Foreign Direct Investment, Markups, Prices and Productivity: Evidence from India

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Abstract

This paper uses a rich panel data set of Indian manufacturing firms to analyze the effects of horizontal and vertical foreign direct investment on various outcomes of domestic firms. We apply recent methodological advances in the estimation of production functions together with detailed product-level information on prices and quantities to estimate physical productivity, markups, marginal costs and proxies for product quality. We also employ instrumental variables based on initial allocations of foreign ownership across industries and exploit cross-industry and time-series variation in FDI reforms. Our preliminary results highlight the importance of price adjustments in identifying the productivity effects of FDI.

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1 Introduction

It is well documented that multinational companies outperform purely domestic firms and that they are responsible for a large share of global innovation activities.[1] Theories of foreign direct investment (FDI) explain this performance premium by a selection effect: due to large sunk costs of entering foreign markets, only firms with superior productivity can operate abroad profitably (e.g., Helpman et al., 2004). Since this productivity advantage might stem from intangible assets such as innovation and knowledge (Markusen, 2002; Guadalupe, et al., 2012) or management practices (e.g., Bloom and Van Reenen, 2010), the theoretical perception is that some of the superior productivity of foreign investors can lead to productivity improvements in domestic firms due to incomplete appropriability, worker mobility or interactions with domestic suppliers and customers. The existing literature has differentiated between horizontal spillovers, i.e. spillovers to firms in the same industry, and vertical spillovers, i.e. to firms in upstream and downstream sectors (e.g., Javorcik, 2004).[2]

Potential efficiency gains can be substantial for FDI flows which transfer superior production techniques or management practices across borders towards less advanced economies. Measuring these gains is, however, a challenging task. Commonly used proxies of revenue-based productivity could vary across firms due to differences in marginal costs, but they might also reflect heterogeneity in markups as well as differences in demand and product quality (e.g., Braguinsky et al., 2015; De Loecker et al., 2016; Forlani et al., 2016).[3] To the extent that FDI inflows affect prices and markups in the destination country, revenue-based measures of total factor productivity (TFP) will be biased. In particular, reduction in prices due to increased competition from foreign investors would lead to lower measured productivity in the absence of changes in efficiency. Further, increases in market power, which could for instance occur after FDI in the form of foreign acquisitions, will lead to higher prices and markups and show up as higher values in common productivity measures (Syverson, 2011). Similar biases might occur for spillovers across vertical chains if changes in demand for intermediate inputs affects input and output prices of suppliers and buyers

This paper provides evidence on the effects of FDI using a rich data set of Indian manufacturing

[1]See, for instance Greenaway and Kneller (2007), Helpman et al. 2004, Criscuolo et al., 2010 to name a few.

[2]Only in a few cases this literaure has differentiated between cross-border mergers & acquisitions (M&As) and greenfield investments (new firms or production units founded by foreign investors) (e.g., Girma et al., 2015).

[3]In recent trade theoretical models, firms are not only heterogeneous in terms of productivity but are also differentiated in terms of product quality (e.g., Antoniades, 2015; Hallak and Sivadasan, 2013). Variation in prices and product quality have indeed been found to be of similar importance as cost based advantages in explaining the performance of firms in international markets (e.g., Eckel et al., 2015; Hallak and Schott, 2011; Hallak and Sivadasan, 2013; Kugler and Verhoogen, 2012). Recent evidence suggests that products produced by multinationals are characterized by higher (perceived) quality due to stronger brands and higher reputation . Knowledge transfer can thus also translate into superior product quality and reputation as opposed to a cost-based advantage (e.g. Eckel et al., 2015; Harding and Javorcik, 2012).

firms. A unique feature of this data set is that it contains information on prices and quantities at the firm-product level next to standard measures of firms' input expenditures. This information, together with recent methodological advances in the estimation of production functions, allows us to estimate markups, marginal costs, physical productivity, and proxies for product quality, and to analyze how these variables change with exposure to FDI.

The lack of reliable information on these variables across a broad set of industries has been a major constraint for the previous literature on FDI. The results of the existing literature on horizontal and vertical spillovers from FDI have been surveyed in Irsova and Havranek (2013) and Havranek and Irsova (2011), respectively.[4] The authors argue that the results of this literature are mixed but that the majority of existing studies shows evidence for positive spillovers to suppliers and little evidence for horizontal spillovers and spillovers to customers.[5]

While the results of FDI spillovers might well be heterogeneous due to target country, industry, and investor heterogeneity, part of the inconclusiveness of previous studies might well be due to data limitations, since this literature has mainly relied on revenue-based measures of firm-level productivity. Evidence on FDI spillovers estimated in the form of quantity-based productivity and product-level outcomes such as markups, prices, and marginal costs is, to our knowledge, still missing. This is unfortunate for two reasons. First, previous studies were unable to disentangle changes in revenue-based productivity into changes in technical efficiency, markups, and quality. Second, product-level data allows much cleaner measurement of firms' exposure to horizontal and vertical FDI, since product categories are available in much more disaggregated form than standard industry classifications.

This paper exploits firm-product level data as well as information on the usage of different types of raw materials to address this gap. We use this data to study how FDI affects the performance of Indian manufacturing firms in various dimensions. The case of India is particularly interesting for several reasons. First, previous research has found that the Indian economy has been characterized by substantial misallocation of inputs across firms (Hsieh and Klenow, 2009) and high within-industry dispersion of productivity compared to other countries (see, for instance, Syverson, 2011). This implies a high potential for efficiency gains from international technology spillovers. Furthermore, various economic reforms, such as a deregulation of foreign ownership caps have induce a large inflow of FDI. Finally, in contrast to most other countries, Indian firms are required by law to report sales and quantities at the product level. This unusually rich information is essential for our empirical

[4]Recent contributions analyzing FDI spillovers include Fons-Rosen et al. (2017) and Lu et al. (2017).

[5]The existing FDI literature focuses on relatively broadly defined industries and is primarily concerned with the estimation of technology spillovers rather than competitive effects. An exception is Aghion et al. (2009) who provide evidence that entry of foreign investors spurs innovation incentives of domestic firms in the UK. Eck and Huber (2016) as well as well as Javorcik et al. (2016) find that horizontal FDI is correlated with higher likelihood of introducing technologically advanced products by domestic firms.

approach.[6]

For the empirical analysis, we apply recent methodological advances in the estimation of production functions proposed by De Loecker et al. (2016). A unique feature of this estimation technique is the explicit treatment of a quantity-based production function and unobserved input allocation across products of multi-product firms. The methodology also accounts for endogeneity of inputs and controls for variation in unobserved input prices. Estimates of production function parameters make it possible to estimate markups at the firm-product level and a measure of physical productivity at the firm level. Estimated markups and observed prices can then be used to recover marginal costs. The availability of product-level data also allows us to construct proxies of product quality, such as variations in quantities conditional on price within product categories.

We use these estimated values along with other outcomes to study the performance of domestic firms and how it varies with exposure to FDI in the same industry as well as in vertically related industries. Since FDI might not be allocated randomly across industries, we will employ instrumental variables exploiting cross-industry and time-series variation in FDI reforms in future versions of this paper. The use of firm-product and firm-input data allows us to measure exposure to foreign firms in a much more precise way as previous empirical studies and to control for firm-year fixed effects which capture all time-varying changes within a firm that are constant across its products.

Our results indicate that when the presence of foreign firms in a product category increases, domestic firms' markups, prices, revenues and quantities in the same product decline substantially. There is little evidence of technology spillovers in the form of marginal cost reductions. These results are consistent with a competition effect which leads to a crowding out domestic firms' production by foreign owned firms.

However, we provide evidence of technology spillovers across product categories. When we define a firm-level measure of exposure to FDI—either defined by market shares of foreign investors weighted by initial sales shares across products within firms or by firms' main industry—we find evidence of reductions in marginal costs and increases in physical TFP. The effects are economically important. A 10 percentage point increase in the market share of foreign owned firms is associated with reductions in marginal costs of about 2% in the same year and more than 5% within a 3 year interval. Interestingly, we estimate small and statistically insignificant increases in commonly used measures of revenue TFP. Although there is evidence of incomplete pass-though as markups rise when marginal costs decline, part of the cost reductions seem to be passed on to consumers. This induces downward biased in revenue-based productivity measures.

[6] Stiebale and Vencappa (2018) and Bircan (2019) provide evidence on the effects of foreign acquisitions exploiting product-level data for India and Turkey, respectively. However, they focus on the effects on acquisition targets rather than spillovers to domestic firms.

Nonetheless, technology spillovers are accompanied by substantial competition effects as our results indicate that domestic firms' quantities do not increase significantly besides falling prices implying a reduction in revenue. The fact that markups increase at the same time indicates that this effect is not predominantly driven by a reduction in product quality. To the best of our knowledge our paper is the first to disentangle competition from spillover effects from FDI using product-level data.

The rest of the paper is organized as follows. Section 2 provides a description of our data sets. The empirical strategy is detailed in section 3, our results are discussed in section 4. Section 5 concludes.

2 Data

Our main data source is the *Prowess* database compiled by the Centre for Monitoring of the Indian Economy (CMIE). Prowess includes data from company balance sheets and income statements for both publicly listed and unlisted firms from a wide cross-section of industries in manufacturing, services, utilities and financial sectors.[7] These firms cover more than 70% of industrial output from the organized sector and 75% of corporate taxes and 95% of excise taxes collected by the government. Prowess also records these firms' product-level data on quantities and values of sales and production.[8] We extracted data spanning the period 1988 (the first year firms appear in the database) until 2017. Since our empirical framework requires a comparable units for quantities and prices, we focus on the manufacturing sector.

Firms report names of each product alongside information on their production and sales. Each product in Prowess is allocated a 20-digits code from CMIE's own internal classification of 5908 sub-industries and products. Of these, 4833 products fall under the manufactured sector.[9] We had to carry out a number of adjustments to original the CMIE product codes. For instance, there were a number of cases where the same product code was attributed to different products, or where different product codes were allocated to the same product. In addition, we noticed a number of cases where product names varied in spelling and also noted frequent differences in levels of aggregation for what constitutes a product. After cleaning the data, accounting for missing values, and aggregating products to a common 12-digit level, there are 2896 clean and unique CMIE product categories in our estimation sample. Following De Loecker et al. (2016), we choose to aggregate products to a

[7] This database has been used in a number of recent papers, e.g. De Loecker et al. (2016); Goldberg et al. (2009, 2010a,b).

[8] The 1956 Companies Act requires Indian firms to disclose data at this level of detail.

[9] CMIE's classification is largely based on the Indian National Industrial Classification (NIC) and the HS schedule. Example of products across different industries include shrimps, corned meat, pig iron, sponge iron, pipe fittings, rail coaches. See Goldberg et al. (2010b) for a detailed description of the product-level data in Prowess.

12-digit level because the number of observations for some narrowly defined products is very small and the degree of disaggregation varies across products. The aggregated product codes were then mapped onto India's 2008 revised National Industrial Classification (NIC). Prowess also contains information at the firm-level such as sales, material costs, wage bill and capital stock (measured by gross fixed assets).[10]

Prowess also contains information about the share of foreign equity for listed firms. For both listed and non-listed firms, information on whether a firm is part of a domestic (private or government) or foreign business group is available. We combine this information, to construct a measure of majority foreign ownership. This measure contains the percentage of foreign promoters for Indian listed companies. We complete this measure for non-listed firms based on firm's ownership type. Following Eck and Huber (2016), we consider privately Indian owned or government owned firms to have 0% foreign equity, and private foreign owned firms to have 100% foreign equity. On average, foreign shares represent 58.5% of listed private-foreign owned firms' shares and 7.8% of listed private-Indian and government owned firms'shares. In our analysis we consider firms having more than 25% of foreign shares as foreign-owned firms.

Table 1 reports the coverage of firms, products and firms' ownership in our sample. Hence, for our empirical analysis, we use data on 9957 firms and 30013 firm-products, distributed across 11 two-digits manufacturing industries. About 7% of the firms in our estimation sample have at least 25% of foreign ownership, and about 60% of the firms are single product firms.[11]

Table 1: Firms, products and ownership across industries

NIC codes	Sector	All firms	Single product firms	No. of products	Domestic ownership	Foreign ownership
10, 11, 12	Food, beverages and tobacco	1741	778	255	1673	103
13, 14, 15	Textiles, wearing apparel and leather	1862	862	209	1832	48
16, 17, 18	Wood, paper products and printing	590	311	81	578	24
19, 20, 21	Coke, Chemicals and Pharmaceuticals	2852	1134	920	2722	221
22	Rubber and plastics	977	426	128	947	58
23	Non-metallic minerals product	606	325	111	580	47
24, 25	Basic metal and fabricated metal	2034	907	225	1984	88
26	Computers & electronics	859	307	340	784	105
27	Electricals	796	292	204	742	87
28	Machinery & Equipment	1085	370	284	1005	138
29, 30	Motor vehicles and transport equipment	732	357	152	680	92
10-30	All manufacturing	9957	5955	2896	9577	692

[10] Unfortunately, the data base does not contain direct information about the skill level of employees or the quality of capital and materials. However, as we discuss in the next section, our empirical framework will control for heterogeneity in quality using a control function approach.

[11] The share of single-product firms is very similar to Bernard et al. (2010) who report a share of single-product firms of 61% in the US for the year 1997. The share of single-product firms in our sample is slightly higher than in a previous study for India by Goldberg et al. (2010b) who report a share of 53%. This difference emerges partly because coverage of relatively small firms is higher in our more recent version of Prowess and partly because we aggregate some similar product into common categories for our estimation approach. Note that in line with other studies on multi-product firms, our definition of a product refers to a category such as motorcycles or sponge iron, not a unique variety within these categories. The share of single-product firms among foreign owned firms is 5%.

3 Empirical strategy

3.1 Estimating productivity, markups and marginal costs

To estimate productivity, markups, and marginal costs, we follow the methodology introduced by De Loecker et al. (2016), henceforth LGKP.[12] This method accounts for endogeneity of production inputs similar to standard techniques in the productivity literature (Ackerberg et al., 2015; Levinsohn and Petrin, 2003; Olley and Pakes, 1996). In addition, it relies on the availability of quantities and prices at the product level to separate physical productivity from revenue based productivity. As most (if not all) firm-product-level data sets, Prowess does not include complete information on prices of all inputs and provides data on inputs at the firm-level with no information about how inputs are allocated across products for multi-product firms.[13] The main innovations of the LGKP approach are the introduction of a control function for unobserved input prices and a method to recover the allocation of inputs across products. We briefly describe the methodology below.

Consider a production function for firm i producing a product j at time t:

$$Q_{ijt} = F_j(M_{ijt}, K_{ijt}, L_{ijt})\Omega_{it} \tag{1}$$

where Q_{ijt} denotes physical output, M_{ijt} denotes a freely adjustable input (materials in our case), K_{ijt} and L_{ijt} are capital stock and labor input respectively and Ω_{it} denotes TFP. All production inputs are defined in physical units. A firm minimizes costs for each product and takes a production function as well as input costs as given.

As shown by De Loecker and Warzynski (2012) and LGKP, this cost minimization yields an expression for the firm-product specific markup as:

$$\mu_{ijt} = \left(\frac{P_{ijt}Q_{ijt}}{W^M_{ijt}M_{ijt}}\right)\frac{\partial Q_{ijt}(.)}{\partial M_{ijt}}\frac{M_{ijt}}{Q_{ijt}} = \frac{\theta^M_{ijt}}{\alpha^M_{ijt}} \tag{2}$$

where P_{ijt} denotes the output price, W^M_{ijt} is the input price of materials, α^M_{ijt} is the ratio of expenditures on input M_{ijt} to a product's revenue and θ^M_{ijt} is the elasticity of output with respect to this input. Intuitively, the output elasticity equals the input's revenue share only in the case of perfect competition. Under imperfect competition, the output elasticity will exceed the revenue share.[14]

[12] These authors investigate the effect of trade reforms on prices, markups and marginal costs in India using the same main data source as our paper, but covering an earlier time period.

[13] While Prowess contains data about the prices of material inputs, it does not contain information about the price of capital. Furthermore, for a large proportion of firms, data exists only on total wage bill but not on number of employees.

[14] This framework assumes that there are no static sources of market power in *input* markets, i.e. $\frac{\partial W^M_{ijt}}{\partial Q_{ijt}} = 0$. Further, it abstracts from misallocation which systemically distorts the use of intermediate inputs relative to other

As we describe below, θ^M_{ijt} can be estimated from a production function and α^M_{ijt} can be calculated, once the allocation of inputs across a firms' product has been estimated. Marginal costs (mc_{ijt}) can then be calculated as the ratio of observed prices to estimated markups:

$$mc_{ijt} = \frac{P_{ijt}}{\mu_{ijt}} \tag{3}$$

The basis for productivity estimation is the logarithmic version of equation (1) with an additive error term, ϵ_{ijt} which captures measurement errors:

$$q_{ijt} = f_j(\boldsymbol{v}_{ijt}; \boldsymbol{\beta}) + \omega_{it} + \epsilon_{ijt} \tag{4}$$

where $\boldsymbol{v}_{ijt}$ denotes a vector of logarithmic physical inputs (capital k_{ijt}, labor l_{ijt} and materials m_{ijt}) allocated to product j and ω_{it} is the log of TFP. For our application, we mainly rely on a translog production function, hence:

$$\begin{aligned} f_j(\boldsymbol{v}_{ijt}; \boldsymbol{\beta}) =& \beta_l l_{ijt} + \beta_m m_{ijt} + \beta_k k_{ijt} + \beta_{lm} l_{ijt} m_{ijt} + \beta_{lk} l_{ijt} k_{ijt} + \beta_{mk} m_{ijt} k_{ijt} \\ &+ \beta_{ll} l^2_{ijt} + \beta_{mm} m^2_{ijt} + \beta_{kk} k^2_{ijt} + \beta_{lmk} l_{ijt} m_{ijt} k_{ijt} \end{aligned} \tag{5}$$

The translog production function yields a physical output-material elasticity:

$$\theta^M_{ijt} = \beta_m + \beta_{lm} l_{ijt} + \beta_{mk} k_{ijt} + 2\beta_{mm} m_{ijt} + \beta_{lmk} l_{ijt} k_{ijt} \tag{6}$$

which varies across firms within industries and nests a Cobb-Douglas production function as a special case.

For the Cobb-Douglas production function:

$$f_j(\boldsymbol{v}_{ijt}; \boldsymbol{\beta}) = \beta_l l_{ijt} + \beta_m m_{ijt} + \beta_k k_{ijt} \tag{7}$$

and $\theta^M_{ijt} = \beta_m$.

Physical inputs can be expressed as $v_{ijt} = \rho_{ijt} + \tilde{v}_{it} - w_{ijt}$ where $\tilde{v}_{it}$ denotes observed input expenditures at the firm-level, ρ_{ijt} is the log of the input share allocated to product j and w_{ijt} denotes the log of an input price index (defined as deviations from industry-specific deflators). When the log of input allocations, ρ_{ijt}, is captured by a function $A(\rho_{ijt}, \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta})$ and the log of the unobserved input price index, w_{ijt}, are captured by a function $B(w_{ijt}, \rho_{ijt}, \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta})$, output can be rewritten as a function of firm-specific input expenditures instead of unobserved product-specific

production factors.

input quantities:[15]

$$q_{ijt} = f_j(\tilde{\boldsymbol{v}}_{ijt}; \boldsymbol{\beta}) + A(\rho_{ijt}, \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta}) + B(w_{ijt}, \rho_{ijt}, \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta}) + \omega_{it} + \epsilon_{ijt} \tag{8}$$

Estimation of the parameters of the production function is based on a sample of single product firms for which $A(.)$ can be ignored. Unobserved input prices w_{it} in $B(.)$ are approximated by output prices (p_{it}), market shares (s_{it}), product dummies ($\boldsymbol{D_j}$),and export status (ex_{it}) to account for differences in product quality and local input markets. We also include a vector of variables capturing FDI ($\boldsymbol{FDI}_{it}$) which we define below, as we want to allow for the possibility that foreign ownership and the presence of foreign investors affects input prices.

Material demand is assumed to be a function of productivity, other inputs, output prices, market share, product, export and FDI, hence: $\tilde{m}_{it} = m(\omega_{it}, \tilde{k}_{it}, \tilde{l}_{it}, p_{it}, \boldsymbol{D}_j, s_{it}, ex_{it}, \boldsymbol{FDI}_{it})$. Inverting the material demand function yields an expression for productivity: $\omega_{it} = h(\tilde{\boldsymbol{v}}_{it}, \boldsymbol{c}_{it})$ where $\boldsymbol{c}_{it}$ includes all variables from the input demand function except input expenditures.

The use of single product firms induces a further complication of endogenous sample selection since single-product firms might be less productive compared to multi-product firms. Analogous to the exit correction proposed by Olley and Pakes (1996), the probability of remaining a single product firm (SP_{it}) is a function of previous year's productivity and an unobserved productivity cutoff.[16]

For the evolution of productivity, the following law of motion is assumed:

$$\omega_{it} = g(\omega_{i,t-1}, ex_{i,t-1}, \boldsymbol{FDI}_{i,t-1}, SP_{it}) + \zeta_{it} \tag{9}$$

In addition to export status and the probability of remaining a single product firm, we allow the evolution of productivity to depend on exposure to FDI. Our initial version of the production function focuses on a simplified version similar to the one implemented by LGKP which related to Wooldridge (2009) and is based on moment conditions on the combined error term $\varsigma_{it} + \epsilon_{it}$.[17] We discuss how we estimate the production functions and recover unobserved input allocation across products of multi-product firms in the Appendix.

[15] See LGKP for the exact functional form of $A(.)$ and $B(.)$ for the translog and the Cobb Douglas case.

[16] SP_{it} is estimated by a Probit regression of a dummy variable for remaining a single-product firm on $\tilde{\boldsymbol{v}}_{i,t-1}$ $\boldsymbol{c}_{i,t-1}$, investment, year and industry dummies.

[17] In future versions of this manuscript, we will implement a two-step approach which allows addressing measurement error explicitly and for a more general version of the Markov process.

3.2 Evaluating the effects of FDI

Our empirical strategy aims to identify the effects of FDI on domestic firms. We start by analyzing the following regression at the firm-level:

$$y_{i(j)t} = \theta FDI_{jt}^{hor} + x'_{i(j)t}\beta + \alpha_j + [\alpha_i] + d_t + u_{it}$$

$y_{i(j)t}$ is a firm-level outcome such as productivity of firm i operating in industry j at time period t. FDI_{jt}^{hor} measures the potential for horizontal spillovers in industry j calculated as the share of sales generated by foreign owned firms:

$$FDI_{jt}^{hor} = \frac{\sum_{i \in j,t} S_{it} \times F_{it}}{\sum_{i \in j,t} S_{it}}$$

where F is a dummy variable indicating foreign ownership. $x'_{i(j)t}$ denotes a vector of control variables at the firm and industry level. In some specifications, we also control for potential spillovers across vertically related industries. FDI_{jt}^{back} captures the potential for spillovers through backward linkages, i.e. the market share of foreign investors in other industries, weighted by an input-output coefficient (α_{jk}) which measures the share of production in the focal firms' industry that is shipped to other industries. It is calculated as:

$$FDI_{jt}^{back} = \sum_{k \neq j} \alpha_{jk} FDI_{kt}^{hor}$$

FDI_{jt}^{forw} captures the potential for spillovers through forward linkages, i.e. exposure to inputs produced by foreign-owned firms.

$$FDI_{jt}^{forw} = \sum_{m \neq j} \sigma_{jm} \frac{\sum_{i \in m,t} (S_{it} - EX_{it}) \times F_{it}}{\sum_{i \in j,t} (S_{it} - EX_{it})}$$

x'_{it} is a vector of firm and industry-specific control variables, α_j (α_i) denotes an industry (firm) fixed effect, d_t captures time dummies and u_{it} is an error term

We also the effect of FDI at the firm-product level:[18]

$$y_{ikt} = \alpha_{ik} + \phi FDI_{kt}^{hor} + x'_{i(j)t}\gamma + d_t + [g_{ik} \times trend_t] + u_{it}$$

where exposure to FDI variables is measured at the product rather than at the firm's main

[18] The effect of forward and backward FDI will be explored in a next version

industry. This regression allows defining a much narrower measure of exposure to FDI than in most of the previous literature. This specification allows for unobserved heterogeneity at the firm-product level (α_{ik}) and even firm-product specific time trends ($g_{ik} \times trend_t$) which capture changes in firms' organization and productivity which are common to all products a firm produces. We estimate the above equation in differences to eliminate time-invariant differences across firms, products and industries as well as firm-product specific trends:

$$\Delta y_{ikt} = \phi \Delta FDI_{kt}^{hor} + \Delta x'_{i(j)t}\gamma + \Delta d_t + [g_{ik}] + \Delta u_{it}$$

where Δy_{ikt} denotes a 1 to 3 year change in the dependent variable. In a next step, we exploit variation across products within firms and include firm-year fixed effects (κ_{it}) into the above specification:

$$\Delta y_{ikt} = \phi \Delta FDI_{kt}^{hor} + \Delta x'_{i(j)t}\gamma + \Delta d_t + g_{ik} + \kappa_{it} + \Delta u_{it}$$

An advantage of this specification is that we can control for time-varying changes that are common to all products of a firm such as changes in productivity or organizational structure. A disadvantage of this specification is that it can only be run for firms that produce at least two products.

4 Results

4.1 Characteristics of firm- and product-level variables

In this subsection, we discuss some characteristics of our variables estimated from production functions.

Table 2 reports means and standard deviations on our measures of revenue, labour, capital, materials and other variables comparing domestic and foreign owned firms. The upper panel reports firm-level variables only. From these, we can note that foreign-owned firms have on average higher sales revenues and capital stock, face higher wage bills and spend more on materials. They also produce more products but report lower export share comparing to domestic-owned firms.

The lower panel reports variables constructed at the product level. Markups and marginal costs are calculated as expressed in equations (2) and (3).

Table 3 depicts median and mean elasticities of output with respect to all inputs estimated from separate production functions for each industry. We use a translog production function that allows for elasticities and return to scale parameters to vary across industries as well as firms and firm-products within industries. The estimates indicate increasing return to scale with an average measure of 1.06 across all industries. Returns to scale for the median firm within each industry are above 1 in 9 out of 11 cases and range between 0.93 and 1.27. Table 4 shows average and median markups of products across industries. The estimates indicate an average markup of 7.01 across all industries with a median markup of 2.14 that ranges from 1.76 and 3.67.

Table 2: Firm characteristics: Means, (standard deviation).

Variables	Definition	Domestic ownership	Foreign ownership
Firm level		N=9577	N= 692
Sales	Income from sales (Rs. million)	2754.82	7071.66
		(9333.412)	(16690.742)
Labour	Salaries and wages (Rs. million)	174.74	495.32
		(617.122)	(1012.399)
Materials	Expenditure on raw materials (Rs. million)	1202.26	2632.91
		(3421.357)	(6033.346)
Capital stock	Gross fixed assets (Rs. million)	1684.26	2997.57
		(6112.142)	(7561.173)
No. of products	Product count	2.75	3.26
		(2.415)	(2.785)
Export share	Foreign exchange earnings/sales	0.21	0.16
		(0.296)	(0.272)
TFP	Physical Total factor productivity	1.77	1.73
		(1.940)	(2.350)
Product level		N=2860	N=966
Sales	ln(product sales residuals)	-0.05	0.60
		(1.793)	(1.769)
Quantity	ln(quantity residuals)	-0.04	0.46
		(2.171)	(2.393)
Price	ln(price residuals)	-0.001	0.02
		(0.485)	(0.635)
Marginal cost	ln(marginal cost residuals)	0.00	-0.01
		(2.263)	(2.404)
Markup	ln(markup residuals)	-0.01	0.15
		(1.561)	(1.551)

Variables presented at product level are demeaned by product-unit of measurement-year.

Table 3: Elasticities from production function: Means, *medians*, (standard deviation).

Sector	Observations	Labour	Materials	Capital	RTS
Food, beverages and tobacco	29621	0.24	0.60	0.08	0.93
		0.23	*0.61*	*0.10*	*0.99*
		(0.16)	(0.19)	(0.10)	(0.21)
Textiles, wearing apparel and leather	24067	0.14	0.71	0.16	1.02
		0.15	*0.72*	*0.17*	*1.08*
		(0.11)	(0.10)	(0.07)	(0.19)
Wood, paper products and printing	6385	0.23	0.85	0.01	1.09
		0.21	*0.85*	*0.01*	*1.01*
		(0.17)	(0.11)	(0.16)	(0.21)
Coke, chemicals and pharmaceuticals	58389	0.27	0.69	0.12	1.09
		0.27	*0.69*	*0.12*	*1.08*
		(0.10)	(0.07)	(0.04)	(0.04)
Rubber and plastics	11839	0.23	0.67	0.03	0.94
		0.22	*0.70*	*0.09*	*1.07*
		(0.18)	(0.16)	(0.22)	(0.40)
Non-metallic minerals products	7898	0.28	0.60	0.14	1.02
		0.28	*0.60*	*0.14*	*1.03*
		(0.15)	(0.09)	(0.07)	(0.10)
Basic metal and fabricated metal	27293	0.16	0.76	0.07	1.00
		0.15	*0.76*	*0.06*	*0.98*
		(0.05)	(0.07)	(0.07)	(0.06)
Computers and electronics	10150	0.29	0.71	0.19	1.20
		0.27	*0.71*	*0.16*	*1.12*
		(0.13)	(0.14)	(0.11)	(0.24)
Electricals	11629	0.08	0.87	0.02	0.98
		0.09	*0.88*	*0.08*	*1.07*
		(0.08)	(0.08)	(0.50)	(0.48)
Machinery and equipment	16671	0.31	0.67	0.17	1.16
		0.29	*0.67*	*0.15*	*1.09*
		(0.13)	(0.09)	(0.11)	(0.20)
Motor vehicles and transport equipment	11720	0.29	0.65	0.30	1.25
		0.28	*0.66*	*0.30*	*1.27*
		(0.14)	(0.12)	(0.18)	(0.20)
All manufacturing	215662	0.23	0.69	0.12	1.05
		0.22	*0.70*	*0.12*	*1.06*
		(0.14)	(0.13)	(0.17)	(0.22)

Table shows output from physical production functions with respect to input quantities.
RTS denotes return to scale.
observations denotes the total number of observations used to identify parameters of the production functions.

Table 4: Markups across industries.

Sector	Observations	Mean	Median
Food, beverages and tobacco	25196	7.24	2.18
Textiles, wearing apparel and leather	19797	4.97	1.96
Wood, paper products and printing	5564	7.01	2.65
Coke, chemicals and pharmaceuticals	50950	6.86	2.14
Rubber and plastics	10071	5.84	1.78
Non-metallic minerals products	6546	9.24	3.67
Basic metal and fabricated metal	23365	6.71	2.40
Computers and electronics	8444	9.07	2.21
Electricals	10020	10.04	2.35
Machinery and equipment	14544	7.63	1.93
Motor vehicles and transport equipment	10467	5.95	1.76
All manufacturing	184964	7.01	2.14

4.2 Results on the impact of FDI

We now analyze how our outcome variables change with respect to increasing exposure to FDI. Table 5 reports our estimates at the firm-product level. In Panel A, we report results using specifications in first differences with firm-product and year fixed effects. The results indicate that a 10 percentage point increase in the market share of foreign investors is associated with a 3.2% $(10(\exp(-0.391)-1))$ in revenue growth of domestic firms. More than two thirds of this decline are due to a reduction in quantities, the remaining reduction is due to declining prices. Price changes can be further decomposed into changes in markups and marginal costs. The results show that markups decline significantly while there is no evidence for significant reductions in marginal costs. These results are consistent with a competition effect rather than technology spillovers from FDI.

In Panel B, we add sector-year fixed effects which control for overall trends across broadly defined industries, which does not change our conclusions qualitatively. Panel C focuses on a sub-sample of multi-product firms and includes firm-year fixed effects which control for firm-specific changes which affect all products of a firm.

Panel D shows results using three-year differences which yields qualitatively similar results. In these specifications, standard errors are clustered at the industry level. However, as Panels E and F show, our results are robust to two-way clustering at the level of firms and industries[19] and block bootstrapping based on draws of firms' time series. Bootstrapped standard errors also account for the fact that some outcome variables have been estimated in a previous step.

[19]Note that firms are not nested within industries since some firms produce products in multiple industries

Table 6 shows lead and lagged effects of FDI exposure. All the lead variables are either insignificant or small and go in the opposite direction of the contemporaneous effect. This results is consistent with a causal relationship between FDI exposure and domestic firms' performance. However, there might still be unobservables driving both variables. For this reason, we will use instrumental variables which exploit India's FDI reform in future version of this paper.

The results so far indicate crowding out of domestic production within product categories. However, they do not tell us much about spillovers to different products. Table 7 reports our estimates at the firm-level. For this purpose we compute FDI exposure at the firm-level by using initial sales shares of products within firms as weights. We use the same procedure to compute firm-level indices of prices, markups, marginal costs and quantities. While the results confirm reductions in sales and quantities, there is evidence for significant reductions in marginal costs. Consistent with marginal cost reductions, we also see an increase in physical TFP. These results indicate that although technology spillovers do not materialize in product categories in which domestic firms compete with foreign investors intensively, domestic firms seem to be able to improve production technologies in different products.

To analyze competition effects versus technology spillovers from FDI in more detail, we ran additional regressions in which we relate domestic firm-product level outcomes to both product and (3-digit) industry level FDI. The results are documented in Table 8. The results indicate that while reductions in prices and markups are concentrated in product categories with intense foreign competition, technology spillovers in the form of lower marginal costs can materialize through FDI in different product categories which belong to the same industry.

Table 5: Horizontal FDI and product level outcomes

	(1)	(2)	(3)	(4)	(5)
Panel(A) First-difference - year and firm-product FE					
	$\Delta ln(sales)$	$\Delta ln(quantity)$	$\Delta ln(price)$	$\Delta ln(markup)$	$\Delta ln(marginalcost)$
ΔFDI_k^{hor}	-0.391***	-0.279***	-0.112***	-0.095*	-0.017
	(0.046)	(0.047)	(0.030)	(0.053)	(0.055)
N	126959	126959	126959	126959	126959
Panel(B) First-difference - year, sector and firm-product FE					
ΔFDI_k^{hor}	-0.371***	-0.268***	-0.103***	-0.110**	0.007
	(0.046)	(0.048)	(0.030)	(0.053)	(0.056)
N	126959	126959	126959	126959	126959
Panel(C) First-difference - firm-product and firm-year FE					
ΔFDI_k^{hor}	-0.372***	-0.280***	-0.092**	-0.211***	0.120
	(0.062)	(0.064)	(0.042)	(0.075)	(0.075)
N	103165	103165	103165	103165	103165
Panel(D) 3 years difference, year and firm-product FE					
ΔFDI_k^{hor}	-0.227***	-0.070	-0.157***	-0.108	-0.049
	(0.083)	(0.088)	(0.055)	(0.097)	(0.102)
N	25568	25568	25568	25568	25568
Panel(E) Robustness check: first difference, cluster at firm and industry level					
ΔFDI_k^{hor}	-0.433***	-0.325***	-0.107***	-0.113*	0.005
	(0.064)	(0.049)	(0.037)	(0.058)	(0.063)
N	131623	131623	131623	131623	131623
Panel(F) Robustness check: first difference, bootstrap standard errors					
ΔFDI_k^{hor}	-0.433***	-0.325***	-0.107***	-0.113**	0.005
	(0.046)	(0.043)	(0.030)	(0.050)	(0.052)
N	131624	131624	131624	131624	131624

Notes. The table reports coefficients from OLS estimation with fixed effects. ΔFDI_k^{hor} denotes horizontal foreign direct investment at the product level. $\Delta ln(sales)$ is the logarithm of products' sales. $\Delta ln(quantity)$ is the logarithm of products' quantity. $\Delta ln(price)$ is the logarithm of products' price. $\Delta ln(markup)$ is the logarithm of products' markup. $\Delta ln(marginalcost)$ is the logarithm of products' marginal cost.
Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 6: Horizontal FDI anticipation effect

	(1) $\Delta ln(sales)$	(2) $\Delta ln(quantity)$	(3) $\Delta ln(price)$	(4) $\Delta ln(markup)$	(5) $\Delta ln(marginalcost)$
$\Delta FDI^{hor}_{k,t+1}$	0.047**	0.049*	-0.001	-0.005	0.004
	(0.024)	(0.025)	(0.016)	(0.029)	(0.031)
$\Delta FDI^{hor}_{k,t}$	-0.312***	-0.227***	-0.085***	-0.100*	0.015
	(0.045)	(0.047)	(0.031)	(0.055)	(0.058)
$\Delta FDI^{hor}_{k,t-1}$	0.003	-0.033	0.036**	-0.015	0.051
	(0.025)	(0.026)	(0.017)	(0.030)	(0.031)
N	88881	88881	88881	88881	88881
Year FE	Yes	Yes	Yes	Yes	Yes

Notes. The table reports coefficients from OLS estimation with fixed effects. ΔFDI^{hor}_{k} denotes horizontal foreign direct investment at the product level. $\Delta ln(sales)$ is the logarithm of products' sales. $\Delta ln(quantity)$ is the logarithm of products' quantity. $\Delta ln(price)$ is the logarithm of products' price. $\Delta ln(markup)$ is the logarithm of products' markup. $\Delta ln(marginalcost)$ is the logarithm of products' marginal cost.
Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 7: Horizontal FDI and firm-level outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta ln(QTFP)_i$	$\Delta ln(RTFP)_i^{acf}$	$\Delta ln(fsales)_i$	$\Delta ln(product)_i$	$\Delta ln(qsales)_i$	$\Delta ln(price)_i$	$\Delta ln(markup)_i$	$\Delta ln(marginalcost)_i$
$\Delta WFDI_k^{hor}$	0.208*	-0.025	-0.253***	0.071**	-0.210***	-0.043	0.143**	-0.186**
	(0.108)	(0.038)	(0.062)	(0.035)	(0.073)	(0.045)	(0.072)	(0.082)
N	33264	33264	33264	33264	33264	33264	33264	33264

Notes. The table reports coefficients from OLS estimation with year and firm fixed effects. $\Delta WFDI_k^{hor}$ denotes horizontal foreign direct investment at the product level weighted using initial sales shares of products within firms. $\Delta ln(QTFP)_i$ denotes the logarithm of physical total factor productivity at the firm-level. $\Delta ln(RTFP)_i^{acf}$ denotes the logarithm of revenue-based total factor productivity at the firm-level measured using Ackerberg et al. (2015) methodology. $\Delta ln(fsales)_i$ is the logarithm of firm-level sales. $\Delta ln(product)_i$ is the logarithm of firm-level total number of products. $\Delta ln(qsales)_i$ is the logarithm of firm-level product' sales weighted using initial sales shares of products within firms. $\Delta ln(price)_i$ is the logarithm of firm-level product' price weighted using initial sales shares of products within firms. $\Delta ln(markup)_i$ is the logarithm of firm-level product' markup weighted using initial sales shares of products within firms. $\Delta ln(marginalcost)_i$ is the logarithm of firm-level product' marginal cost weighted using initial sales shares of products within firms.
Standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Competition vs. technology spillovers

	(1)	(2)	(3)	(4)	(5)
	$\Delta ln(sales)$	$\Delta ln(quantity)$	$\Delta ln(price)$	$\Delta ln(markup)$	$\Delta ln(marginalcost)$
ΔFDI_j^{hor}	-0.154**	0.019	-0.173***	0.071	-0.244***
	(0.069)	(0.071)	(0.045)	(0.079)	(0.083)
ΔFDI_k^{hor}	-0.374***	-0.281***	-0.093***	-0.103*	0.011
	(0.046)	(0.048)	(0.030)	(0.053)	(0.056)
N	126959	126959	126959	126959	126959

Notes. The table reports coefficients from OLS estimation with year and firm-product fixed effects. ΔFDI_j^{hor} denotes horizontal foreign direct investment at the 3-digit industry level. ΔFDI_k^{hor} denotes horizontal foreign direct investment at the product level. $\Delta ln(sales)$ is the logarithm of products' sales. $\Delta ln(quantity)$ is the logarithm of products' quantity. $\Delta ln(price)$ is the logarithm of products' price. $\Delta ln(markup)$ is the logarithm of products' markup. $\Delta ln(marginalcost)$ is the logarithm of products' marginal cost.
Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

5 Conclusion

This paper analyzes the effects of FDI on various firm- and product-level outcomes of domestic firms in India. Exploiting a rich firm-product level data set which includes prices and quantities, we apply recent advances in the estimation of production functions to estimate markups, marginal costs, and physical productivity. Our preliminary results indicate that exposure to FDI in the same product category is associated with declining markups and prices but little changes in marginal costs. However, we find evidence for substantial spillovers across products within industries in the form of lower marginal costs and higher physical TFP. Since these productivity improvements are partly passed on to consumers in the form of lower prices, measures of revenue TFP that have been commonly used in the FDI literature might be biased downwards. This can potentially explain the lack of evidence for technology spillovers from horizontal FDI in the previous literature.

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6 Appendix

Since for single product firms, we do not face the problem of unobserved input allocation across products and can drop the product-specific subscript, the production function becomes:

$$q_{ijt} = f(\tilde{\boldsymbol{v}}_{ijt};\boldsymbol{\beta}) + B(w_{ijt}, \rho_{ijt}, \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta}) + \omega_{it} + \epsilon_{ijt} \tag{10}$$

One can combine $f(.)$ and $B(.)$ into a function $\theta(\tilde{\boldsymbol{v}}_{ijt}, \boldsymbol{c}_{it})$ such that output can be expressed as a function of observable variables and measurement errors: $q_{it} = \theta(\tilde{\boldsymbol{v}}_{it}, \boldsymbol{c}_{it}) + \epsilon_{it}$.

$\theta(.)$ is approximated by a linear combination of all its elements and a polynomial in all continuous variables. While this expression does not identify any parameters of the production and input price functions, it identifies output net of measurement error ϵ_{it} which is denoted by $\hat{\phi}_{it}$. Productivity can then be expressed as:

$$\omega_{it} = \hat{\phi}_{it} - f(\tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta}) - B(\boldsymbol{c}_{it}, \boldsymbol{c}_{it} \times \tilde{\boldsymbol{v}}_{it}, \boldsymbol{\beta}, \boldsymbol{\delta}) \tag{11}$$

where $\boldsymbol{\delta}$ are the parameters of the input price function to be estimated. LGKP suggests that the function $B(.)$ can additionally be allowed to depend on interactions between input prices and input expenditures. We also followed this alternative modelling procedure, which led to similar estimated production function coefficients. However, it led to collinearity problems in some industries, and we settled on the more parsimonious specification. For identification of parameters, the law of motion for productivity can be used to construct moment conditions:

$$E[\varsigma_{it}(\boldsymbol{\beta}, \boldsymbol{\delta})\boldsymbol{Z}_{it}] = 0 \tag{12}$$

$\boldsymbol{Z}_{it}$ is a vector which includes current values of capital, lagged values of materials and labour and their higher order and interaction terms as they appear in the production function. It further includes lagged values of market shares and prices as well as interactions of lagged prices with lags of production factors and market share. Our initial estimation are undertaken using the GMM procedure suggested by Wooldridge (2009) which is based on moment conditions on the combined error term $\zeta it + \epsilon_{it}$.

As an example, for the Cobb Douglas case, our modified production function is:

$$q_{it} = \beta_l \tilde{l}_{it} + \beta_m \tilde{m}_{it} + \beta_k \tilde{k}_{it} - \Gamma w(p_{it}, ms_{it}) + \omega_{it} + \epsilon_{it} \tag{13}$$

where $\Gamma = \beta_l + \beta_m + \beta_k$. Productivity is captured by a control function based on inverted factor demand which depends on state variables such as capital and prices. We therefore estimate:

$$q_{it} = \beta_l \tilde{l}_{it} + \beta_m \tilde{m}_{it} + \beta_k \tilde{k}_{it} - \Gamma w(p_{it}, ms_{it}) + \omega_{i,t-1}(k_{i,t-1}, p_{i,t-1}, \hat{pr}_{i,t-1}) + \zeta_{it} + \epsilon_{it} \tag{14}$$

We then use instruments $l_{i,t-1}$, $m_{i,t-1}$, k_{it}, $\hat{pr}_{i,t-1}$, ms_{it} and lagged values of prices and their interaction with lagged values of inputs.

This estimation procedure yields estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$, hence, it identifies all parameters from the production and input price functions. We estimate $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ separately for each industry to allow for industry-specific production technologies and input prices. Under the assumption that $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ are the same for multi- and single-product firms within industries, input allocations across products within multi-product firms can be recovered which allows estimation of markups and marginal costs for each firm-product-year. Note that as discussed by LGKP, this assumption does not rule out differences in productivity levels between single- and multi-product. Since productivity is modelled to be factor-neutral, differences in TFP do not imply differences in $\boldsymbol{\beta}$ or output elasticities. The approach also allows for TFP to depend on the number of products which can imply (dis)economies of scope. Under the assumption of a common production technology within industries, one can express predicted output as: $\hat{q}_{ijt} = f(\tilde{\boldsymbol{v}}_{ijt}, \boldsymbol{\beta}, \hat{w}_{ijt}, \rho_{ijt}) + \omega_{it}$ and divide the production function into two parts, f_1 and f_2, such that only f_2 depends on input allocations across products. This yields a system of equation for each firm-year which allows identifying productivity ω_{it} for each firm-year and the input share allocation ρ_{ijt} for each firm-product-year:

$$\begin{aligned} \hat{q}_{ijt} - f_1(\tilde{\boldsymbol{v}}_{ijt}, \boldsymbol{\beta}, \hat{w}_{ijt}) &= f_2(\tilde{\boldsymbol{v}}_{ijt}, \hat{w}_{ijt}, \rho_{ijt}) + \omega_{it} \\ \sum_j \exp(\rho_{ijt}) &= 1 \end{aligned} \tag{15}$$

For multi-product firms, we predict $\hat{q}_{ijt}$ from a first stage regression and use parameters $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ from the sample of single product firms to construct f_1 and f_2. The equation system (15) is then solved numerically for each firm-year.

For the Cobb-Douglas case, we solve the equation system:

$$\begin{aligned} \hat{q}_{ijt} - \beta_l \tilde{l}_{it} - \beta_m \tilde{m}_{it} - \beta_k \tilde{k}_{it} &= \omega_{it} + \hat{w}_{ijt} \rho_{ijt} (\beta_m + \beta_l + \beta_k) \\ \sum_j \exp(\rho_{ijt}) &= 1 \end{aligned}$$