Technological Catch-Up and Productivity Spillovers From FDI: Evidence From Indian Manufacturing

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Abstract: This paper estimates productivity spillovers to domestic firms from inward FDI using firm-level panel data on Indian manufacturing firms from 2001-2016. I account for firms' relative position in the productivity distribution within their industry, and examine if FDI facilitates catch-up to the industry's productivity frontier. I find robust evidence for productivity spillovers in technology intensive sectors, that appear uniform across the productivity distribution. In contrast, spillovers in less technology intensive sectors are concentrated at the top of the productivity distribution. I corroborate these findings by providing evidence that FDI is associated with increased productivity dispersion in less technology intensive sectors. I argue that these findings suggest the presence of distributional effects from inward FDI that are not accounted for in policies promoting foreign investment in developing countries.

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1 Introduction

Policies designed to attract foreign direct investment (FDI) in developing countries have become common. Many governments now provide costly incentives tailored to foreign investment and multinational enterprises (MNEs) in the form of tax holidays and subsidized industrial infrastructure (Haskel et al., 2007; Blalock and Gertler, 2008). Beyond the short-term benefits of attracting capital investments, much of this policy action is based on the belief that foreign investment facilitates technology transfer, and disseminates best practices to domestic firms. Theoretical work has emphasized that these positive externalities or spillovers may result from direct observation or imitation of advanced production techniques, as well as labor turnover from workers that have acquired sophisticated production knowledge. In principle, these spillovers can spur economic development through increased domestic productivity, and justify the cost of favorable policies towards foreign investors. According to the World Bank (1993), "Many developing countries will need to be more effective in attracting FDI flows if they are to close the technology gap with high-income countries, upgrade managerial skills, and develop their export markets."

Despite this enthusiasm, evidence from a large body of literature that has empirically examined the existence and magnitude of these productivity spillovers in developing countries is not encouraging. While there is some evidence of positive interindustry vertical spillovers from MNEs to domestic firms connected through supply chain linkages, intraindustry horizontal spillovers have been found to be nonexistent, or even negative. That is, the increasing presence of competing foreign firms in developing countries has not been shown to raise the productivity of domestic firms. In a meta-analysis of 32 empirical studies, Wooster and Diebel (2010) argue that "evidence of intrasectoral spillovers from FDI in developing countries is weak, at best." In his overview of the literature, Keller (2010) states that "some observers have concluded that ... there are no horizontal technology spillovers from FDI in less developed countries."

The most prominent hypothesis put forward to explain the apparent lack of horizontal spillovers in developing countries centers on the technological disparity between foreign and domestic firms. Several authors have argued that the technological gap between MNEs and domestic firms may be too wide for most domestic firms to effectively incorporate their production techniques (Haskel et al., 2007; Blalock and Gertler, 2008). While positive spillovers may exist for a subset of technologically advanced firms, most domestic firms lack sufficient absorptive capacity to benefit from new technology, and become disadvantaged with the introduction of more productive foreign firms. In addition, this hypothesis has gained indirect empirical support from findings of positive horizontal spillovers from FDI in rich, developed economies. In both the U.S. and U.K., where the average technology gap between domestic and foreign firms is much less significant, empirical studies have found robust evidence of positive spillovers (Haskel et al., 2007; Keller and Yeaple, 2009).

Although this argument is prevalent in the literature, there is little direct evidence supporting its relevance in developing countries. Indeed, the underlying logic runs counter to recent empirical work examining firm-level productivity convergence, or catch-up, to a technological frontier. Numerous studies have provided evidence that low productivity firms relative to the most productive firms in the same industry, referred to as the frontier, are associated with increased rates of productivity growth (Griffith et al., 2009; Wang et al., 2014). That is, the same technological gap that is purported to inhibit productivity spillovers from FDI, has been found to spur productivity growth more generally. Given that, as Griffith et al. (2009) notes, "any high productivity establishment within the industry, whether its foreign or domestically owned, provides a potential source of productivity catch-up," the foundation for this distinction is unclear.

In this paper, I use firm-level panel data in India's manufacturing sector to bring fresh evidence to bear on this issue. I adopt an empirical specification used in the macroeconomics literature on productivity convergence to analyze how the presence of foreign firms within an industry impacts the productivity growth of domestic firms. I consider the standard measure of foreign presence based on output share within an industry, as well foreign presence based on geographic proximity. In addition, I stratify the sample based on the classification of technology intensive manufacturing sectors used in Keller and Yeaple (2009), to analyze if productivity spillovers are more prominent in sectors where technology creation, acquisition, and utilization are more integral to the production process.

I account for firms' relative position to the productivity frontier within their industry, and examine how this influences both average productivity growth, and productivity spillovers from FDI. In this way, I analyze both the general catch-up tendency of firms in the sample, as well as how the presence of foreign firms impacts this relationship. The baseline econometric model is consistent with persistent productivity dispersion within industries over time, even after accounting for technological catch-up. However, to the extent that the catch-up process is influenced by foreign presence, which varies over industries and time, the distribution of within industry productivity will also be affected. In a separate empirical specification, I examine how productivity dispersion is influenced by foreign presence.

Consistent with the consensus in the literature, I find mixed evidence for productivity spillovers associated with FDI when considering the entire sample of domestic firms. I find a negligible, or even negative, association between contemporaneous measures of foreign presence and productivity growth in domestic firms. Evidence for positive productivity spillovers does appear when considering lagged values of foreign presence, suggesting a delay between FDI and the incorporation of production techniques by domestic firms. However, the estimated spillovers differ sharply in the subsamples of high-tech and low-tech industries. Estimated spillovers are uniformly larger in magnitude, and exhibit a higher degree of statistical significance, in technology intensive industries. Moreover, these spillovers are not tied to geographical proximity between foreign and domestic firms. In contrast, productivity spillovers in low-tech industries appear geographically dependent. I find that foreign presence is positively associated with domestic firm's productivity growth in low-tech sectors only when the firms operate in the same geographical region.

I find strong empirical support for the overall catch-up tendency of domestic firms to the productivity frontier within their industry. Regardless of industry, firms further away from the frontier exhibit faster rates of average productivity growth. However, the impact of distance to the productivity frontier on productivity spillovers from FDI varies substantially across the low and high-tech subsamples. I find no evidence that relative position in the intraindustry productivity distribution impacts the FDI spillovers that accrue to firms in high-tech industries. This contrasts with the subsample of low-tech industries, where firms' distance to frontier is negatively associated with productivity spillovers from FDI. That is, firms at the top of the productivity distribution experience greater spillovers than firms at the bottom in low-tech industries. These findings are corroborated by the direct estimations of FDI's affect on productivity dispersion within industries. While FDI is not associated with productivity dispersion in high-tech industries, I find that it substantially increases short-run dispersion in low-tech industries.

These findings suggest that policy makers should account for heterogeneity in productivity spillovers when instituting incentives for inward FDI. While broad investment subsidies may be economically justifiable in high-tech industries, where spillovers are substantial and relatively uniform across firms, they may carry unintentional distributional effects in low-tech industries. To the extent that productivity spillovers in low-tech industries are concentrated both geographically and towards the top of the productivity distribution, more targeted investment subsidies are warranted.

The remainder of this paper is organized as follows. Section 2 presents the empirical model used to analyze technological catch-up and productivity spillovers from inward FDI. Section 3 provides an overview of foreign investment policies and FDI inflows in India, discusses the data set, presents descriptive statistics, and discusses potential issues in the estimation procedure. Empirical findings are presented in Section 4. Section 5 concludes.

2 Empirical Specification

I begin with a preliminary specification adapted from the macroeconomic literature on covergence to incorporate the presence of foreign firms within an industry.

$$\text{ln}A_{ijt} = \text{ln}A_{ijt-1} + \beta \ \text{Horizontal}_{jt-1} + \alpha \ X_{ijt} + \delta \ Z_{jt} + \phi_i + u_t + \epsilon_{ijt} \tag{2.1}$$

where i, j, and t denote firm, industry, and year. The log total factor productivity (TFP) of firm i in industry j at time t (lnA_{ijt}) is modeled as a function of its log TFP in the prior period to capture persistence, the degree of within industry foreign presence in the prior period (Horizontal), a vector of firm level controls (X), and a vector of industry level controls (Z). In addition, individual firm and year fixed effects are included to control for underlying firm characteristics, and common elements over time that influence productivity growth such as macroeconomic shocks. Horizontal is defined following the standard in the literature as

$$\text{Horizontal}_{jt} = \frac{\sum_{i \in j} \text{Foreignshare}_{it} \cdot Y_{it}}{\sum_{i \in j} Y_{it}} \tag{2.2}$$

where Foreignshare represents the fraction of ownership in firm i held by foreign investors, and Y is firm output. In the numerator, I include the output of all firms at or above 10% foreign ownership, which is the standard threshold for FDI classification. Thus, Horizontal approximates the share of total output in an industry attributable to foreign invested firms, and varies with both changes to firm equity ownership and output of foreign invested firms.

Rearrange equation (2.1) to obtain the baseline growth equation,

$$\Delta \ln A_{ijt} = \beta \text{ Horizontal}_{jt-1} + \alpha \ X_{ijt} + \delta \ Z_{jt} + \phi_i + u_t + \epsilon_{ijt} \tag{2.3}$$

As firm level controls, I include each firm's age (Age_{ijt}), market share in industry j at time t (Mktshare_{ijt}), and a dummy variable indicating if the firm reports exports in period t (Exporter_{ijt}). For industry wide controls, I following Javorcik (2004) & Eck and Huber (2016) among others and use the Herfindahl-Hirschman index to measure industry concentration. In addition, I proxy total industry size by calculating the total log value added of all firms within that industry in each year. I include both of these measures in first difference form (ΔHHI_{jt} & $\Delta\text{IndSize}_{jt}$) to capture how changes to the overall size and concentration of each industry influence productivity growth in that industry.

The inclusion of Mktshare, ΔHHI, and ΔIndSize explicitly control for the competition effects of foreign entry described in Aitken and Harrison (1999). The introduction of relatively productive foreign firms into a market is expected to cause a reduction in the market share of domestic firms. To the extent that firms' factors of production cannot adjust immediately, the reduction in market share will initially increase the average production cost, and appear as a reduction in firm productivity. Although this effect may have important economic implications, I argue they represent temporary factor adjustment rather than meaningful changes to domestic firms' productivity. By controlling for this effect, I am able to interpret the estimated spillovers as substantive changes to efficiency of the production process.

In the estimation of the baseline growth equation, $\hat{\beta}$ estimates the relationship between foreign presence within an industry and the productivity growth of firms in that industry. To measure the intraindustry spillover effect, I exclude foreign owned firms from the sample, and estimate (2.1) for the remaining domestic firms. In addition, I follow the classification of technology intensive sectors used in Keller and Yeaple (2009), and examine the presence of spillovers in these high-tech sectors and the remaining low-tech sectors separately. Of the 21 total manufacturing industries, six are considered technology intensive and include chemicals, computer and office equipment, electrical components, and medical products.[1]

In addition to examining the level of foreign presence, I include foreign industry presence in lagged first difference form ($\Delta\text{Horizontal}_{jt-1}$) to analyze how new foreign investment or disinvest-

[1]Keller and Yeaple (2009) use average R&D intensity of firms to classify industries at the three digit BEA code level. I translate their classification into coarser two digit ISIC codes, and include one extra industry, motor vehicles, which exhibits the highest R&D intensity among industries in the sample. See Table 2 for a list of high-tech sectors, and associated summary statistics.

ment affects the productivity growth of domestic firms. I use lagged measures of foreign presence to allow for a delay from the entry of foreign firms, and the incorporation of production techniques by domestic firms. The focus on a one year lag is consistent with the findings in Mansfield and Romeo (1980), in which 42% of U.S. based multinationals reported their technology in foreign competitors in under 1.5 years. In all specifications, heteroskedasticity robust standard errors are clustered for each industry, year to allow for correlation in the error term among firms within the same industry.[2]

2.1 Geographical Concentration

Next, I examine if geographic proximity to foreign firms impacts spillovers to domestic firms within the same industry. Each firm in the data set lists the geographical region within India where the firm is officially registered. There are a total of 35 regions in the data set, including Indian states and union territories. I augment the definition of Horizontal in (2.2) to reflect the output share of foreign firms in each industry, j, and region, k, combination.

$$\text{StateHorizontal}_{jkt} = \frac{\sum_{i \in j, i \in k} \text{Foreignshare}_{it} \cdot Y_{it}}{\sum_{i \in j, i \in k} Y_{it}} \tag{2.4}$$

Notice that the calculation of StateHorizontal uses output only within a particular industry, region pair. That is, StateHorizontal captures a relative measure of foreign presence within an industry, region, rather than an absolute measure of foreign production.

To examine the impact of proximity, I estimate the following regression specification.

$$\Delta lnA_{ijt} = \beta_1 \text{ Horizontal}_{jt-1} + \beta_2 \text{ StateHorizontal}_{jkt-1} + \alpha\ X_{ijt} + \delta\ Z_{jt} + \phi_i + u_t + \epsilon_{ijt} \tag{2.5}$$

Equation (2.5) allows for the separate estimation of intraindustry horizontal spillovers for foreign presence within the same region, or in a different region as the domestic firm. That is, $\hat{\beta}_1$ estimates the impact on productivity growth of domestic firms of a change in overall foreign presence within an industry, holding constant the foreign presence within the domestic firm's region. In contrast, $\hat{\beta}_2$ provides an estimate of intraindustry spillovers are effected by additional foreign presence within a state, holding constant the total foreign share of output within the industry.

2.2 Distance to the Productivity Frontier

To examine if firms closer to the technological frontier are better able to absorb productivity spillovers, I construct a measure of the distance, or gap, of each firm's productivity to the most productive firms in the same industry. As noted in Griffith et al. (2009), defining the technological frontier based on the single highest TFP firm within an industry, year can be problematic if there

[2]Ideally, standard errors should be clustered at the industry level to also allow for error term correlation within establishments across time. However, the 21 industries in the sample are well below the recommended number of clusters of about 50 (Bertrand et al., 2004).

is measurement error among sample firms. To alleviate these measurement error concerns, I define this frontier productivity, denoted A_{Fjt}, as the average TFP of firms in the top decile of productivity in each industry, year pair. Each firm's distance to technological frontier is defined as

$$\text{TFPGAP}_{ijt} = ln\Big(\frac{A_{Fjt}}{A_{ijt}}\Big) \tag{2.6}$$

where a higher value of TFPGAP indicates lower productivity of firm i relative to productivity frontier in the same industry, year.

After constructing TFPGAP_{ijt} for all sample firms, I estimate the following modified version of (2.3)

$$\Delta lnA_{ijt} = \beta_1 \text{ TFPGAP}_{ijt-1} + \beta_2 \text{ Horizontal}_{jt-1} + \beta_3 \text{ TFPGAP}\cdot\text{Horizontal}_{ijt-1} + \alpha\ X_{ijt} + \delta\ Z_{jt} + \phi_i + u_t + \epsilon_{ijt} \tag{2.7}$$

In the estimation of (2.7), the coefficient of the one year lag of the TFPGAP term, $\hat{\beta}_1$, captures the overall convergence to frontier tendency of the sample. A positive $\hat{\beta}_1$ indicates firms further away for the industry's frontier exhibit faster productivity growth, implying technological catch-up on average. The estimated coefficients of the one year lag of the Horizontal and interaction of TFPGAP and Horizontal, $\hat{\beta}_2$ and $\hat{\beta}_3$, together capture intraindustry productivity spillovers as a function of distance to the productivity frontier. $\hat{\beta}_2$ provides an estimate of spillovers for frontier firms, while $\hat{\beta}_3$ estimates how the spillover effect varies with distance to the productivity frontier. A positive (negative) $\hat{\beta}_3$ indicates that firms further from (closer to) the productivity frontier within their industry appropriate larger productivity spillovers from foreign firms.

As discussed in Griffith et al. (2009), the notion of technological catch-up of non-frontier firms is consistent with long run productivity dispersion within an industry. If expected productivity growth at the frontier equals expected growth of non-frontier establishments including catch-up, then firms settle at a steady state distance from the frontier. However, if the presence of foreign firms meaningfully alters the productivity catch-up of domestic firms, then the dispersion of productivity within an industry will be affected as well. In order to test how foreign presence affects the dispersion of productivity of firms within an industry, I examine the following regression specification,

$$\text{TFPvar}_{jt} = \beta_1 \text{ TFPmean}_{jt} + \beta_2 \text{ Horizontal}_{jt-1} + \delta\ Z_{jt} + \phi_i + u_t + \epsilon_{ijt} \tag{2.8}$$

where TFPvar_{jt} and TFPmean_{jt} denote the variance and mean of log TFP among domestic firms in industry j respectively. In addition, I estimate (2.8) in first differences to examine the association between changes in foreign presence and changes to productivity dispersion within an industry.

2.3 Total Factor Productivity Estimation

I follow Griffith et al. (2009) & Eck and Huber (2016) and adopt the superlative index (SI) number approach as my primary TFP estimation methodology. The SI approach avoids the restrictive assumptions on the form of the production function used in deriving TFP through production function estimation methodologies.[3] Instead, the SI approach assumes perfect competition and constant returns to scale in production in order to allow for a more flexible translog production technology. In addition, the SI approach accommodates productivity catch-up across firms, which is a critical component to the theoretical underpinnings of the empirical literature on productivity convergence. As a robustness check on the main results using the SI methodology, I include results using the Levinsohn and Petrin (2003) algorithm. See appendix A for a description of the Levinsohn and Petrin (2003) algorithm, and associated results.

The SI approach estimates the growth rate of TFP as,

$$\Delta \ln \hat{A}_{ijt} = \Delta \ln Y_{ijt} - \sum_{z=1}^{Z} \tilde{\alpha}_{ijt}^{z} \Delta \ln x_{ijt}^{z} \tag{2.9}$$

where the x_{ijt}'s represent factors of production, Z is the number of factors considered, and Y_{ijt} is firm output. I include the value of fixed assets stock, wages, and intermediate input expenditures as factors of production in Z. The coefficients on changes in log factor use are defined as $\tilde{\alpha}_{ijt}^{z} = (\alpha_{ijt}^{z} + \alpha_{ijt-1}^{z})$, where α_{ijt}^{z} denotes the share of factor z in output. Factor shares may vary over time, but the assumption of constant returns to scale ensures that $\sum_z \tilde{\alpha}_{ijt}^{z} = 1$. Thus, similar in spirit to production function estimation methodologies, the SI approach defines productivity growth as changes to firm output that are unexplained by the firms changes to factors of production.

Following Griffith et al. (2009), I estimate each firm's distance to the productivity frontier in the following two steps. First, each firm's TFP is estimated relative to the geometric mean of all other firms within the same industry.

$$\ln \tilde{A}_{ijt} = ln(Y_{ijt}/\bar{Y}_j) - \sum_{z=1}^{Z} \sigma_i^z ln(x_{ijt}^z/\bar{x}_j^z) \tag{2.10}$$

where $\bar{Y}_j$ and $\bar{x}_j^z$ denote the geometric mean of output and factors of production usage in industry j. The coefficient $\sigma_i^z = (\alpha_i^z + \bar{\alpha}_j^z)/2$, where α_i^z is the share of factor z in output, and $\bar{\alpha}_i^z$ is the geometric mean factor share. Constant returns to scale implies again implies that $\sum_z \sigma_i^z = 1$.

Next, each firm's distance to the productivity frontier is defined as

$$\text{TFPgap}_{ijt} = \ln \tilde{A}_{jt}^{F} - \ln \tilde{A}_{ijt} \tag{2.11}$$

where $\ln \tilde{A}_{jt}^{F}$ denotes the estimated frontier productivity level in industry j at time t. As noted in section 2.2, $\ln \tilde{A}_{jt}^{F}$ is defined as the average log TFP level of firms in the top decile of estimated $\ln \tilde{A}$ within an industry in a given year.

[3] The Olley and Pakes (1996) & Levinsohn and Petrin (2003) both assume Cobb-Douglas production technology.

3 Research Setting

In many ways, India exemplifies the pattern seen in developing countries of increasing openness to foreign capital, and corresponding increases in FDI inflows.[4] Beginning in 1991, India has passed a series of reforms liberalizing foreign capital flows. India has opened all sectors except retail trading, atomic energy, gambling, and agriculture to foreign capital (Satyanand and Raghavendran, 2010). In most cases, foreign investments do not need government approval or face equity cap restrictions. Since the 1990s, India has signed bilateral investment promotion and protection agreements with over 80 countries. Moreover, India provides additional incentives to foreign investors in the form of tax holidays and additional depreciation on new investments. Forgone revenue from the depreciation policy alone was estimated to be five billion USD in 2011-2012 (Eck and Huber, 2016).

Since these reforms, India has seen explosive growth in FDI inflows. Prior to reform in 1990, annual FDI inflow totaled just 0.25 billion. Today, India receives over 44 billion annually. India now ranks as the ninth largest recipient of FDI flows in the world, and is consistently ranked in the top five of desirable investment locations (UNCTAD, 2015). In addition, the average investment size quadrupled from 2000-2009, and an estimated 80% of all FDI in India over this period has been greenfield investments (Satyanand and Raghavendran, 2010). Large contributors to India's FDI inflow include Singapore, the United States, the United Kingdom, Japan, and Germany.

Prior to additional reforms in 2005, FDI inflows were concentrated in the manufacturing sector with chemical, pharmaceutical, and transportation industries receiving the largest share of foreign investment. Like many developing countries, India has experienced a surge in FDI in services over the past decade, now accounting for over 50% of FDI inflow. Despite its declining share, the value of manufacturing FDI in India has continued to increase, and employment in the manufacturing sector by foreign affiliates was estimated at 1.6 million in 2009 (National Council of Applied Economic Research, 2009). Unlike FDI in services, which is concentrated in large urban areas, the majority of manufacturing FDI occurs in small cities, and semi-urban areas (Satyanand and Raghavendran, 2010).

3.1 Data and Descriptive Statistics

This paper employs micro-level panel data from Indian manufacturing firms made available through the Centre for Monitoring the Indian Economy (CMIE) Prowess database. The database has been used in academic research such as Franco and Sasidharan (2010) and Eck and Huber (2016). According to CMIE, firms in the data set account for approximately 80% of manufacturing output in India. Through annual financial statements, firms in the database disclose the market value of gross output, fixed assets, employee compensation, exports, and material input expenditures. Detailed product information, industry classification according to two digit ISIC codes, and

[4]FDI into developing countries have grown sharply over the past several decades and now account for over 50% of global FDI inflow (UNCTAD, 2015)

geographical Indian state of registration are provided. The resulting data set is an unbalanced panel of 9,561 distinct Indian manufacturing firms over the 16 year period 2001-2016. There are a total of 75,160 firm - industry- year observations for which total factor productivity can be calculated, with an average number of firms of 4,698 per year.

In addition, all firms are classified as government, privately Indian, or privately foreign owned. More detailed foreign ownership share information including the percent of equity held by foreign investors is available for a subset of firms in the database, accounting for 35.5% of all observations. Following Eck and Huber (2016), I supplement firms ownership share information with ownership classification in the following way. Firms lacking ownership share data are considered to be 0% foreign owned if classified as government or privately Indian owned, and 100% foreign ownership if classified as privately foreign owned. I use the standard threshold of 10% foreign equity ownership to classify as a firms that has received foreign direct investment. These foreign invested firms comprise 8.30% of sample firms, but account for 17.77% of total sales.[5]

Table 1 displays descriptive statistics for the sample of domestic and foreign invested firms.[6] The last variable, Frontier, is a dummy variable taking a value of one when the firm is included in the top decile of TFP for each industry, year. Thus, the mean of Frontier indicates the percentage of firms that are included in the calculation of an industries technological frontier. As expected, foreign invested firms are, on average, larger, more productive, and more likely to export than domestic firms. Foreign invested firms average three times the market share, and are almost twice as likely to export as domestic firms. The values of log TFP indicate that foreign firms have 11.14% higher TFP than domestic firms on average. Indeed, foreign invested firms are 55.32% more likely than domestic firms to be included in the productivity frontier of their respective industries.

Table 1: Descriptive Statistics

	Domestic		Foreign	
	Mean/total	Std. Deviation	Mean/total	Std. Deviation
Obs	68,923	–	6,237	–
Mktshare	0.383	0.183	1.150	0.405
Exporter	0.488	0.500	0.813	0.390
Age	24.88	18.59	29.65	20.78
$\ln\hat{A}$	-0.189	0.668	-0.084	0.635
Frontier	0.094	0.291	0.146	0.354

Firms are divided into 21 distinct manufacturing industries based on the 2008 version (revision 4) of ISIC codes, and 35 geographical Indian regions.[7] Table 2 displays summary statistics for the 21 industries in the sample, averaged across the 16 year time period. Foreign presence varies considerably across industries from 3.15% of firms and 3.36% of output share in textiles (ISIC code

[5]Majority owned foreign firms comprise 5.98% of sample firms and account for 13.30% of total sales.

[6]The first three variables correspond to the establishment level control variables included in the main regressions discussed in section 2.

[7]Indian regions include official states and union territories.

13) to 32.02% of firms and 58.71% of output share in motor vehicles, trailers, and semi-trailers (ISIC code 29). Overall, foreign presence is concentrated in the technology intensive, or high-tech, industries. In high-tech industries, foreign firms comprise 12.43% of the sample and 22.34% output share, compared to 6.20% and 12.37% respectively in low-tech industries. In addition, the high-tech sectors have attracted a disproportionate amount of new investment over the 16 year period. Firms in high-tech sectors comprise 32.26% of the sample but account for 44.43% of positive FDI changes.

The median annual growth rate of TFP from 2001-2016 for firms in the sample was 0.32%. There is substantial variation in estimated growth rates, with a standard deviation of 0.634 of median growth across industries, and 0.332 across all sample firms. Many firms exhibit negative TFP growth over this period. This may be influenced by the inclusion of great recession in the sample period. Although India's financial sector was relatively insulated from the global crisis, India experienced a significant decline in manufacturing tailored to export markets. I include yearly time dummies in all regression specifications to control for this and other macroeconomic shocks during this period.

Table 2: Industry Summary Statistics

Industry (ISIC Code)	Firms	Foreign Firm (%)	No. of Positive FDI Changes	Horizontal (%)	Median TFP Growth (%)	Log TFP Variance
Food (10)	816	4.22	28	13.31	0.31	0.427
Beverages (11)	411	5.21	17	12.64	0.54	1.089
Tobacco prod. (12)	278	8.96	9	71.68	0.99	0.695
Textiles (13)	1028	3.15	44	3.36	-0.23	0.439
Wearing apparel (14)	295	5.93	21	5.66	0.42	0.424
Leather prod. (15)	81	8.29	2	22.44	0.48	0.499
Wood/cork prod.(16)	92	7.69	3	15.99	0.61	0.576
Paper/paper prod. (17)	326	4.81	22	6.63	0.24	0.324
Printing (18)	51	3.89	0	1.51	2.10	0.369
Coke/refined petrol. (19)	82	13.40	5	3.39	1.17	0.390
Chemical prod.(20)*	1089	10.26	110	19.93	0.45	0.429
Pharmaceuticals (21)*	594	10.02	56	18.13	0.36	0.478
Rubber/plastics (22)	590	8.07	57	8.07	0.65	0.344
Minerals (23)	383	10.39	37	14.88	1.88	0.458
Basic metals (24)	1144	4.56	59	9.21	0.12	0.354
Fab. metal prod. (25)	331	3.27	10	3.41	0.43	0.292
Computer/electron. (26)*	354	12.30	28	7.85	-0.55	0.694
Electrical Equip. (27)*	449	12.89	40	32.37	0.21	0.495
Machinery(28)*	553	16.69	39	27.83	0.47	0.330
Motor vehicles (29)*	70	32.02	5	58.71	-0.33	0.258
Transport equip.(30)	544	13.16	35	17.18	-0.02	0.275
Low-tech total/mean	6452	6.20	349	12.37	0.33	0.433
High-tech total/mean	3109	12.43	278	22.34	0.29	0.456
Total/mean	9561	8.30	627	15.73	0.32	0.440

* Denotes classification as high-tech sector. Observations are averaged over the 16 year period 2001-2016. Positive FDI changes are defined as an increase of a least 1% foreign equity ownership.

3.2 Estimation Issues

The endogeneity of the measure of foreign presence within an industry, denoted Horizontal in this paper, is a common concern in the empirical literature on spillovers from FDI. If foreign investment is driven by factors external to domestic productivity growth, such as foreign investment policies or the economic environment in the origin country, then spillover estimates will generally be unbiased. However, if foreign firms select into an industry based on their productivity growth, changes in foreign investment may be correlated with unobservable productivity shocks to domestic firms included in the error term. As Haskel et al. (2007) note, the direction of the resulting bias is not conceptually obvious. Foreign investment may select into high growth industries, where the expected return on investment may be larger. This would lead to upward bias in the estimated coefficients on Horizontal, and overstate the spillovers resulting from inward FDI. On the other hand, selecting into slower growth industries may allow foreign firms to maintain a competitive advantage over an extended period, leading to downward bias in spillover estimates.

I use two main approaches to account for this endogeneity. First, I follow a common practice in the literature and examine lagged measures of Horizontal. These lagged measures will be exogenous as long as foreign firms do not select into industries based on predicted, future productivity shocks. Second, I consider an alternate construction of Horizontal, in which only the output of wholly foreign owned firms is included.[8] I argue that the location of wholly foreign firms is more likely to be based on strategic factors relevant to the firm's parent company, rather than the productivity growth of domestic firms. While maintaining a competitive advantage over domestic firms may still be a consideration for these firms, if this bias is present it will lead to conservative spillover estimates.

Next, I include standard checks to ensure that measurement error is not causing significant bias in spillover estimates. While some degree of measurement error is unavoidable, it is of particular concern when relying on a sample of firms in a developing country. In addition to results using the entire sample, I also consider restricted samples where I exclude firms in the top and bottom one percentile of productivity in each industry, and firms that appear in the sample for less that three years. In this way, I can examine the sensitivity of the main results to the presence of outliers in the sample. Moreover, measurement error has not been found to be severe in empirical work that has utilized the same data source (Eck and Huber, 2016).

Finally, it is possible that the spillover estimates are biased as a result of sample selection, since I obtain information only on the set of surviving firms. As the introduction of productive foreign firms may increase competition within an industry, it may force firms with lower productivity growth to exit. As a result, the remaining sample of firms may exhibit relatively high productivity growth for reasons independent from positive productivity spillovers. To account for the possibility of selection bias, I include results incorporating a Heckman (1976) correction. I model the probability of firm survival with a probit regression on a polynomial expansion of firm age and log capital stock.[9] I

[8]These firms are likely the result of Greenfield FDI, although the data does not indicate this specifically.

[9]Unfortunately, I do not have reliable data on firm investment.

then include the corresponding inverse Mills ratio in the estimation of productivity spillovers.

4 Empirical Results

Table 3 presents the estimation results of the baseline growth equation given in (2.3) for the entire sample of domestic firms, and subsamples of low and high-tech industries separately. Beginning with the control variables, we see that the estimated effect of firm age on productivity growth is near zero and insignificant in all specifications. Similarly, the estimated coefficient on the exporter dummy variable is consistently positive, but significant in only one specification. The positive and significant estimated coefficient on firm market share indicates that relatively large, established firms within an industry exhibit faster productivity growth on average. Turning to the two industry level controls, the estimates imply that increases in overall industry size and industry competitiveness are associated with increased average productivity growth of firms within the industry.

Table 3: Baseline Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Horizontal}_{ijt-1}$	0.184***		0.143**		0.249***	
	(0.048)		(0.071)		(0.058)	
$\Delta\text{Horizontal}_{ijt-1}$		0.122**		0.054		0.180**
		(0.059)		(0.089)		(0.090)
Age_{ijt}	0.007	0.023	0.0001	-0.0003	0.006	0.026
	(0.029)	(0.063)	(0.002)	(0.002)	(0.030)	(0.063)
MktShare_{ijt}	0.014***	0.018***	0.012***	0.015***	0.034***	0.034***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.010)
Exporter_{ijt}	0.009	0.016**	0.004	0.013	0.017	0.022
	(0.006)	(0.007)	(0.007)	(0.008)	(0.013)	(0.015)
Δ Indsize_{ijt}	0.118***	0.121***	0.122***	0.127***	0.114***	0.116***
	(0.017)	(0.019)	(0.024)	(0.025)	(0.019)	(0.025)
ΔHHI_{ijt}	-0.465***	-0.337**	-0.463***	-0.348**	-0.421	-0.241
	(0.145)	(0.145)	(0.168)	(0.168)	(0.273)	(0.308)
Sample	Domestic	Domestic	Low-tech	Low-tech	High-tech	High-tech
Observations	56,501	46,177	38,135	31,072	18,366	15,105
Firms	8,343	7,144	5,698	4,866	2,645	2,278
R-squared	0.008	0.008	0.009	0.009	0.008	0.008

All regressions include firm and year fixed effects. Robust standard errors clustered at the industry, year level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

The estimated coefficients on measures of foreign presence indicate the presence of substantial positive productivity spillovers to domestic firms. When considering the entire sample of domestic firms, we see that both the level and changes in foreign output share within an industry are associated with positive productivity growth. The results of column one imply that a 10% increase in foreign output share within an industry is associated with an additional 1.84% annual productivity growth of firms in the same industry. The estimated spillovers are uniformly larger, and exhibit a higher degree of statistical significance, in the subsample of high-tech firms. These findings mirror those in Keller and Yeaple (2009), which examined spillovers in the context of U.S. manufacturing firms. Perhaps not surprisingly, this indicates that firms in sectors where technology creation and utilization are more fundamental to production are better able to incorporate foreign production techniques. Indeed, I do not find evidence that new entry of foreign firms is associated with positive spillovers in low-tech industries. Moreover, these findings are not driven by overall differences in productivity growth between industries. As the summary statistics in Table 2 show, low-tech industries exhibit slightly higher rates of productivity growth than high-tech industries over this period.

Next, I consider the influence of geographical proximity of domestic and foreign firms on productivity spillovers. Table 4 displays the estimation results of equation (2.5) for the entire sample of domestic firms, and the low and high-tech subsamples separately. While all regressions include the same control variables as Table 3, I have omitted their estimated coefficients to conserve space. Since the variable StateHorizonal is defined for each industry, region pair individually, analyzing the variable in first difference results in significant clustering of observations around zero. This limited cross sectional variation may result in estimated coefficients that are biased towards zero. For this reason, I focus on estimating equation (2.5) in levels.

Table 4: Geographical Proximity

	(1)	(2)	(3)	(4)	(5)	(6)
StateHorizontal$_{kjt-1}$	0.074***	0.057**	0.083***	0.074***	0.056	0.025
	(0.023)	(0.024)	(0.025)	(0.025)	(0.048)	(0.050)
Horizontal$_{jt-1}$		0.155***		0.109		0.235***
		(0.050)		(0.072)		(0.059)
Sample	Domestic	Domestic	Low-tech	Low-tech	High-tech	High-tech
Observations	56,501	56,501	38,135	38,135	18,366	18,366
Firms	8,343	8,343	5,698	5,698	2,645	2,645
R-squared	0.008	0.008	0.009	0.009	0.008	0.008

All regressions include the control covariates included in Table 3, as well as firm and year fixed effects. Robust standard errors clustered at the industry, year level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Examining the entire sample of domestic firms, we see that geographical proximity to foreign firms is associated with increased productivity spillovers. The results of column two imply that an additional 10% of foreign output share within an industry, region pair is associated with average additional productivity growth of 0.57%, holding constant the total foreign output share within the industry. However, the overall foreign presence within an industry is clearly also important. The positive and significant estimated coefficient on Horizontal shows that additional foreign output share in an industry is associated with productivity spillovers even if the change occurs in a different geographical region.

Once again, we see stark differences in the subsamples of low and high-tech industries. Despite lower overall productivity spillovers, proximity to foreign firms appears to generate substantially larger spillovers in low-tech industries. Indeed, holding constant regional foreign output share, there is weak evidence that additional foreign presence in other geographical regions contributes to productivity spillovers at all. In contrast, geographical proximity appears to have an insignificant impact on productivity spillovers in high-tech industries.

4.1 Productivity Spillovers and Distance to the Frontier

Following equation (2.7), Table 5 examines the overall catch-up trend of domestic firms, and how productivity spillovers from FDI varies across the productivity distribution within an industry. The positive and statistically significant coefficients on TFPGAP across all specifications show that domestic firms exhibit a strong trend of technological catch-up to the productivity frontier. That is, firms further away from the frontier, and therefore towards the bottom of the productivity distribution in their industry, enjoy higher annual productivity growth. The estimated coefficients range from $[0.349, 0.453]$, and are consistent with the estimated coefficient of about 0.44 for Chinese manufacturing firms found in Wang et al. (2014). The magnitude of these coefficients suggest that this effect is quantitatively substantial. Using the intermediate estimate from column (2), a firm with a TFPGAP value of 0.1, corresponding to productivity 10.5% lower than the industry's frontier, is associated with 3.8% additional productivity growth.[10]

Table 5: Spillovers and Technological Catch Up

	(1)	(2)	(3)	(4)	(5)	(6)
TFPGAP_{ijt-1}	0.435***	0.380***	0.453***	0.376***	0.349***	0.395***
	(0.021)	(0.016)	(0.022)	(0.019)	(0.053)	(0.028)
Horizontal_{jt-1}	0.298***		0.399***		-0.036	
	(0.102)		(0.148)		(0.177)	
$\text{TFPGAP} \cdot \text{Horz}_{ijt-1}$	-0.090		-0.147*		0.256	
	(0.075)		(0.084)		(0.186)	
$\Delta\text{Horizontal}_{jt-1}$		0.337***		0.546**		0.119
		(0.122)		(0.209)		(0.197)
$\text{TFPGAP} \cdot \Delta\text{Horz}_{ijt-1}$		-0.255**		-0.411***		0.022
		(0.123)		(0.151)		(0.247)
Sample	Domestic	Domestic	Low-tech	Low-tech	High-tech	High-tech
Observations	56,493	46,174	38,127	31,069	18,366	15,105
Firms	8,341	7,143	5,696	4,865	2,645	2,278
R-squared	0.200	0.157	0.215	0.157	0.178	0.161

All regressions include the control covariates included in Table 3, as well as firm and year fixed effects. Robust standard errors clustered at the industry, year level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

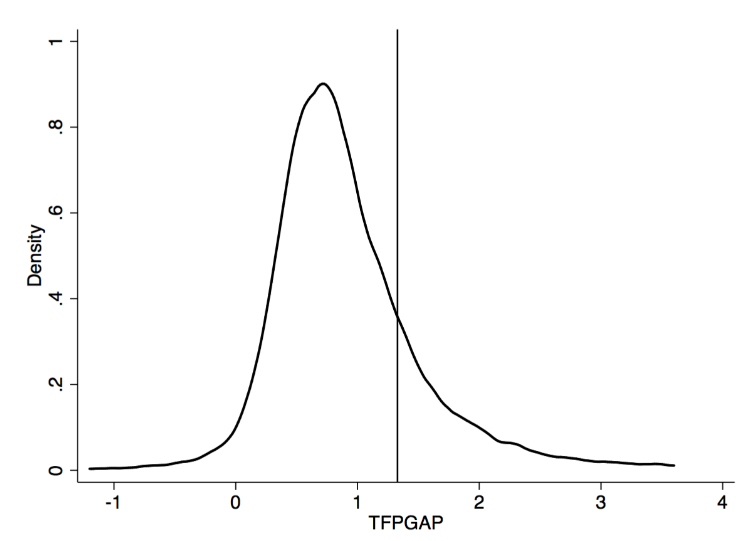
Turning to the estimated productivity spillovers across the productivity dispersion, the negative

[10] As defined in (2.11), $\text{TFPGAP}_i = \ln(A^F/A_i)$, and $\exp(0.1) = 1.105$.

estimated coefficient on the interaction term of TFPGAP and foreign presence using the entire sample of domestic firms indicates that relative position in an industry's productivity distribution is positively associated with productivity spillovers from inward FDI. That is, controlling for the overall catch-up tendency of firms, firms closer to the productivity frontier within their industry experience greater spillovers from FDI. This is much more pronounced in the specification using first differences, column (2), suggesting this effect is particularly associated with new foreign entry. From these results it is clear that estimates of productivity spillovers that ignore the productivity distribution mask substantial heterogeneity in the benefits from attracting FDI. Once again, we see fundamental differences in the subsamples of low and high-tech firms. The association of distance to the productivity frontier and spillovers from FDI appear entirely driven by the subsample of firms in low-tech industries. I find no evidence of this relationship in high-tech industries.

Moreover, this estimated heterogeneity suggests *qualitative* differences in spillovers across the productivity distribution of low-tech firms. That is, it is not only that firms closer to the frontier experience greater spillovers, but that firms firms beyond a cutoff TFPGAP experience negative spillovers from FDI. Using the estimates of column (4), the annual productivity growth associated with new foreign investment accounting for 10% output share within an industry is given by $\%\Delta A = 5.46 - 4.11{*}\text{TFPGAP}$. This implies that a firm at the frontier, with TFPGAP = 0, experiences a large 5.46% increase in productivity growth. The median value among low-tech firms of TFPGAP=0.809 is associated with 2.14% increased productivity growth. However, firms with a TFPGAP larger than 1.328 experience negative spillovers from the same investment. Given the distribution of TFPGAP, these negative spillovers apply to 19.3% of all domestic firms in low-tech industries. The following figure displays the empirical density of TFPGAP across firms in low-tech industries and the cutoff $TFPGAP = 1.328$, in which the mass of firms to the right of the cutoff are associated with negative spillovers.

Figure 1: Spillover Cut-Off in Low-Tech Industries



Next, I examine the direct impact of inward FDI on the dispersion of productivities of domestic firms within an industry. The results of Table 5 provide a clear implication that inward FDI will increase the productivity dispersion in low-tech industries, while the effect in high-tech industries will be negligible. However, as mentioned in section 3.2, there is some concern of biased spillover estimates resulting from endogeneity if foreign firms select into industries based on their growth rate. Thus, analyzing productivity dispersion directly, provides a check on the primary results.

Table 6 displays the estimates for equation (2.8) in both level, and first difference form. Consistent with the results of Table 5, we see strong evidence that inward FDI increases productivity dispersion of domestic firms in low-tech industries. Using that the median variance of productivity in low-tech industries of 0.396, the results of column (2) imply that an additional 10% foreign output share within an industry is associated with a 19.1% increase in the productivity variance of domestic firms. In contrast, FDI in high-tech industries has a negligible, or even negative effect on productivity dispersion. Moreover, although not displayed in Table 6, the time dummies included in the regressions are largely insignificant, and show no discernible trend over time. This finding lends support to the presence of long-run productivity dispersion within an industry despite the catch-up tendency of firms, which is accommodated by the empirical specification.

Table 6: Productivity Dispersion

	(1) TFPvar	(2) TFPvar	(3) TFPvar		(4) ΔTFPvar	(5) ΔTFPvar	(6) ΔTFPvar
TFPmean$_{jt}$	-0.683***	-0.689***	-0.770***	ΔTFPmean$_{jt}$	-1.110***	-1.024***	-1.196***
	(0.078)	(0.091)	(0.128)		(0.122)	(0.145)	(0.221)
Horizontal$_{jt-1}$	0.382**	0.757***	-0.191	ΔHorizontal$_{jt-1}$	0.331	0.668**	-0.031
	(0.175)	(0.218)	(0.197)		(0.260)	(0.312)	(0.358)
ΔIndsize$_{jt}$	0.094**	0.161***	-0.038	ΔIndsize$_{jt}$	0.234***	0.256***	0.169*
	(0.044)	(0.056)	(0.058)		(0.059)	(0.072)	(0.097)
ΔHHI$_{jt}$	-0.073	-0.236	0.151	ΔHHI$_{jt}$	-0.707**	-0.616*	-1.060
	(0.236)	(0.247)	(0.585)		(0.328)	(0.371)	(0.756)
Sample	Domestic	Low-tech	High-tech	Sample	Domestic	Low-tech	High-tech
Observations	57,019	38,512	18,507	Observations	46,360	31,224	15,136
Firms	8,481	5,800	2,681	Firms	7,230	4,931	2,299
R-squared	0.284	0.304	0.419	R-squared	0.287	0.314	0.333

All regressions include firm and year fixed effects. Robust standard errors clustered at the industry, year level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

5 Conclusion

Many developing countries continue to offer subsidies to inward foreign investment based on the belief that spillovers associated with FDI will increase the productivity growth of domestic firms. However, most empirical evidence of productivity spillovers comes from analyses in developed countries, and existing empirical research has not found robust evidence of significant spillovers in developing countries. To explain this discrepancy, several authors have argued that the technological disparity between domestic and foreign firms operating in developing countries may be too large for domestic firms to benefit from the increasing presence of foreign firms. If this is indeed the case, the large subsidies given to foreign investors are not economically justified.

In this paper, I analyze the presence of productivity spillovers from FDI using firm-level panel data on Indian manufacturing firms from 2001-2016. I account for domestic firms' relative position in the productivity distribution within their manufacturing industry by constructing a measure of technological distance to the industry frontier. Using an econometric specification that accommodates both technological catch-up to the frontier and long-run productivity dispersion within industries, I provide empirical estimates of productivity spillovers to domestic firms. I allow for productivity spillovers to vary across an industry's productivity distribution, and analyze how inward FDI affects the productivity dispersion of domestic firms within an industry. In addition, I classify industries into low and high-tech subsamples based on their average R&D intensity, and estimate spillovers in each subsample separately.

While I find some evidence for productivity spillovers using the entire sample of domestic firms, the magnitude and concentration of these spillovers differ sharply in the subsamples of low and high-tech industries. Spillovers in low-tech industries are overall less significant, and are dependent on geographical proximity to foreign firms. In addition, there is substantial heterogeneity in spillovers to low-tech firms across the productivity distribution within an industry. I find that positive spillovers are concentrated towards the top of the productivity distribution, while relatively unproductive firms within an industry experience negative spillovers from FDI. I corroborate these findings by showing that inward FDI directly increases productivity dispersion in low-tech industries. In contrast, spillovers in high-tech industries appear substantial, are not geographically dependent, and are largely even across the productivity distribution.

I argue that these findings suggest the presence of heterogenous effects from inward FDI in developing countries that are typically unaccounted for in investment subsidies to foreign investors. Although broad subsidies may by warranted in high-tech industries, where estimated spillovers are large and uniform, they may carry unintentional distributional implications in low-tech industries. With a better understanding of where productivity spillovers are concentrated, policy makers can target subsidies to areas where they have the largest effect, and address the trade-offs associated with inward FDI.

6 Appendix A

6.1 Levinsohn and Petrin Approach

Following notation in Van Beveren (2012), I assume a Cobb-Douglass production function of the form

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m} \tag{6.1}$$

where Y_{it} is output of firm (gross revenue), K, L, M are capital, labor, and intermediate materials. A_{it} is the TFP to be recovered. After taking logs,

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + v_{it} + u_{it} \tag{6.2}$$

where u_{it} is i.i.d. error, and $\omega_{it} = \beta_0 + v_{it}$ is log TFP. One estimates (6.2) and calculates log TFP by:

$$\hat{\omega}_{it} = \hat{v}_{it} + \hat{\beta}_0 = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} \tag{6.3}$$

However, this specification is known to suffer from simultaneity bias if input choices are (partially) determined by firms' knowledge of their productivity. If positive productivity shocks lead to higher usage of variable inputs, the estimated coefficients on variable inputs will be biased upwards. To correct for this endogeneity, I follow the Levinsohn and Petrin (2003) approach, and use expenditure on intermediate materials to proxy productivity. That is, I assume intermediate input demand is given by an increasing function of the firms state variables k and ω, so that $m_{it} = m(k_{it}, \omega_{it})$, which can be inverted to yield $\omega_{it} = \omega(k_{it}, m_{it})$. Following Petrin et al. (2004), I estimate

$$v_{it} = \beta_l l_{it} + \phi(k_{it}, m_{it}) + u_{it}, \quad \text{where} \quad \phi(k_{it}, m_{it}) = \beta_0 + \beta_k k_{it} + \omega(k_{it}, m_{it}) \tag{6.4}$$

where v_{it} is firm i's value added in year t (gross output less intermediate inputs). $\phi(k_{it}, m_{it})$ is estimated with a third-order polynomial approximation. Finally, assuming a first-order Markov process for productivity, Levinsohn and Petrin (2003) show total factor productivity can be estimated consistently up to a constant.

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