship between Chinese import competition and patenting activity in the United States. Yet, Bugamelli, Fabiani and Sette (2015) find no significant effect on the productivity of Italian firms. Bloom, Draca and Van Reenen (2016) and Dhyne et al. (2017) find that increase in imports from China increased the productivity of European and Belgian firms, respectively. I add to this literature by further analyzing the impact on product-specific productivity and focusing on India as a developing country.[8]

More broadly, I relate to the empirical literature examining the relationship between globalization and productivity. In this literature, trade shocks generally come from an episode of trade liberalization or intensified import competition. There is a consensus that trade liberalization increases firm

[6]This result may not hold for developed economies. For example, Mayer, Melitz and Ottaviano (2014) and Mayer, Melitz and Ottaviano (2016) find evidence of selection in product mix for the sample of French exporters.

[7]Several studies have examined the impact of Chinese import competition on other economic outcomes, including product quality in Peru (Medina, 2018), plant reallocation and survival in the U.S. (Bernard, Jensen and Schott, 2006), and labor market outcomes in the U.S. (Autor, Dorn and Hanson, 2013; Pierce and Schott, 2016; Acemoglu et al., 2016).

[8]Iacovone, Rauch and Winters (2013) examine the effect of Chinese import competition on a panel of Mexican firms. While their study focuses on a developing country, they do not directly estimate any measure of productivity as their data is insufficient for productivity estimation.

productivity; studies have documented positive effects of liberalization on firm-level productivity in Chile (Pavcnik, 2002), Brazil (Muendler, 2004), Columbia (Fernandes, 2007), Argentina (Bustos, 2011), Canada (Trefler, 2004), Mexico (Iacovone, 2012), India (Sivadasan, 2009; Topalova and Khandelwal, 2011), and Indonesia (Amiti and Konings, 2007).[9] Yet, it is unclear whether the increase in productivity stems from the rise in competition (as foreign firms entering the domestic market) or the expansion in market size (as firms gain access to foreign markets) (Steinwender, 2015). There is no ambiguity, however, in analyzing the impact of import competition. In this case, clearly, there is no expansion in market size and the rise in competition is the main driver of firm productivity. While the market force is known, the results on the impact of import competition on firm productivity are mixed as mentioned above. I add to this literature by providing new evidence on the effect of intensified import competition on firm productivity. Specifically, I estimate within-firm productivity adjustments in response to import competition.

My work is also closely related to the strand of literature examining the link between competition and productivity. Aghion et al. (2005) demonstrates that this relationship can be explained with an inverted-U curve by comparing the reductions in pre-innovation versus post-innovation rents following an increase in competition. Alternative theories suggest that a rise in competition can affect productivity by releasing the trapped factors of production (Bloom et al., 2014), adopting new technologies (Holmes, Levine and Schmitz, 2012), reducing X-inefficiencies (Leibenstein, 1966), and reducing managerial slack (Hart, 1983). Empirical studies in this literature are usually focused on a narrow industry such as concrete manufacturing (Collard-Wexler, 2013), cement manufacturing (Dunne, Klimek and Schmitz, 2008), and the textile industry (De Loecker, 2011) among others. Holmes, Levine and Schmitz (2012) provide a detailed survey of this literature. I contribute to this literature by exploring the relationship between competition and productivity for a broad set of manufacturing firms.

Last but not least, this paper contributes to the growing body of research on productivity measurement and production function estimation of multi-product firms. The productivity literature has emphasized that recovering productivity from revenue data—commonly known as TFPR—gives poor estimates of true productivity (Klette and Griliches, 1996; Foster, Haltiwanger and Syverson, 2008; Katayama, Lu and Tybout, 2009).[10] This is mainly because TFPR reflects variation in output prices along with the true productivity. Recent studies have developed new methods to recover true productivity using physical quantity data—which is referred to as TFPQ (De Loecker, 2011; De Loecker et al., 2016; Valmari, 2016; Dhyne et al., 2017; Orr, 2018; Garcia-Marin and Voigtländer, 2019). I take advantage of detailed energy use data and contribute to this literature by estimating

[9] Goldberg and Pavcnik (2016) and Shu and Steinwender (2019) provide a survey of literature on the trade and productivity linkages.

[10] Depending on the subject, TFPR might be useful in some applications (Hsieh and Klenow, 2009).

firm-product-level TFPQ. When estimating product-specific productivity, a careful treatment of multi-product firms is required. The following section provides more detailed discussion of the challenges and methods in productivity estimation at the firm level and firm-product level.

2 Empirical Framework

In this section, I broadly discuss how productivity is typically estimated at the firm level, and what complications are added if a researcher wants to estimate productivity at the firm-product level. Then, I discuss in detail how exactly I estimate productivity at the firm-product level. Finally, I explain my identification strategy to estimate the causal effect of Chinese import competition.

2.1 Firm-level vs. firm-product-level productivity

2.1.1 Firm-level productivity

Production functions are typically defined and estimated at the firm level. A firm's production function shows the ability of the firm to transform inputs into outputs. It is mostly assumed that firms in the same industry have access to the same production technology. However, this assumption does not allow for any firm heterogeneity within an industry. Therefore, economists add a new firm specific characteristic in the production function known as productivity, which shows how much more or less a firm can produce, relative to a comparison firm with the same level of inputs.

Formally, a firm's production function is defined as:

$$Q_{it} = F_s(\mathbf{X}_{it}, \Omega_{it}) \tag{1}$$

where Q_{it} is the output produced by firm i at time t, $\mathbf{X}_{it}$ indicates the vector of inputs such as capital, labor, and material, Ω_{it} denotes the firm-level productivity, and $F_s(.)$ is the sector-specific production technology which satisfies the following standard conditions:

Assumption 1. *$F_s(.)$ is continuous and differentiable, quasi-concave, and strictly increasing in all arguments.*

Assumption 2. *Productivity scalar is Hicks-Neutral, log-additive, and follows first-order Markov process.*

Assumption (2) implies that output elasticities of all inputs are not affected by the productivity term. Therefore, I can re-write the equation (1) as follows:

$$Q_{it} = F_s(\mathbf{X}_{it})\Omega_{it} \tag{2}$$

where Ω_{it} is interpreted as Hick-neutral total factor productivity. Another feature of production function is the timing of input choices which depends on the context of industry or country, and whether there are adjustments costs associated with the choice of inputs. I impose the following assumption regarding the timing of input choices:

Assumption 3. *At the firm level, capital and labor are assumed to be fixed inputs which are effectively chosen one period ahead, and material is static input which can be set at the time of production.*

Assumption (3) implies that there are adjustment costs associated with the capital and labor at the *firm level*. Moreover, allowing labor to have dynamic implications generally depends on the structure of labor market (Ackerberg, Caves and Frazer, 2015). In the context of Indian economy where there are relatively high costs associated with the hiring and firing of workers, it is more appropriate to assume labor as a dynamic input. Therefore the set of state variables of the firm include capital, labor, productivity, set of products produced by firm. I collect all these state variables into a vector and call it information set $\mathcal{I}_{it}$.

Now, one can specify a functional form for the production function, $F_s(.)$, estimate it using OLS, and simply recover the productivity term Ω_{it}. However, there are multiple reasons why OLS is naive in this setting. The main challenge is that the static inputs are endogenous. Firms choose their static inputs according to the (unknown to the econometrician) productivity level. This is referred to as "*simultaneity bias*", and a vast body of literature on production function estimation is devoted to provide solutions to this source of bias (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves and Frazer, 2015). Another challenge is that firms' exit decision is endogenous as low productivity firms are more likely to leave the market. This endogenous exit introduces another source of bias, known as the "*selection bias*". This bias has also received attention in the literature and some methods are suggested to correct it (Olley and Pakes, 1996).

Apart from the simultaneity and selection bias, there is another important econometric issue in the estimation of production function: measurement error, which depends on data availability. In practice, researchers may face various versions of measurement error. The most common type of which is the measurement error in output, where revenue is observed as opposed to output. There are two different approaches to deal with the revenue measures. The first and most common approach is to use the revenue measures in the production function estimation and recover revenue-based productivity, TFPR. While the TFPR is a biased estimate of the physical productivity, TFPQ, it may be useful in some settings (Hsieh and Klenow, 2009). Second approach is to deflate revenues by the industry price indices to obtain a measure of firm-level output, and then recover firm-level TFPQ. In this case, the main concern is that it ignores the price variation within industries. Other type of measurement error refers to the measurement error in inputs such as capital and material. Generally, failing to control for input prices will cause a downward bias in the estimation of production function coefficients.[11] I will show this bias more formally in the next subsection, where I explain my production function estimation procedure.

While various estimation procedures are introduced to correct for the several biases mentioned above, at the end, a firm-level productivity measure cannot capture the variation within a firm. In other words, if there is a change in firm-level productivity, it is unclear whether it stems from specialization—reallocation across products—or technical change. Thus, I need to estimate firm-product-level productivity to analyze the sources of firm-level productivity change.

2.1.2 Firm-product-level productivity

Estimation of productivity at the firm-product level requires treatment of multi-product firms. Consider outputs are observed for each product of the firm, and the econometrician wants to estimate the following model:

$$Q_{ijt} = F_s(\mathbf{X}_{ijt})\Omega_{ijt} \tag{3}$$

where $j \in \{1, ..., J_{it}\}$ is an index for the products produced by firm i at time t. In this context, one can just apply the firm-level estimation methods if they have information on all inputs at the firm-product level. In fact, if the input data exist at the firm-product level, then the estimation is as if one wants to estimate production function for a large set of single-product firms. However, no dataset currently reports firm-product specific information for all inputs, and inputs are usually observed at the firm level.

The lack of firm-product-level data on inputs imposes an important identification issue because it is not clear how inputs are allocated across products within multi-product firms. To see the identification challenge, consider a firm that produces J_{it} products. Suppose output for all J_{it} products are observed, but inputs are observed at the firm level. Therefore, there are $4J_{it}$ unobservables to be identified (there are 3 unobserved inputs and 1 unobserved productivity term for each product of the firm), while there exists only J_{it} restrictions, which are the production function equations for each product. At this point, one can use the subsample of single product firms, $J_{it} = 1$, to estimate the production function $F_s(.)$ because firm-level inputs are exactly equal to the firm-product-level inputs for single product firms and there is no unobserved input (De Loecker et al., 2016).

I have assumed the production technology is sector specific. This means that the coefficients of production function estimated for single-product firms are exactly the same as multi-product firms within a sector. Therefore, the production technology for multi-product firms are now known. But,

[11] Moreover, De Loecker and Goldberg (2014) provides an extensive discussion on how one can deal with measurement errors in outputs and inputs, and under which assumptions, one can consistently estimate production function coefficients and recover the firm-level productivity.

is this sufficient to recover firm-product-level productivity for multi-product firms? The answer is simply no, even knowing the production technology for multi-product firms is not sufficient because the econometrician does not observe how inputs are allocated across products within a multi-product firm, hence, it is not possible to back out residual term for each product of the firm.

There remains only one option to proceed estimation: impose some structure to reduce the number of unobservables and make identification possible. There is, indeed, a growing body of literature which tries to provide a framework for identification of firm-product-level productivity (Foster, Haltiwanger and Syverson, 2008; Atalay, 2014; Valmari, 2016; Dhyne et al., 2017; Orr, 2018; Garcia-Marin and Voigtländer, 2019; Brandt et al., 2019).[12] These studies, however, are generally specific to the information available in their data.

Nevertheless, there are a few datasets which report some information related to inputs at the firm-product level, including the Chilean data used by Garcia-Marin and Voigtländer (2019) which report total variable costs of production, and the Chinese steel producers data used by Brandt et al. (2019) which report quantity of material inputs, energy, and number of workers. Similarly, the dataset that I use for this study includes rich information on energy input quantity at the firm-product level. Section 3 describes data in more detail. Taking advantage of this information, I only need an additional assumption in order to identify firm-product-level productivity.

Assumption 4. *Firms proportionally allocate all their inputs into products without incurring any costs.*

This is a crucial assumption for identification and requires more explanation. Basically, assumption (4) implies that all inputs are allocated to products with the same intensities. Moreover, there are no adjustment costs within a firm. Note that this does not rule out assumption (3) where I assumed there are adjustment costs for dynamic inputs at the firm level. Instead, assumption (4) implies that conditional on the total level of inputs available at the firm level, firms can freely transfer their inputs across product lines, including capital and labor.

More formally, assumption (4) implies inputs used for producing product j at firm i, $\mathbf{X}_{ijt}$, can be calculated as

$$\mathbf{X}_{ijt} = \bar{\tau}_{ijt}\mathbf{X}_{it} \tag{4}$$

where $\bar{\tau}_{ijt} \in [0, 1]$ is the input share common across all inputs and $\sum_j \bar{\tau}_{ijt} = 1$. While it sounds restrictive, this assumption is standard in production function estimation with multi-product firms. For example, De Loecker et al. (2016) shows how this assumption allows for economies of scope.

[12]The studies by Collard-Wexler and De Loecker (2015) and De Loecker et al. (2016) also deal with the production function estimation of multi-product firms. However, they abstract from firm-product-level productivity for identification purposes and estimate productivity at the firm-level, which is not the focus of my paper.

By using assumption (4) and firm-product specific energy data, I can derive a proxy for input share, $\bar{\tau}_{ijt}$. This proxy is the share of energy for each product of the firm. The underlying assumption is that inputs for each product j are used in proportion to energy share. Similar proxies have been used in the literature. For example, Garcia-Marin and Voigtländer (2019) uses the total variable cost shares as a proxy for the input shares. In the subsequent subsection, I formally discuss my production function estimation procedure and the identification strategy I use to obtain firm-product-level productivity for both single- and multi-product firms.

2.2 Estimation of firm-product-level productivity

In this subsection, I set up and describe the estimation method and how I deal with various sources of bias. I build on the method developed by De Loecker et al. (2016) to estimate productivity at the firm-product level. I start by taking logarithm of the production function in equation (3) and introducing log-additive measurement error, ϵ_{ijt}, to account for any unanticipated shocks to output. I obtain:

$$q_{ijt} = f_s(\mathbf{x}_{ijt}) + \omega_{ijt} + \epsilon_{ijt} \tag{5}$$

where q_{ijt} represents the log of output, $\mathbf{x}_{ijt}$ is the vector of the log of inputs, ω_{ijt} is the log of physical productivity, and ϵ_{ijt} is the measurement error.

I specify a gross output production function, $f_s(.)$, with three inputs: capital, k_{ijt}, labor, l_{ijt}, and material, m_{ijt}.[13] Moreover, I consider second order translog production technology as follows:

$$\begin{aligned} f_s(k_{ijt}, l_{ijt}, m_{ijt}) = \beta_{sk}k_{ijt} + \beta_{sl}l_{ijt} + \beta_{sm}m_{ijt} + \beta_{skk}k_{ijt}^2 + \beta_{sll}l_{ijt}^2 + \beta_{smm}m_{ijt}^2 \\ +\beta_{skl}k_{ijt}l_{ijt} + \beta_{skm}k_{ijt}m_{ijt} + \beta_{slm}l_{ijt}m_{ijt} + \beta_{sklm}k_{ijt}l_{ijt}m_{ijt} \end{aligned} \tag{6}$$

Since I am working with firm-product-level data, I separately observe prices and quantities of output in addition to the sales revenues. Therefore, using quantity of output in the production function estimation automatically eliminates the concerns of output price bias, which arises if output was constructed through deflating revenues by sector level price indices (Foster, Haltiwanger and Syverson, 2008).

While output data are not concerning, the input data require some attention. The challenge is that I observe total expenditures for capital, labor, and material, at the firm level as opposed to input quantities at the firm-product level. To put formally, I introduce some additional notation based

[13] Ideally, I also add energy as a factor of production. However, I do not have data on *energy expenditures*. I cannot use energy quantity in the production function estimation because input price control function requires all inputs to be entered as expenditures.

on De Loecker et al. (2016). Let $\tilde{\mathbf{x}}_{it} = (\tilde{k}_{it}, \tilde{l}_{it}, \tilde{m}_{it})$ represent the log of observed input expenditure for firm i at time t, $\mathbf{w}_{ijt}$ denote the vector of the log of input prices, and τ_{ijt} denote the log of input share $\bar{\tau}_{ijt}$. Then assumption (4), which assumes all firm-level inputs are proportionally attributed to product lines, allows me to write the vector of input quantities, $\mathbf{x}_{ijt}$, of product j from firm i as:

$$\mathbf{x}_{ijt} = \tau_{ijt} + \tilde{\mathbf{x}}_{it} - \mathbf{w}_{ijt} \tag{7}$$

Substituting equation (7) into (5) and rearranging, I obtain:

$$q_{ijt} = f_s(\tilde{\mathbf{x}}_{it}) + A(\tau_{ijt}, \tilde{\mathbf{x}}_{it}) + B(\mathbf{w}_{ijt}, \tau_{ijt}, \tilde{\mathbf{x}}_{it}) + \omega_{ijt} + \epsilon_{ijt} \tag{8}$$

where $A(.)$ collects all the terms with unobserved input allocations and refers to the input allocation bias, and $B(.)$ collects all the terms with unobserved input prices and refers to the input price bias. In general, these two functions depend on the specified production function. In the appendix, I derive the exact functional forms of each of these terms for the translog specification.

Equation (8) indicates that controlling for unobserved productivity, ω_{ijt}, is not sufficient to obtain an unbiased estimate of the production function coefficients since both $A(.)$ and $B(.)$ depend on the vector of input expenditures, $\tilde{\mathbf{x}}_{it}$. Thus, estimation of production function requires correcting for several issues, including input allocation bias, input price bias, simultaneity bias, and selection bias. I follow the method by De Loecker et al. (2016) to address each of these below.

2.2.1 Input Allocation Bias

To deal with the unobserved input allocations, I assume that a firm's technology is independent across its products. This allows me to rely only on single-product firms to estimate the product-specific production function. Note that using the sample of single-product firms implies that the term $A(.)$ drops from equation (8) as $\tau_{ijt} = 0$ for these firms.[14] Therefore, I can rewrite equation (8) for single-product firms as:

$$q_{it} = f(\tilde{\mathbf{x}}_{it}) + B(\mathbf{w}_{\mathbf{it}}, \tilde{\mathbf{x}}_{it}) + \omega_{it} + \epsilon_{it} \tag{9}$$

where the product subscript j is also dropped as the sample is restricted to single-product firms.

This approach may suffer from selection bias specially if one believes that firms' choice to become multi-product is affected by the unobserved productivity or input usage. I address this in two ways. First, using an unbalanced panel that includes both firms who always remain single-product and those that are single-product at some periods is helpful in addressing the selection correction. Second, I use sample selection correction procedure to capture the possible correlation between the

[14] τ_{ijt} is the logarithm of input shares, $\bar{\tau}_{ijt}$. For a single-product firm, $\bar{\tau}_{ijt} = 1$ which implies that $\tau_{ijt} = 0$.

productivity threshold that may determine the transition from single- to multi-product status and the choice of production input. Details of sample correction are provided below when I discuss simultaneity and selection bias.

2.2.2 Input Price Bias

To deal with the unobserved input prices, a similar approach to the control function method is used. In particular, I can use the information on observed output prices to infer input prices. The intuition behind this approach is documented by Kugler and Verhoogen (2012), which can be explained in three steps: (*i*) input prices are an increasing function of input quality. (*ii*) Input quality is an increasing function of output quality. (*iii*) Output quality is an increasing function of output price. Going from (*i*) to (*iii*) implies that output price is an increasing function of input prices. Therefore, I can use the observed output prices to proxy for input prices. I impose the same input price control function across all inputs. Formally, I can write down input price control function for each input as

$$\mathbf{w}_{it}^{x} = w_t(p_{it}) \tag{10}$$

where $\mathbf{w}_{it}^{x}$ is the price of the input x and p_{it} is the log of output price. Substituting this control function into equation (9), I obtain:

$$q_{it} = f(\tilde{\mathbf{x}}_{it}) + B(p_{it} \times \tilde{\mathbf{x}}_{it}^{c}) + \omega_{it} + \epsilon_{it} \tag{11}$$

where $\tilde{\mathbf{x}}_{it}^{c} = \{1, \tilde{\mathbf{x}}_{it}\}$. Note that the function $B(.)$ is different from the input price function $w(.)$. In particular, $B(.)$ takes all the arguments of the $w_t(.)$ and all the interactions of the input prices with the vector of deflated input expenditures, $\tilde{\mathbf{x}}_{it}$ which are shown in $\tilde{\mathbf{x}}_{it}^{c}$.

2.2.3 Simultaneity and Selection Bias

The last sources of bias are stemming from the unobserved productivity where I should control for simultaneity and selection bias. I use the control function approach to deal with the simultaneity bias (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves and Frazer, 2015). I use material input demand as my control function with the following form:

$$\tilde{m}_{it} = m_t(\tilde{k}_{it}, \tilde{l}_{it}, p_{it}, \omega_{it}) \tag{12}$$

This control function shows that the choice of material depends on capital, labor, and productivity level. I also include observable output price as an exogenous firm-specific variation (Ackerberg, Caves and Frazer, 2015).[15] Now, I can invert the control function for productivity and obtain:

$$\omega_{it} = h_t(\tilde{k}_{it}, \tilde{l}_{it}, \tilde{m}_{it}, p_{it}) \tag{13}$$

Substituting equation (13) into (11), I obtain:

$$\begin{aligned} q_{it} &= f(\tilde{\mathbf{x}}_{it}) + B(p_{it} \times \tilde{\mathbf{x}}^c_{it}) + h_t(\tilde{\mathbf{x}}_{it}, p_{it}) + \epsilon_{it} \\ &= \phi_{it}(\tilde{\mathbf{x}}_{it}, p_{it}) + \epsilon_{it} \end{aligned} \tag{14}$$

where the term ϕ_{it} in the second line is a general flexible function of all inputs and prices and I use a third order polynomial regression model for it.

Finally, I address the selection bias. Selection bias arises if the choice of becoming multi-product depends on productivity and/or input use. In a model, Mayer, Melitz and Ottaviano (2014) show that the number of products a firm produces is an increasing step function of the firm's productivity. Their structure suggests that firms introduce a new product when they go beyond some productivity threshold. Therefore, I determine a productivity cutoff, $\bar{\bar{\omega}}_{it}$, that shows firms with productivity level above it are multi-product firms and firms below this cutoff remain single-product.

I follow the selection correction method of Olley and Pakes (1996), extended by De Loecker et al. (2016), and estimate the probability of remaining single-product in the next period. In particular, I use selection correction to model the probability that a firm continues to remain single-product.[16] According to the productivity cutoff introduced above, this means the probability of productivity remaining below $\bar{\bar{\omega}}_{it}$:

$$SP_{it} = Pr\left[\omega_{it} \leq \bar{\bar{\omega}}_{it}(\mathbf{s}_{it}) | \mathcal{I}_{it}\right] \tag{15}$$

where $\mathcal{I}_{it}$ is the information set of firm i at time t. In practice, I estimate this probability using fitted values from a probit estimation of single-product indicator on the information set of firm at $t-1$ which includes a thrid order polynomial of capital, labor, material, prices, export status, and market share.

2.2.4 Estimation

Estimation is based on the GMM method introduced by Wooldridge (2009). To form moment conditions, I assume first order Markov process for productivity term which is a common assumption

[15] Ideally, I prefer to include input prices into my control function as an exogenous firm-specific variation, similar to Doraszelski and Jaumandreu (2013). However, input prices are not observable in my dataset and I use output price.

[16] I am not worried about exit mainly because the data consists medium and large Indian firms and exit is not a usual feature of the data (Topalova and Khandelwal, 2011).

in the production function literature. In particular, the Markovian assumption implies:

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}, SP_{it}] + \eta_{it} = g(\omega_{it-1}, SP_{it}) + \eta_{it} \tag{16}$$

where the actual productivity, ω_{it} in period t can be decomposed into expected productivity $g(.)$ and a random shock η_{it}. The conditional expectation function $g(.)$ depends on previous year's productivity, ω_{it-1}, and the probability of remaining single product, SP_{it}. The productivity shock, η_{it}, represents the uncertainties linked to productivity. The timing of decisions in this context are very important. As mentioned in assumption (3), I assume that capital and labor are dynamic inputs which are chosen by the firm at $t-1$, while material is the static input chosen at time t. The implication of this assumption is that the decision on material is correlated with the productivity innovation, η_{it}.

Substituting ω_{it} from equation 16 into 14 gives:

$$q_{it} = f(\tilde{\mathbf{x}}_{it}) + B(p_{it} \times \tilde{\mathbf{x}}^c_{it}) + g\Bigg(h(\tilde{\mathbf{x}}_{it-1}, p_{it-1})\Bigg) + \eta_{it} + \epsilon_{it} \tag{17}$$

Now, I can construct the moment conditions based on equations 14 and 17 which have the following form:

$$E\begin{bmatrix} \epsilon_{it}|\mathcal{I}_{it} \\ \eta_{it} + \epsilon_{it}|\mathcal{I}_{it-1} \end{bmatrix} = E\begin{bmatrix} q_{it} - \phi_{it}(\tilde{\mathbf{x}}_{it}, p_{it})|\mathcal{I}_{it} \\ q_{it} - f(\tilde{\mathbf{x}}_{it}) - B(p_{it} \times \tilde{\mathbf{x}}^c_{it}) - g\big(h(\tilde{\mathbf{x}}_{it-1}, p_{it-1})\big)|\mathcal{I}_{it-1} \end{bmatrix} = 0 \tag{18}$$

The first line uses the fact that measurement error and/or unanticipated shocks to production is not correlated with the information set in period t, $\mathcal{I}_{it}$. It resembles to the first stage of Ackerberg, Caves and Frazer (2015). The second line implies that that η_{it} and ϵ_{it} are uncorrelated with the information set in period $t-1$ and corresponds to the second-stage in Ackerberg, Caves and Frazer (2015).

One potential concern is that the current output price p_{it} may be correlated with the current period productivity innovation η_{it} and needs to be instrumented for. Note that according to equation (17), instruments have to be uncorrelated with η_{it} but not necessarily with the level of productivity ω_{it}. As noted by Doraszelski and Jaumandreu (2013), a change in productivity that is not anticipated by the firm is not correlated with its past decision and therefore, I use the lag of output price as the instrument for the current period price. While p_{it-1} is uncorrelated with η_{it} in equation (17), it is correlated with ω_{it}.

In this empirical application, the production function coefficients are identified even though input expenditures enter both the production function and the input price control function in equation (17). The reason is that input expenditures enter the input price control function only through their interaction with input prices. In appendix (B), I show this by choosing a functional form for the production function, input price control function, and productivity process.

Finally, I restrict the sample of single product firms to those that manufacture for at least two consecutive years because the moment conditions require at least two years of data due to lagged values. Using moment conditions in (18), I estimate the model with GMM procedure introduced by Wooldridge (2009). I also follow the standard literature and estimate production functions at the sector level (Levinsohn and Petrin, 2003; De Loecker et al., 2016).

2.2.5 Recover Productivities

Estimating output elasticities is not sufficient to recover productivity for multi-product firms at the firm-product level. I still need the individual inputs, which are observed at the firm level, to be assigned to each product j produced by firm i. While De Loecker et al. (2016) relies on numerical methods to recover input allocations, I use insights from Garcia-Marin and Voigtländer (2019) to compute input allocations. In particular, I take advantage of the energy quantity data that I observe to calculate a proxy for product-specific inputs. The underlying assumption is that the amount of inputs used for producing each product is proportional to the amount of energy used for that product. More specifically, I consider the same input shares for energy and other inputs. Thus, rather than estimating product-specific input use, I can just calculate them as:

$$\mathbf{X}_{ijt} = \frac{E_{ijt}}{\sum_j E_{ijt}} \mathbf{X}_{it} \tag{19}$$

where E_{ijt} is the quantity of energy used to produce product j. Taking logs of $\mathbf{X}_{ijt}$, and substituting into the production function, I can derive firm-product-level physical productivity as:

$$\omega_{ijt} = \hat{q}_{ijt} - \hat{f}_j(\mathbf{x}_{ijt}) \tag{20}$$

where $\hat{q}_{ijt}$ is the predicted output obtained similar to the first-stage regression in the production function estimation, and $\hat{f}_j(.)$ is calculated based on estimated production function coefficients and actual input quantities. I also recover firm-product-level TFPR by substituting quantities with revenues,r_{ijt}, in equation (20).[17] Therefor, by construction, the following relationship holds between TFPR and TFPQ:

$$\tilde{\omega}_{ijt} = p_{ijt} + \omega_{ijt} \tag{21}$$

where $\tilde{\omega}_{ijt}$ denotes TFPR. In section 4, I provide results for both efficiency measures and discuss how using TFPR as an efficiency measure could affect my results.

[17]Recall that the main difference between TFPR and TFPQ is to use revenues rather than quantities.

2.3 Effect of Chinese import competition

In this subsection, I explain the identification strategy used to estimate the causal effect of Chinese import competition on the performance of Indian manufacturing firms. The model is as follows:

$$y_{ijt} = \alpha IMP_{jt-1} + \gamma_{ij} + \delta_{st} + \nu_{ijt} \tag{22}$$

where y_{ijt} denotes the variable of interest for product j produced by firm i at time t, IMP_{jt-1} is the share of imports in product j originating from China at $t-1$, γ_{ij} is a set of firm-product fixed effects, and δ_{st} is a full set of sector-year fixed effects to absorb macroeconomic shocks.

The main concern regarding above specification is that changes in Chinese imports might be correlated with the omitted variables which also affect firms' outcome in India. Thus, OLS estimates are likely to underestimate the effect of Chinese import exposure as Chinese imports are likely to increase more for products where domestic producers are not performing very well. To deal with this source of bias, I use an instrumental variable introduced by Autor, Dorn and Hanson (2013), and instrument Chinese import shares in India with the Chinese import shares in other low to medium economies. Therefore, I construct the instrument as:

$$Z_{jt} = \frac{1}{N} \sum_{n} IMP^{n}_{jt} \tag{23}$$

where Z_{jt} is the simple average of import shares for product j at time t across other low- to medium-income economies, n.[18] Z_{jt} is a valid instrument as long as exposure to Chinese imports in other countries is not driven by factors determining firm-product-level performance in India.

Finally, I cluster the standard errors at the product level because that is the level of variation from imports.

3 Data

This section describes the data sources and descriptive statistics. The data come from two main sources: Prowess and UN-Comtrade database. In what follows, I explain each of these datasets.

3.1 Prowess data

Prowess is a panel of Indian firms maintained by the Centre for Monitoring the Indian Economy (CMIE).[19] It includes detailed information on both outputs and inputs of the firm. On the output

[18] I use import shares from Indonesia, Thailand, Turkey, and Brazil to construct the IV.

[19] Overall, Prowess represents about 60 to 70 percent of the economic activity in organized industrial sector (Goldberg et al., 2009).

side, it provides both prices and quantities of all products produced by the firm.[20] On the input side, it reports usual input expenditures at the firm level such as capital, labor, and material expenditures. What differentiates Prowess from other datasets is that it reports quantity of energy used for each product of the firm. This firm-product-level energy data has been collected by the Indian government as part of the Indian Companies Act of 1956. The CMIE has digitized and published this information in its Prowess database to be used by researchers, investors, and policy makers (Barrows and Ollivier, 2018). In Appendix A, I describe how I construct the final sample using the output and input data.

Despite all the advantages, Prowess is not suitable for analyzing firm entry and exit because it consists of medium and large firms. In a series of studies using Prowess dataset, Goldberg et al. (2009, 2010); Topalova and Khandelwal (2011) emphasize that the firm entry/exit in Prowess is mostly because firms start/stop reporting their data rather than truly entering/exiting the market. Hence, I exclude firm entry/exit analyses in this study.

The final sample covers 7,435 firms in 11 manufacturing sectors between 1994 and 2008. Table 1 presents summary statistics of the sample. All values are reported as weighted averages across sectors and years. This ensures that different sectors are weighted by their size and economic significance. On average, there are 438 firms in each sector. The largest sector typically has 823 firms on an average year and 90% of sectors have more than 149 firms in a year. Among these firms, 43.7% are single-product producers. High share of single-product firms enables me to estimate production function by only using this subset of firms.[21]

Table 1: Sample statistics of Indian manufacturing firms

	(1) Mean	(2) Median	(3) 10th percentile	(4) 90th percentile	(5) Standard deviation	(6) Max value
No. of firms	438	385	149	788	240.4	823
Share of single-prod. firms (%)	43.7	44.7	55.7	41.9	38.6	45.1
Firm sales	26.38	4.54	.23	45.46	112.2	1759.39
No. of products per firm	2	1	1	4	2	13

Note: All calculations are weighted by sector-year sales. The sample covers 1994-2008. Sales are reported in million Indian rupees.

An important feature of the sample is the presence of substantial heterogeneity in the firm size. Firms on average sell 26.38 million rupees, but the largest firm in a sector sells 387 times more than the median firm. Moreover, there exists heterogeneity in the product scope. A median firm

[20]Prowess contains information on the value and quantity of products produced. Unit values or prices can be calculated by dividing values by quantities.

[21]Appendix Table 11 provides more details on the share of single-product firms by sector.

produces only one product. However, firms can produce up to 13 products. The definition of product is relatively broad. For example, in the beverages, products include beer, wine, hard liquor, water, fruit juice and other non alcoholic drinks. Prowess does not differentiate between different varieties of wine. This level of product definition is typical in other studies working with supply-side data (for example, see Bernard, Redding and Schott, 2010; Garcia-Marin and Voigtländer, 2019). In total, there are 1,434 products in the sample.

Table 2 provides more details on the size distribution of firms by number of products. Reassuringly, close to half of the firms are single-product producers. Among the multi-product firms, most of them produce 2 to 5 products on average, and 17 firms produce more than 6 products.

Table 2: Size distribution by number of products

No. of products per firm	(1) No. of Firms	(2) Sales Share (%)	(3) Mean Sales	(4) Median Sales
1	211	23.12	11.4	2.48
2–5	213	57.77	34.83	7.94
> 6	17	19.74	180.62	97.19

Note: Each column shows the weighted average within product category. All calculations are weighted by sector-year sales. The sample covers 1994-2008.

Despite high share of single-product firms, these firms account for less than on fourth of output (23.12%). In other words, most of the output is produced by multi-product firms. The dominance of multi-product firms has been emphasized in the literature for other economies as well (for example, see Bernard, Redding and Schott, 2010, for the US). Another important fact is that the multi-product firms sell much more than single-product firms. A typical multi-product firm producing between 2 and 5 products sells three times more than a single-product firm, while a firm with more than 6 products generates 16 times more revenue than a single-product firm.

In summary, the overview of the sample shows the importance of multi-product firms. These firms are large and account for about 77% of the output. Hence, it is not proper to treat all firms as single-product producers.

3.2 UN-Comtrade

I supplement the Prowess data with UN-Comtrade data. The UN-Comtrade is a product level annual data which provides bilateral trade flows between countries. In UN-Comtrade database, products are defined at the 6 digit level Harmonised System (HS) codes. I rely on the publicly available crosswalk between 6 digit HS codes and 4 digit ISIC Rev. 3 codes to merge import and export data to the manufacturing data (see Appendix A for more details).

Table 3: China's percentage share of all imports, 1994-2008

Sector	(1) 1994	(2) 2008	(3) Change 1994-2008
15 Food and Beverages	2.79	7.36	4.57
17 Textiles and Apparel	7.03	35.82	28.79
21 Pulp and Paper	0.85	17.95	17.10
24 Chemicals	3.59	19.09	15.50
25 Rubber and Plastic	3.53	30.50	26.98
26 Nonmetallic mineral products	1.04	37.91	36.87
27 Basic metals	1.05	13.17	12.12
28 Fabricated metal products	1.01	37.06	36.05
29 Machinery and Equipment	1.59	19.23	17.65
31 Electrical Machinery and Comm.	3.13	38.88	35.75
34 Motor Vehicles	0.04	17.70	17.66
Average	2.33	24.97	22.64

Note: Note: Columns (1) and (2) are calculated using final sample for 1994 and 2008. Each cell shows the average percentage share of Chinese imports within sector. Sectors correspond to the 2-digit NIC codes. Column (3) shows the difference in percentage of import shares between 1994 and 2008.

Table 3 presents the summary statistics of the China's import shares for the base year 1994 and the final year 2008 by sector. On average, the Chinese import shares significantly increased from 2.33% in 1994 to 24.97% in 2008 within the sample. Moreover, there is a large heterogeneity in changes in Chinese import shares across sectors. The food and beverage sector, for example, received an increase of just 4.57 percentage points, whereas nonmetallic mineral sector faced an over 36 percentage point increase between 1994 and 2008.

4 Empirical results

In this section, first, I present elasticities estimated for the production function. Then, I discuss the effect of import competition on the performance of Indian firms at the firm-product level. Moreover, I explore the heterogeneous effects of competition and provide some robustness checks. Finally, I decompose the firm-level results to understand the contribution of reallocation and technical efficiency in aggregate firm-level productivity.

4.1 Estimates of elasticities

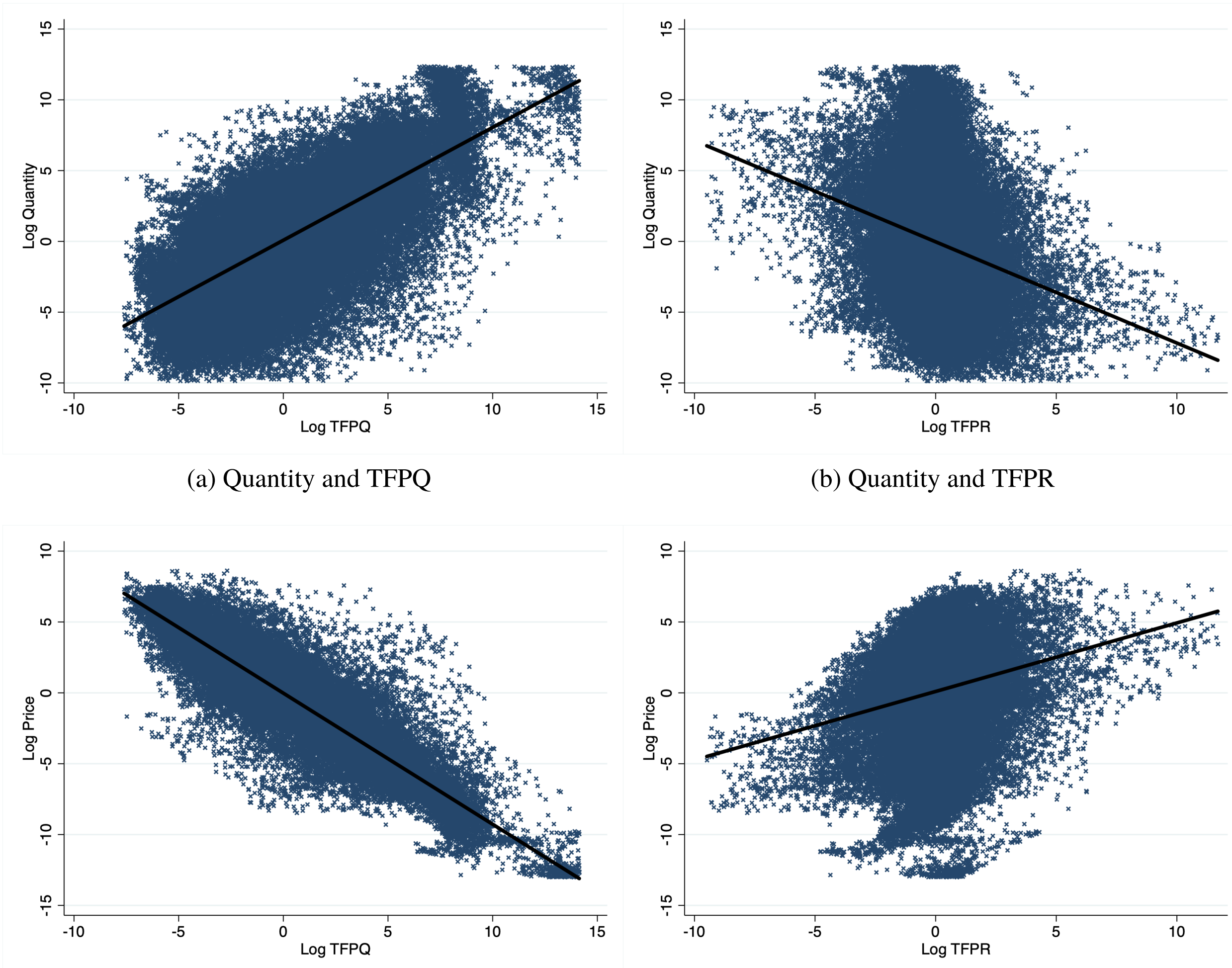
Table 4 presents the median estimates of output elasticity of inputs. In general, the estimates of elasticities are reasonable and consistent with other studies using product level data (De Loecker et al., 2016; Garcia-Marin and Voigtländer, 2019). Materials have the largest elasticities, followed by labour and capital. Column (4) reports the median returns to scale (RTS), where most sectors exhibit to be close to constant returns to scales. However, note that there is a lot of heterogeneity across firms and products. Since I do not put any restrictions or assumptions on the returns to scale, firms can potentially show increasing returns to scale. The last row shows the simple average of median elasticities across all sectors, which again shows a returns to scale of 1.02 for the whole manufacturing sector in the sample.

Table 4: Output Elasticities, Median

Sector	(1) Labour	(2) Material	(3) Capital	(4) RTS
15 Food and Beverages	0.16	0.73	0.09	0.97
17 Textiles and Apparel	0.08	0.79	0.16	1.05
21 Pulp and Paper	0.11	0.82	0.10	1.02
24 Chemicals	0.21	0.76	0.09	1.08
25 Rubber and Plastic	0.14	0.84	0.02	1.00
26 Nonmetallic mineral products	0.16	0.78	0.05	1.03
27 Basic metals	0.08	0.82	-0.04	0.89
28 Fabricated metal products	0.04	0.82	0.06	0.95
29 Machinery and Equipment	0.19	0.79	0.12	1.10
31 Electrical Machinery and Comm.	0.16	0.89	0.02	1.02
34 Motor Vehicles	0.11	0.91	0.03	1.06
Total	0.13	0.81	0.06	1.02

Note: Median output elasticity of inputs are reported in columns (1)-(3). Production function estimation procedure is explained in section 2. Since I consider translog specification, there is variation in the output elasticity of each input within a sector. As an example, output elasticity of material for each firm i producing product j at time t is calculated as $\beta_m m_{ijt} + 2\beta_{mm} m_{ijt} + \beta_{km} k_{ijt} + \beta_{lm} l_{ijt}$. Last column reports the median returns to scale (RTS).

Using these elasticities, I recover both TFPQ and TFPR at the firm-product level. TFPQ is a direct measure of physical productivity which is calculated from quantity data, and TFPR is the typical productivity measure used in the literature which is calculated from revenue data. Figure (1) plots the correlations between these productivity measures and prices and quantities. Not surprisingly, figure (1a) shows a strong negative correlation between quantity and TFPQ which suggests more productive firms produce more output. Figure (1b), however, shows a negative relationship between quantity and TFPR. The positive correlation between quantity and TFPR could be due to the price



(a) Quantity and TFPQ (b) Quantity and TFPR

(c) Price and TFPQ (d) Price and TFPR

Figure 1: Correlation between TFPQ, TFPR, Price, and Quantity

effects since price and quantity are negatively correlated (demand slopes downward).[22] Figure (1c) shows the relationship between price and TFPQ, which indicates a negative correlation. This is because more productive firms have lower marginal costs which leads to charging lower prices (Foster, Haltiwanger and Syverson, 2008; Eslava et al., 2013). TFPR, on the other hand, shows a positive correlation with price in Figure (1d) which suggests the price component of TFPR is driving the correlation between TFPR and price. These basic correlation patterns are reflected in the estimates of increase in Chinese competition as well.

[22]Appendix Table 12 presents the basic correlation matrix between output quantity, price, TFPQ, and TFPR. It also confirms the negative correlation between price and quantity

4.2 Impact of Chinese import competition

In this subsection, I provide the main results for the impact of import competition on various measures of firm performance. A good starting point is to look at observed variables in the data such as sales, prices, and quantities. I then gradually build on these estimates and provide more detailed evidence on different productivity measures.

4.2.1 Baseline results

Table 5 reports both the OLS and IV results for sales, prices, and quantities. Column (1) shows the increase in Chinese imports had no effects on sales. The effect appears to be statistically insignificant in both OLS and IV regressions. The IV estimates in panel (B) are also very close to zero in magnitude. However, it would be misleading to say that exposure to Chinese imports had no effects at all. By decomposing the effects into prices and quantities, I find large negative effects on prices and positive effects on quantities.[23] Hence, the opposing responses in prices and quantities has led to no significant effect on sales. In addition, it is worth noting that while the sign of the estimates remains unchanged, OLS results tend to be smaller in magnitude relative to the IV results.[24]

Table 6 shows the main results for the impact of import competition on revenue and physical productivity. While the coefficients for both TFPR and TFPQ regressions are positive, the estimates are statistically significant only in the IV specification. Moreover, the difference between the OLS and IV specifications, as Autor et al. (2016) suggest, indicates the bias introduced by correlation between productivity and the import competition is negative and dominates the bias originated from demand shocks. Throughout the paper, I mainly rely on the IV results as evidence of a causal relationship.[25]

I find a 10 percentage point increase in Chinese import shares is associated with a 6.75 percent increase in physical productivity. Note that these productivity measures are direct measures of the firm-product-level productivity and the estimates are not affected by reallocation effects (if there is any). Thus, I can interpret my results as improvement in technical efficiency in response to tougher import competition. My results are somewhat comparable with Bloom, Draca and Van Reenen (2016), which finds about 2.5 percent increase in productivity of European firms for a 10 percentage point increase in Chinese import shares. However, my results deviate from their estimates in the sense that I am using a direct measure of technical efficiency at the firm-product-level, while they use firm-level TFPR measures to quantify the impact of Chinese import competition. My estimates for

[23] While large in magnitude, the coefficient on quantity is not statistically significant in the IV regressions. This might be due to the fact that quantities are noisier than prices. Moreover, estimation of the three regressions as a simultaneous system of equations would not bring efficiency gains because all three equations include the same set of fixed effects and explanatory variables.

[24] The F-statistics for the first stage is also greater than 10, indicating the power of instrument.

[25] Figure 2 of Appendix C shows the first-stage results.

Table 5: within-firm-product response to Chinese import competition

Dependent Variable =	(1) ln(sales)	(2) ln(price)	(3) ln(quantitiy)
Panel A: OLS estimates			
IMP_{t-1}	0.151	-0.146**	0.297**
	(0.188)	(0.065)	(0.142)
Observations	79455	79455	79455
Firm-Product FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Panel B: IV estimates			
IMP_{t-1}	-0.005	-0.338***	0.333
	(0.202)	(0.123)	(0.273)
Observations	79455	79455	79455
F-Stat	312.0	312.0	312.0
Firm-Product FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes

Note: Each column reports the results from one regression specified in equation (22). The unit of observation is a firm-product-year. Sample covers the period 1994-2008. Panel A reports the OLS results, whereas panel B reports the IV results. Instrument used in panel B is defined in equation (23). First stage F-stats are reported for the IV regressions. All regressions include firm-product and sector-year fixed effects. Reported in parentheses are robust standard errors clustered at the product level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

TFPR as a measure of efficiency shows a 3.4 percent increase in productivity which is slightly larger than estimates from Bloom, Draca and Van Reenen (2016). Assuming a lower level of competition in India relative to Europe, my results are consistent with the Aghion et al. (2005) model. Next, I explore the magnitude of these effects in total manufacturing TFP growth to obtain a better sense of the economics importance of these results.

4.2.2 Interpretation of Results

Are the productivity effects found in the previous subsection large? I answer this question by comparing my estimates with the total TFP growth in Indian manufacturing sector. First, I calculate how much productivity has increased due to the rise of Chinese import penetration. Chinese import share in India has increased on average by 22.64 percentage points. This implies a 15.28% (= 22.64×0.675) increase in physical productivity between 1994 and 2008. Deb and Ray (2014) estimates the productivity growth in India and finds average annual growth of 2.73% between 1992 and 2007 (their sample period is very close to my sample period, hence, I consider the same growth

Table 6: Chinese import competition and productivity

Dependent Variable =	(1) ln(TFPR)	(2) ln(TFPQ)
Panel A: OLS estimates		
IMP_{t-1}	0.141	0.288
	(0.203)	(0.267)
Observations	79455	79455
Firm-Product FE	Yes	Yes
Sector-Year FE	Yes	Yes
Panel B: IV estimates		
IMP_{t-1}	0.337*	0.675***
	(0.184)	(0.092)
Observations	79455	79455
F-Stat	312.0	312.0
Firm-Product FE	Yes	Yes
Sector-Year FE	Yes	Yes

Note: Each column reports the results from one regression specified in equation (22). The dependent variable is the logarithm of revenue productivity (TFPR) in column (1) and logarithm of physical productivity (TFPQ) in column (2). The unit of observation is a firm-product-year. Sample covers the period 1994-2008. Panel A reports the OLS results, whereas panel B reports the IV results. Instrument used in panel B is defined in equation (23). First stage F-stats are reported for the IV regressions. All regressions include firm-product and sector-year fixed effects. Reported in parentheses are robust standard errors clustered at the product level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

rate in my sample). This suggests 49.78% increase in productivity of manufacturing firms in 15 years. This means that the increase in Chinese import competition accounts for about 30% of the productivity growth in India. This back-of-the-envelope calculation only shows the short-run effects and it does not take into account any longer term productivity gains. Moreover, another underlying assumption is that the effect of Chinese import competition on the productivity of all other Indian firms is the same as firms in my sample. However, I can put zero weight on the firms not in my sample and consider no effect of Chinese imports on the productivity of other firms. Since my sample covers about 65% of the manufacturing output, I can infer the contribution of Chinese import competition on the total manufacturing productivity growth to be around 20%.

An alternative approach is to focus on my sample and calculate the contribution of productivity growth due to Chinese imports in total growth within the sample. My estimates show that the productivity of manufacturing firms in sample grew by 55% between 1994 and 2008. Therefore, 27.7% of the total productivity growth can be attributed to the increase in Chinese import competition.

4.2.3 Robustness checks

I run various tests to see if my baseline estimates are robust to different specifications. One of the key concerns in my baseline specification is whether the increases in productivity is affected by the trade liberalization that took place in India in early 1990's. To ensure that the results are not driven by the liberalization episode, I split the sample into two periods: 1994-2000, and 2000-2008. I choose 2000 because it is one year before China's accession to WTO.

Panel A and B of Table 7 shows the effect of import competition for the two periods in OLS and IV specifications, respectively. Comparing column (2) and (3), it confirms that China's accession to WTO had causal effects on productivity. In panel C, I explore whether the results are driven by outliers. I find no significant change in results by excluding top and bottom 1 percent observations. In panel D, I control for the exports to China to see if the productivity has increased due to market expansion through access to Chinese market or not. Overall, I find no significant effects from changes in exports on productivity. In panel E, I find the main results are robust to the sample of domestic firms. In other words, the increase in productivity is not driven by the foreign owned firms.

4.2.4 Heterogeneous effects

In this subsection, I investigate the heterogeneous effects in two dimensions. First, I explore if productivity differently responds when facing different levels of competition. Second, I investigate whether there is any heterogeneity in the response of products with different levels of initial productivity.

Table 8 shows how productivity is affected by different levels of competition. In particular, I split the changes in import shares into three bins: low, medium, and high. The average annual change in import shares are negative and equal to -1 percentage point for the first bin, suggesting that on average some products have received less competition from China. The average annual change is 1 percentage point for the moderate change, and 4 percentage points for the high changes. Column (1) shows that the low changes in import shares has no significant effects on productivity. However, the effects are large and highly significant for both medium and high levels of change in competition. Moreover, changes in productivity are increasing as the level of competition increases. While productivity increases 8.7 percent with a moderate increase in import shares, it increases by 9.5 percent for large positive changes in import competition.

Next, I split the sample by the outcome variable, TFPQ. In particular, I categorize a product as low/medium/or high productivity product according to the position of its initial productivity level within the sector. Then, I separately trace the impact of increase in import competition on each of these categories. Table 9 shows that the sign of all coefficients are positive. Interestingly, initially low and high productivity products are showing close to 8 percent increase in their productivity due

Table 7: Chinese import competition and productivity, robustness checks

Dependent Variable =	ln(TFPQ)			ln(TFPR)		
Sample =	(1) Full sample	(2) 1994-2000	(3) 2000-2008	(4) Full sample	(5) 1994-2000	(6) 2000-2008
A. OLS estimates						
IMP_{t-1}	0.288	-0.086	0.200	0.141	-0.084	0.105
	(0.267)	(0.210)	(0.387)	(0.203)	(0.164)	(0.259)
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79455	24679	53133	79455	24679	53133
B. IV estimates						
IMP_{t-1}	0.675***	-0.022	0.502**	0.337*	0.268*	0.272
	(0.092)	(0.402)	(0.207)	(0.184)	(0.160)	(0.195)
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Product FE	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	312.0	35.3	98.9	312.0	35.3	98.9
Observations	79455	24679	53133	79455	24679	53133
C. IV estimates (exclude outliers)						
IMP_{t-1}	0.537***	-0.269	0.471***	0.210	0.171*	0.171
	(0.070)	(0.248)	(0.144)	(0.159)	(0.092)	(0.160)
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Product FE	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	317.0	36.2	100.5	317.0	36.2	100.5
Observations	76902	23896	51342	76902	23896	51342
D. IV estimates (control for exports to China)						
IMP_{t-1}	0.675***	1.095*	0.496**	0.337*	0.453**	0.262
	(0.092)	(0.563)	(0.207)	(0.183)	(0.202)	(0.191)
EXP_{t-1}	-0.001	0.033***	0.002	0.001*	0.006	0.003***
	(0.002)	(0.007)	(0.002)	(0.001)	(0.004)	(0.001)
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Product FE	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	295.3	231.5	97.0	295.3	231.5	97.0
Observations	79455	24679	53133	79455	24679	53133
E. IV estimates (exclude foreign owners)						
IMP_{t-1}	0.596***	-0.069	0.433*	0.316	0.204	0.250
	(0.148)	(0.390)	(0.259)	(0.222)	(0.192)	(0.229)
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Product FE	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	403.5	36.2	105.7	403.5	36.2	105.7
Observations	75253	23321	50358	75253	23321	50358

Note: The dependent variables are the logarithm of physical productivity (TFPQ) and logarithm of revenue productivity (TFPR). I split the sample into two subsamples 1994-2000 and 2000-2008. Full sample covers the period 1994-2008. Each column reports the results from one regression specified in equation (22). The unit of observation is a firm-product-year. Instrument in the IV regressions is defined in equation (23). All regressions include firm-product and sector-year fixed effects. Reported in parentheses are robust standard errors clustered at the product level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 8: Chinese import competition and productivity, heterogeneous effects by the level of change in competition

Dependent Variable =	ln(TFPQ)		
	(1)	(2)	(3)
Change in import shares =	low	moderate	high
IMP_{t-1}	-0.365	0.871**	0.952***
	(0.354)	(0.432)	(0.133)
Observations	25138	25709	20558
F-Stat	43.2	113.0	67.1
Firm-Product FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes

Note: The dependent variable is the logarithm of physical productivity (TFPQ). I split the sample into three subsamples based on the level of change in the share of Chinese imports between two consecutive years. Each column reports the results from one regression specified in equation (22). The unit of observation is a firm-product-year. Sample covers the period 1994-2008. Only the results from IV regressions are reported. Instrument is defined in equation (23). All regressions include firm-product and sector-year fixed effects. Reported in parentheses are robust standard errors clustered at the product level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

to competition. However, the results are not as large and insignificant for the products in the middle of distribution.

4.3 Decomposition Approach

Using estimated firm-product-level productivity, ω_{ijt}, I construct firm-level TFPQ as the sum of firm-product-level TFPQ, weighted by firm-product-level revenue shares s_{ijt}:

$$\omega_{it} = \sum_j s_{ijt}\omega_{ijt} \tag{24}$$

where ω_{it} is the physical productivity of firm i at time t. Note that the firm-level efficiency measure includes both reallocation and technical efficiency effects. If there is any reallocation from low productivity products to high productivity products due to import competition, I should find a larger firm-level impacts on productivity relative to the firm-product-level results.

Next, I decompose the firm-level productivity effect into between and within-firm-product effects. To do this, I borrow a static decomposition of productivity from Olley and Pakes (1996). I decompose the output weighted average productvity, ω_{it}, into an unweighted mean and a covariance term as follows:

Table 9: Chinese import competition and productivity, heterogeneous effects by the level of productivity in initial period

Dependent Variable =	(1) Low-TFPQ	(2) Medium-TFPQ	(3) High-TFPQ
IMP_{t-1}	0.808*	0.353	0.832***
	(0.482)	(0.374)	(0.145)
Observations	27355	25744	26356
F-Stat	396.5	62.5	128.9
Firm-Product FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes

Note: The dependent variable is the logarithm of physical productivity (TFPQ). I split the sample into three subsamples based on the level of TFPQ in initial period in comparison with the TFPQ of products in the same sector. Each column reports the results from one regression specified in equation (22). The unit of observation is a firm-product-year. Sample covers the period 1994-2008. Only the results from IV regressions are reported. Instrument is defined in equation (23). All regressions include firm-product and sector-year fixed effects. Reported in parentheses are robust standard errors clustered at the product level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

$$\omega_{it} = \bar{\omega}_{it} + \sum_j (s_{ijt} - \bar{s}_{it})(\omega_{ijt} - \bar{\omega}_{it}) \tag{25}$$

where $\bar{\omega}_{it}$ is the unweighted productivity average, and $\bar{s}_{it}$ is the unweighted average of sales shares. The second term in equation (25) refers to the covariance of firm-product-level productivity and output share, cov_{it}, which is taken as a direct measure of reallocation in the literature.

Before, I take my different outcome variables into the data and estimate the impact of import competition, I have to carefully create a variable to measure the firm-level exposure to Chinese imports. Note that I cannot construct this variable as a revenue-weighted average of import shares across products because the revenue shares are potentially endogenous to changes in import shares. Therefore, I need to hold the weights constant and allow the firm-level import shares to be affected only through changes in firm-product-level import shares.

I construct the weights using the following steps. First, I calculate the average revenue share of each product of the firm across all years. Then, I normalize the average revenue share at each year by the number of products produced by the firm. More formally, in the first step, I calculate:

$$\bar{s}_{ij} = \frac{1}{T} \sum_t s_{ijt} \tag{26}$$

where $\bar{s}_{ij}$ is a simple average of revenue shares across all years that the product j is produced by firm i. Note that even if $\bar{s}_{ij}$ is constant weight at the firm-product-level, I cannot directly use it to construct the firm-level exposure to Chinese imports. Consider, for example, a firm produces product A in period 1 and adds a product B in period 2. Let the revenue share of product A and B in period 2 be 0.6 and 0.4, respectively. In this simple example, the weights calculated by equation (26) are 0.8 and 0.4 for products A and B.[26] This simple example shows two flaws when using average shares $\bar{s}_{ij}$. First, the sum of shares does not add up to 1 if there are product adding and dropping. Second, even if the shares were adding up to 1, for example by using a balanced panel and assigning zero to revenue share of product B for the first year and then calculate average revenue shares for A and B, I would still be down-scaling the exposure to Chinese imports in period 1 by a factor of 0.8.

To ensure that my weights correctly measure the firm exposure to Chinese imports, I normalize the at each period as follows:

$$weight_{ij} = \frac{\bar{s}_{ij}}{\sum_j \bar{s}_{ij}}, \quad \forall t \tag{27}$$

The term $weight_{ij}$ essentially shows conditional on the products produced by the firm at time t, what is the revenue share of each product that is not affected by the current revenue shares.[27] Using the weights in equation (27), I aggregate the firm product level import shares to the firm-level import shares as follows:

$$FIMP_{it} = \sum_j weight_{ij} \; IMP_{jt} \tag{28}$$

where $FIMP_{it}$ shows the firm-level exposure to Chinese import penetration.

Since the weights in equation (27) are not affected by current period revenue shares, it seems plausible to use them as weights to aggregate firm-product-level TFPQ to firm-level TFPQ. In particular, I calculate a new weighted average productivity term, ω'_{it}, where weights remain constant conditional on the set of products and it is calculated as $\omega'_{it} = \sum_j weight_{ij}\omega_{ijt}$. Therefor, any changes in ω'_{it} comes from changes in TFPQ and not reallocations.

Finally, I estimate my model at the firm-level. In particular, I estimate the following specification:

$$y_{it} = \alpha FIMP_{it-1} + \gamma_i + \delta_{st} + \nu_{it} \tag{29}$$

[26]The share of the product B is 0.4 because I have assumed that it has only been produced in one period and its share was 0.4 for that single period. I can alternatively calculate the average share across both period and come up with a share of 0.2, assuming the share of product B has been 0 in the first period. However, even this would not solve the issue inherent in the firm-level exposure for the first period.

[27]Alternatively, I could have used the revenue shares of the first period as the weights if the mix of products produced by every single firm were not changed in the sample. However, this is impossible as firms sometimes add and drop products.

where $y_{it} \in \{\omega_{it}, \bar{\omega}_{it}, cov_{it}, \omega'_{it}\}$ is the variable of interest at the firm-level rather than firm-product-level, and $FIMP_{it-1}$ is the measure of firm-level exposure to Chinese imports. I also include the firm fixed effects,γ_i, and sector-year fixed effects, δ_{st}. I report the results from IV estimates in Table 10.

Table 10: Chinese import competition and firm-level productivity decomposition

Dependant Variable =	(1) ω_{it}	(2) $\bar{\omega}_{it}$	(3) cov_{it}	(4) ω'_{it}
$FIMP_{t-1}$	0.797*	1.176***	-0.379	0.843**
	(0.447)	(0.448)	(0.242)	(0.410)
Observations	40496	40496	40496	40496
F-Stat	2105.4	2105.4	2105.4	2105.4
Firm FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes

Note: Each column reports the results from one regression specified in equation (29). The unit of observation is a firm-year. Firm exposure to Chinese imports is defined in equation (28). firm-level productivity in column (1) is a revenue-weighted TFPQ shown in equation (24). firm-level productivity in column (2) is an unweighted average of TFPQ, and cov_{it} is obtained from definition in equation (25). Finally, productivity term in column (4) is a weighted TFPQ measure where weights are calculated based on equation (27). All regressions include firm and sector-year fixed effects. Reported in parentheses are robust standard errors clustered at the firm-level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Column (1) suggests that a 10 percentage point increase in Chinese import shares is associated with 7.9 percent increase in average firm-level productivity. The fact that the point estimates are close to the firm-product-level estimates implies that the reallocation effect was not significant. Column (3) confirms that there is no statistically significant correlation between import competition and reallocation across products. Column (4), which uses a productivity measure not affected by reallocation across products as the dependant variable, shows a very similar effects to the column (1) where I allow firm-level productivity to be affected by reallocations within a firm. This result also ensures that reallocation is not a source of productivity improvement at the firm-level. Therefore, improvement in technical efficiency remains as the main channel through which an intensified import competition affects manufacturing firms in India.

5 Conclusion

I examine the effect of Chinese import competition on productivity. Recent studies have emphasized on the sources of productivity change within a firm (Bernard, Redding and Schott, 2010; Eckel and Neary, 2010; Mayer, Melitz and Ottaviano, 2014, 2016). Yet, the empirical evidence is left behind due to challenges in estimating product-specific productivity. Extending the production function estimation methods for multi-product firms, in combination with rich data on energy use by product, I estimate physical productivity at the firm-product level. This enables me to investigate the impact of increase in Chinese import competition on two within-firm margins of adjustment: (i) productivity of existing products and (ii) reallocation across products. Moreover, while most studies are focused on the impact of China shock on developed economies, this study provides new evidence on the response of manufacturing firms in India as a developing country in which firms are mostly involved in head-to-head competition with Chinese firms.

Using detailed firm-product-level data for a sample of Indian manufacturing firms between 1994 and 2008, I find that more exposure to Chinese products caused a significant productivity gains in India. These productivity gains come from the physical productivity improvements, not reallocation across products. Back-of-the-envelope calculations suggest that these gains are large and account for 20-30 percent of the overall productivity growth in manufacturing sector. Furthermore, I analyze the effects on physical productivity and find that productivity improvements are larger for the products faced a higher increase in competition with Chinese products. Moreover, I find that almost all of the increase in productivity comes from the improvements in the productivity of products on the two tails of productivity distribution.

While this study has reported new evidence on two margins of within-firm adjustment in response to intensified Chinese import competition, it is silent about the mechanisms causing the productivity of the existing products to increase. These productivity gains can be attributed to innovation, adoption of new technologies, reduction of X-inefficiencies, or changes in managerial slack. I leave this avenue of research for future work.

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A Data construction

There are multiple steps involved in the construction of final sample. First, I describe how I create the sample of manufacturing firms. Then, I discuss merging the UN-Comtrade data to the manufacturing data.

A.1 Manufacturing Data

In this subsection, I describe the construction of firm-product level data for the main analysis.[28] The data in Prowess are maintained in three different modules: First module is called "Standalone Financial", which maintains firm-level data on total sales, exports, cost of intermediate inputs, gross fixed capital, and total wage bills. These are typical firm-level information available in most panel datasets. Second module is called "Products Produced", which includes firm-product level data on the output of the firm such as product name, sales revenue, physical quantity of production, and the unit of production. Using sales and quantities, I can calculate unit values (prices) for each product. Finally, the "Product-wise Energy" module records information on the quantity of energy used to produce one unit of output by fuel type.[29]

I merge all three modules to obtain the final sample of firm-product-year data. Combining the three modules is challenging since products and their units are not consistently reported across all modules. There are several steps involved as follows: To clean the energy input data, first I convert the product-specific fuel consumption into the product-specific energy intensities by assigning energy content of each fuel type in Mega Joules (MJ). Then I calculate the aggregate energy used for each unit of output. For example, I convert KWh of electricity and Kls of furnace oil into their energy contents in MJ. Then, I calculate total energy required to produce one unit of output by summing energy across all fuel types. In the next step, I standardize output units in the product-specific energy input data. Then I merge the input data into the output data. This step is tricky because product names and units are not consistently reported in the two modules. I use fuzzy text matching to merge the to modules. Finally, I multiply the energy intensities by the quantity of output to obtain total energy used for each firm-product line.

At firm level, I observe capital, labor, and material expenditures. All these inputs are reported in terms of total values and not quantities. For example, I observe total wage bills for labor rather than hours of work or number of employees.

On the output side, I observe sales revenues and quantities of production at the firm-product level. Using sales and quantities, I can directly calculate unit values (prices). Each product is

[28] I generally follow the steps provided by Barrows and Ollivier (2018).

[29] For example, a firm reports how many Kilowatt Hour (KWh) of electricity and Kilo Litres (Kls) of furnace oil needed in 2008 to produce one tonne of steel pipes.

identified with a unique product code. There are 1,434 products in the sample. Prowess has its own product classification codes which cannot be used directly to merge to the trade data. Therefore, I map each product code to its respective 4 digit National Indian Classification (NIC) code which corresponds to the International Standard Industrial Classification (ISIC) Revision 3.

A.2 Trade data

I supplement the Prowess data bilateral trade data from UN-Comtrade database. The UN-Comtrade provides product-level annual data which includes trade flows between countries. In UN-Comtrade database, products are defined by the Harmonised System (HS) codes. While Prowess database has its own coding system. Therefore, I match each product in Prowess into a 4 digit International Standard of Industrial Classification (ISIC) Revision 3 code. Then, I rely on the publicly available crosswalk between HS codes and 4 digit ISIC Rev. 3 codes to merge import and export data to the Prowess manufacturing data.

B Translog production function

In this appendix section, I derive all equations of the main text for a translog production function. I start with the translong production function specification of equation (6) in the text:

$$\begin{aligned} q_{ijt} \quad = \quad & \beta_k k_{ijt} + \beta_l l_{ijt} + \beta_m m_{ijt} + \beta_{kk} k_{ijt}^2 + \beta_{ll} l_{ijt}^2 + \beta_{mm} m_{ijt}^2 \\ & + \beta_{kl} k_{ijt} l_{ijt} + \beta_{km} k_{ijt} m_{ijt} + \beta_{lm} l_{ijt} m_{ijt} + \omega_{it} + \epsilon_{ijt} \end{aligned} \tag{B.1}$$

where all inputs, $\mathbf{x} = (k, l, m)$, and output, q, represent (log) quantities at the firm-product level.

Using the assumption that relates firm-product level input quantities to firm-level input expenditures in equation (7), I have:

$$\mathbf{x}_{ijt} = \tau_{ijt} + \tilde{\mathbf{x}}_{it} - w_{ijt}^x \tag{B.2}$$

By substituting equation (B.2) into equation (B.1), I obtain:

$$
\begin{aligned}
q_{ijt} \;\; = \;\; & \beta_k(\tau_{ijt} + \tilde{k}_{it} - w^k_{ijt}) + \beta_l(\tau_{ijt} + \tilde{l}_{it} - w^l_{ijt}) + \beta_m(\tau_{ijt} + \tilde{m}_{it} - w^m_{ijt}) + \beta_{kk}(\tau_{ijt} \\
& + \tilde{k}_{it} - w^k_{ijt})^2 + \beta_{ll}(\tau_{ijt} + \tilde{l}_{it} - w^l_{ijt})^2 + \beta_{mm}(\tau_{ijt} + \tilde{m}_{it} - w^m_{ijt})^2 + \beta_{kl}(\tau_{ijt} + \\
& \tilde{k}_{it} - w^k_{ijt})(\tau_{ijt} + \tilde{l}_{it} - w^l_{ijt}) + \beta_{km}(\tau_{ijt} + \tilde{k}_{it} - w^k_{ijt})(\tau_{ijt} + \tilde{m}_{it} - w^m_{ijt}) + \\
& \beta_{lm}(\tau_{ijt} + \tilde{l}_{it} - w^l_{ijt})(\tau_{ijt} + \tilde{m}_{it} - w^m_{ijt}) + \omega_{it} + \epsilon_{ijt}
\end{aligned} \tag{B.3}
$$

Equation (8) shows that the production function can be written as:

$$
q_{ijt} \;\; = \;\; f(\tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) + A(\tau_{ijt}, \tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) + B(\mathbf{w}_{ijt}, \tau_{ijt}, \tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) + \omega_{it} + \epsilon_{ijt} \tag{B.4}
$$

where $\boldsymbol{\beta}$ is the set of all coefficients, $\boldsymbol{\beta} = \{\beta_k, \beta_l, \beta_m, \beta_{kk}, \beta_{ll}, \beta_{mm}, \beta_{kl}, \beta_{km}, \beta_{lm}\}$.

Rearranging terms of equation (B.3), I obtain functions $f(\tilde{\mathbf{x}}_{it}), A(.)$ and $B(.)$ for a translog specification as:

$$
\begin{aligned}
f(\tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) \;\; = \;\; & \beta_k \tilde{k}_{it} + \beta_l \tilde{l}_{it} + \beta_m \tilde{m}_{it} + \beta_{kk} \tilde{k}^2_{it} + \beta_{ll} \tilde{l}^2_{it} + \beta_{mm} \tilde{m}^2_{it} + \\
& \beta_{kl} \tilde{k}_{it} \tilde{l}_{it} + \beta_{km} \tilde{k}_{it} \tilde{m}_{it} + \beta_{lm} \tilde{l}_{it} \tilde{m}_{it}
\end{aligned} \tag{B.5}
$$

$$
\begin{aligned}
A(\tau_{ijt}, \tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) \;\; = \;\; & (\beta_k + \beta_l + \beta_m)\tau_{ijt} + (\beta_{kk} + \beta_{ll} + \beta_{mm} + \beta_{kl} + \beta_{km} + \beta_{lm})\tau^2_{ijt} + \\
& (2\beta_{kk} + \beta_{kl} + \beta_{km})\tau_{ijt}\tilde{k}_{it} + (2\beta_{ll} + \beta_{kl} + \beta_{lm})\tau_{ijt}\tilde{l}_{it} + (2\beta_{mm} + \beta_{km} + \\
& \beta_{lm})\tau_{ijt}\tilde{m}_{it}
\end{aligned} \tag{B.6}
$$

$$
\begin{aligned}
B(\mathbf{w}_{ijt}, \tau_{ijt}, \tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) \;\; = \;\; & -(\beta_k + \beta_l + \beta_m)w_{ijt} + (\beta_{kk} + \beta_{ll} + \beta_{mm} + \beta_{kl} + \beta_{km} + \beta_{lm})w^2_{ijt} \\
& -(2\beta_{kk} + \beta_{kl} + \beta_{km})\tilde{k}_{it}w_{ijt} + (2\beta_{ll} + \beta_{kl} + \beta_{lm})\tilde{l}_{it}w_{ijt} + (2\beta_{mm} + \\
& \beta_{km} + \beta_{lm})\tilde{m}_{it}w_{ijt} - 2(\beta_{kk} + \beta_{ll} + \beta_{mm} + \beta_{kl} + \beta_{km} + \beta_{lm})\tau_{ijt}w_{ijt}
\end{aligned} \tag{B.7}
$$

Following the first step of the estimation procedure, I can restrict the sample to only single-product firms. Since $\tau_{ijt} = 0$ for all single-product firms, the term $A(.)$ becomes equal to zero, and equation (B.4) collapses to:

$$
q_{it} \;\; = \;\; f(\tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) + B(\mathbf{w}_{it}, \tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) + \omega_{it} + \epsilon_{it} \tag{B.8}
$$

where all the product subscripts, j, drop because each firm produces only one product. Function $f(.)$ remains the same as equation (B.5) and function $B(.)$ becomes:

$$
\begin{aligned}
B(\mathbf{w}_{it}, \tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}) \quad = \quad & -(\beta_k + \beta_l + \beta_m)w_{it} + (\beta_{kk} + \beta_{ll} + \beta_{mm} + \beta_{kl} + \beta_{km} + \beta_{lm})w_{it}^2 \\
& -(2\beta_{kk} + \beta_{kl} + \beta_{km})\tilde{k}_{it}w_{it} + (2\beta_{ll} + \beta_{kl} + \beta_{lm})\tilde{l}_{it}w_{it} + \\
& (2\beta_{mm} + \beta_{km} + \beta_{lm})\tilde{m}_{it}w_{it}
\end{aligned} \tag{B.9}
$$

Let the input price control function to be defined as a linear function of output prices:

$$
w_{it} = w(p_{it}) = \gamma p_{it} \tag{B.10}
$$

Substituting equation (B.10) into (B.9), I obtain:

$$
\begin{aligned}
B(p_{it}, \tilde{\mathbf{x}}_{it}; \boldsymbol{\beta}, \gamma) \quad = \quad & -\gamma(\beta_k + \beta_l + \beta_m)p_{it} + \gamma^2(\beta_{kk} + \beta_{ll} + \beta_{mm} + \beta_{kl} + \beta_{km} + \beta_{lm}) \\
& p_{it}^2 - \gamma(2\beta_{kk} + \beta_{kl} + \beta_{km})\tilde{k}_{it}p_{it} + \gamma(2\beta_{ll} + \beta_{kl} + \beta_{lm})\tilde{l}_{it}p_{it} + \\
& \gamma(2\beta_{mm} + \beta_{km} + \beta_{lm})\tilde{m}_{it}p_{it}
\end{aligned} \tag{B.11}
$$

By plugging function $f(.)$ from equations (B.5) and function $B(.)$ from equation (B.11) into (B.8), I have:

$$
\begin{aligned}
q_{it} \quad = \quad & \beta_k\tilde{k}_{it} + \beta_l\tilde{l}_{it} + \beta_m\tilde{m}_{it} + \beta_{kk}\tilde{k}_{it}^2 + \beta_{ll}\tilde{l}_{it}^2 + \beta_{mm}\tilde{m}_{it}^2 + \\
& \beta_{kl}\tilde{k}_{it}\tilde{l}_{it} + \beta_{km}\tilde{k}_{it}\tilde{m}_{it} + \beta_{lm}\tilde{l}_{it}\tilde{m}_{it} - \\
& \gamma(\beta_k + \beta_l + \beta_m)p_{it} + \gamma^2(\beta_{kk} + \beta_{ll} + \beta_{mm} + \beta_{kl} + \beta_{km} + \beta_{lm})p_{it}^2 - \\
& \gamma(2\beta_{kk} + \beta_{kl} + \beta_{km})\tilde{k}_{it}p_{it} + \gamma(2\beta_{ll} + \beta_{kl} + \beta_{lm})\tilde{l}_{it}p_{it} + \\
& \gamma(2\beta_{mm} + \beta_{km} + \beta_{lm})\tilde{m}_{it}p_{it} + \omega_{it} + \epsilon_{it}
\end{aligned} \tag{B.12}
$$

where now q_{it} is expressed as a function of all observables except for the productivity, ω_{it}.

For simplicity, let the general form of control function for productivity process to be a function of inputs and output price as follows:

$$
\omega_{it} = h_t(\tilde{\mathbf{x}}_{it}, p_{it}) \tag{B.13}
$$

which is treated non-parametrically in the first stage of the estimation. By approximating function h_t with a third-degree polynomial and substituting it into equation (B.12), I have:

$$q_{it} = \phi(\tilde{\mathbf{x}}_{it}, p_{it}) + \epsilon_{it} \tag{B.14}$$

where $\phi(.)$ is a flexible function of all observable variables. By regressing output quantity q_{it} on a flexible third-degree polynomial function for $\phi(.)$, I can purge the shock ϵ_{it}. Note that none of the parameters are identified in the first stage. The only reason for this stage is to purging out the unanticipated shock from physical quantity. Using first stage, I obtain estimates of expected output, $\hat{\phi}_{it}$, and an estimate for ϵ_{it}. Expected output is given by:

$$\begin{aligned}
\phi_{it} = \; & \beta_k \tilde{k}_{it} + \beta_l \tilde{l}_{it} + \beta_m \tilde{m}_{it} + \beta_{kk} \tilde{k}_{it}^2 + \beta_{ll} \tilde{l}_{it}^2 + \beta_{mm} \tilde{m}_{it}^2 + \\
& \beta_{kl} \tilde{k}_{it} \tilde{l}_{it} + \beta_{km} \tilde{k}_{it} \tilde{m}_{it} + \beta_{lm} \tilde{l}_{it} \tilde{m}_{it} - \\
& \gamma(\beta_k + \beta_l + \beta_m) p_{it} + \gamma^2(\beta_{kk} + \beta_{ll} + \beta_{mm} + \beta_{kl} + \beta_{km} + \beta_{lm}) p_{it}^2 - \\
& \gamma(2\beta_{kk} + \beta_{kl} + \beta_{km}) \tilde{k}_{it} p_{it} + \gamma(2\beta_{ll} + \beta_{kl} + \beta_{lm}) \tilde{l}_{it} p_{it} + \\
& \gamma(2\beta_{mm} + \beta_{km} + \beta_{lm}) \tilde{m}_{it} p_{it} + \omega_{it}
\end{aligned} \tag{B.15}$$

Rearranging (B.15) gives ω_{it} as a function of expected output and all $\boldsymbol{\beta}$s as follow:

$$\begin{aligned}
\omega_{it} = \; & \hat{\phi}_{it} - \beta_k \tilde{k}_{it} - \beta_l \tilde{l}_{it} - \beta_m \tilde{m}_{it} - \beta_{kk} \tilde{k}_{it}^2 - \beta_{ll} \tilde{l}_{it}^2 - \beta_{mm} \tilde{m}_{it}^2 - \\
& \beta_{kl} \tilde{k}_{it} \tilde{l}_{it} - \beta_{km} \tilde{k}_{it} \tilde{m}_{it} - \beta_{lm} \tilde{l}_{it} \tilde{m}_{it} + \\
& \gamma(\beta_k + \beta_l + \beta_m) p_{it} - \gamma^2(\beta_{kk} + \beta_{ll} + \beta_{mm} + \beta_{kl} + \beta_{km} + \beta_{lm}) p_{it}^2 + \\
& \gamma(2\beta_{kk} + \beta_{kl} + \beta_{km}) \tilde{k}_{it} p_{it} - \gamma(2\beta_{ll} + \beta_{kl} + \beta_{lm}) \tilde{l}_{it} p_{it} - \\
& \gamma(2\beta_{mm} + \beta_{km} + \beta_{lm}) \tilde{m}_{it} p_{it}
\end{aligned} \tag{B.16}$$

The second stage of the estimation identifies all the structural parameters of the model. To form the moment conditions for the second stage, I start with the first order Markovian process for productivity, where:

$$\omega_{it} = g(\omega_{it-1}) + \eta_{it} \tag{B.17}$$

After the first stage and using equation (B.16), I can compute productivity for any value of $\boldsymbol{\beta}$ and γ. Given $\boldsymbol{\beta}$, γ and the Markovian process in equation (B.17), I can recover the innovation to productivity $\eta_{it}(\boldsymbol{\beta}, \gamma)$ by nonparametrically regressing $\omega_{it}(\boldsymbol{\beta}, \gamma)$ on $\omega_{it-1}(\boldsymbol{\beta}, \gamma)$.

Now, I can form moments to obtain the estimates of production function where I rely on:

$$E[\eta_{it}(\boldsymbol{\beta}, \gamma)\mathbf{z}_{it}] = 0 \tag{B.18}$$

where $\mathbf{z}_{it}$ contains current capital and labor, lagged materials, and their higher order and interaction terms, as well as lagged output prices and lagged expected output.[30] I rely on lagged material and price to identify their coefficients since current material and price are expected to react to shocks to productivity. The model is identified since there are ten parameters and ten moment conditions. The coefficient γ can be calculated by dividing the coefficient on p_{it-1} by $\beta_k + \beta_l + \beta_m$.

[30] $\mathbf{z} = \{\tilde{k}_{it}, \tilde{l}_{it}, \tilde{m}_{it-1}, \tilde{k}_{it}^2, \tilde{l}_{it}^2, \tilde{m}_{it-1}^2, \tilde{k}_{it}\tilde{l}_{it}, \tilde{k}_{it}\tilde{m}_{it-1}, \tilde{l}_{it}\tilde{m}_{it-1}, \tilde{p}_{it-1}\}$

C Supplementary results

Table 11: Summary statistics of Indian manufacturing firms

Industry	(1) Share of Sample Output (%)	(2) All Firms	(3) Single-product Firms	(4) Products
15 Food and Beverages	9.76	599	216	130
17 Textiles and Apparel	9.41	611	221	88
21 Pulp and Paper	1.71	147	92	29
24 Chemicals	23.47	752	279	485
25 Rubber and Plastic	4.37	193	97	81
26 Nonmetallic mineral products	6.61	147	83	58
27 Basic metals	15.96	391	172	90
28 Fabricated metal products	1.56	72	40	41
29 Machinery and Equipment	6.50	230	100	176
31 Electrical Machinery and Comm.	11.10	227	129	186
34 Motor Vehicles	9.54	95	58	70
Total	100.00	3465	1488	1434

Note: The sample covers 1994-2008. All numbers are reported for an average year in the sample. Unit of observation is a firm-product-year. Column (1) shows the percentage share of output for each sector in the sample. Column (2) reports the number of all firms on an average year. Column (3) reports the number of single-product firms on an average share. Comparing column (2) and (3) shows the high share of single-product firms in the sample which is necessary for the production function estimation. Column (4) shows the total number of products in each sector and the whole sample.

Table 12: Correlation matrix for outcome variables

	Quantity	Price	TFPQ	TFPR
Quantity	1.00			
Price	-0.81	1.00		
TFPQ	0.71	-0.93	1.00	
TFPR	-0.24	0.18	0.20	1.00

Note: Each cell shows the basic correlation pattern between the two variables. The correlations are calculated after absorbing 2-digit sector-year effects. Unit of observation is firm-product-year. TFPQ refers to physical productivity and TFPR refers to revenue productivity.

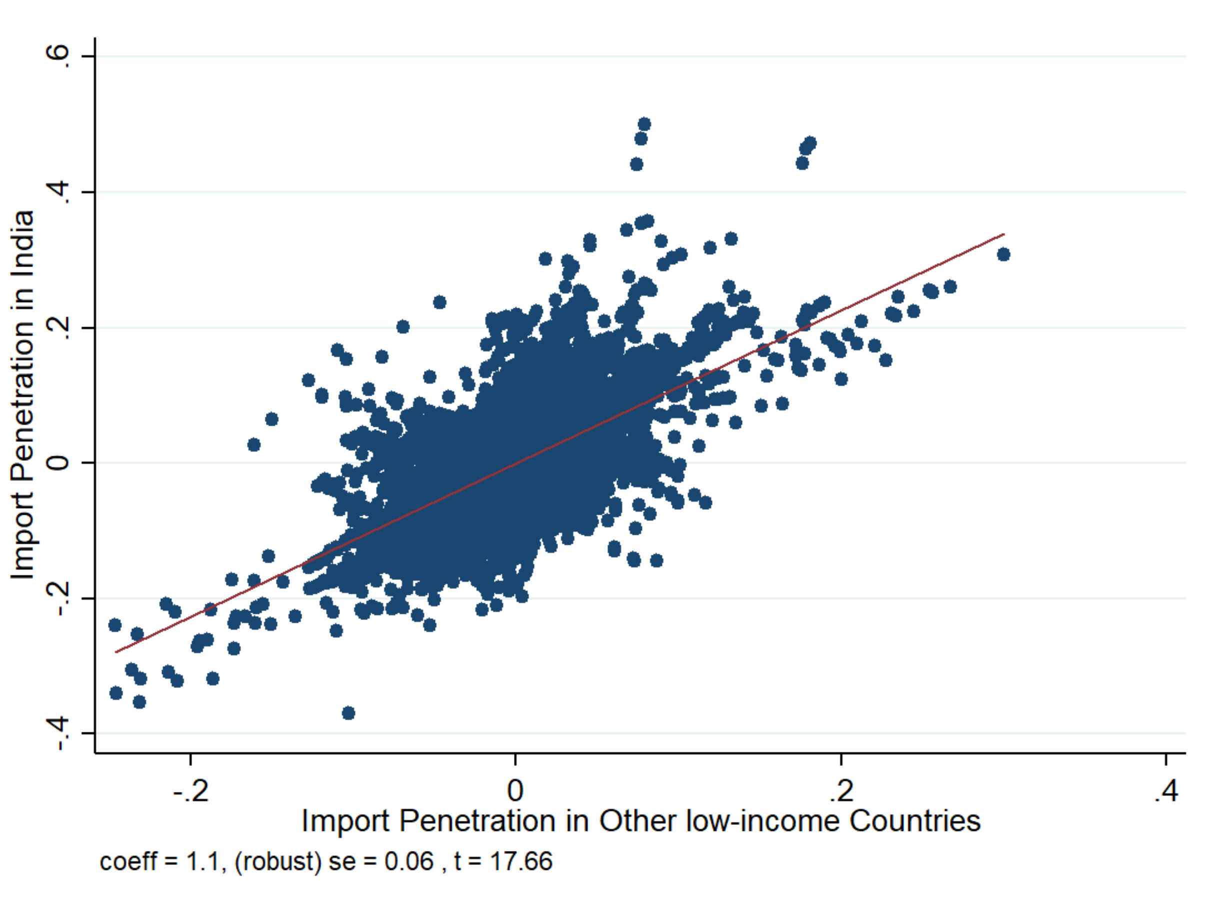

Figure 2: 2SLS First Stage Regression, 1994-2008

Table 13: Within firm-product response to Chinese import competition, 5-year effects

Dependent Variable =	(1) ln(sales)	(2) ln(price)	(3) ln(quantitiy)
Panel A: OLS estimates			
IMP_{t-5}	0.115	-0.174	0.289**
	(0.241)	(0.192)	(0.139)
Observations	40430	40430	40430
Firm-Product FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Panel B: IV estimates			
IMP_{t-5}	0.189	-0.762***	0.951*
	(0.540)	(0.147)	(0.576)
Observations	40430	40430	40430
F-Stat	73.7	73.7	73.7
Firm-Product FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes

Note: Each column reports the results from one regression specified in equation (22). The unit of observation is a firm-product-year. Sample covers the period 1994-2008. Panel A reports the OLS results, whereas panel B reports the IV results. Instrument used in panel B is defined in equation (23). First stage F-stats are reported for the IV regressions. All regressions include firm-product and sector-year fixed effects. Reported in parentheses are robust standard errors clustered at the product level. $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 14: Chinese import competition and productivity, 5-year effects

Dependent Variable =	(1) ln(TFPR)	(2) ln(TFPQ)
Panel A: OLS estimates		
IMP_{t-5}	-0.053	0.121
	(0.142)	(0.101)
Observations	40430	40430
Firm-Product FE	Yes	Yes
Sector-Year FE	Yes	Yes
Panel B: IV estimates		
IMP_{t-5}	0.306	1.068***
	(0.193)	(0.261)
Observations	40430	40430
F-Stat	73.7	73.7
Firm-Product FE	Yes	Yes
Sector-Year FE	Yes	Yes

Note: Each column reports the results from one regression specified in equation (22). The dependent variable is the logarithm of revenue productivity (TFPR) in column (1) and logarithm of physical productivity (TFPQ) in column (2). The unit of observation is a firm-product-year. Sample covers the period 1994-2008. Panel A reports the OLS results, whereas panel B reports the IV results. Instrument used in panel B is defined in equation (23). First stage F-stats are reported for the IV regressions. All regressions include firm-product and sector-year fixed effects. Reported in parentheses are robust standard errors clustered at the product level. $*p < 0.1, **p < 0.05, ***p < 0.01$.