Effects of Chinese Import Competition on Plant Productivity and Product Scope: Evidence from India

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Abstract

How trade shocks emanating from a low-wage country affect the productivity of manufacturing plants in other low-wage countries has been little researched. This paper investigates the impact of Chinese import competition on the performance of Indian manufacturing sector through the lens of theoretical models of multiple-product firms using plant-level ASI panel data from 1998 to 2009. Increased import competition from China leads to an improvement in revenue productivity, and a reduction in product scope. A 10 percentage point increase in exposure to Chinese imports leads to a 3.8 percent increase in revenue productivity of large plants and a 1 percent decrease in the number of products within-plant. However, the impact on selection of products within-plant is not symmetric. The evidence suggests that product rationalization is one of the key channels through which trade shocks can affect plant productivity. Although import competition from high-wage countries has no statistically significant impact on plant performance or product scope, plant product-level adjustment shows that import competition shocks from high-wage countries and China have similar impact on selection of products within-plant.

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1. Introduction

The extraordinary growth of China's manufacturing exports in the aftermath of its WTO accession in 2001 reshaped the competitive environment across countries. While a few recent studies (Bernard, Jensen, and Schott 2006; Khandelwal 2010; Autor, Dorn, and Hanson 2013; Utar 2014; Acemoglu et al. 2016; Bloom, Draca, and Van Reenen 2016) investigate the impact of low-wage import competition on high-wage economies, there is little research on its impact on low-wage countries. This research is particularly interesting because firms in developing countries are often protected from competition by high trade-barriers, entry regulation and licensing requirements. The lack of competition allows low-productivity firms to survive (Bloom and Van Reenen 2007; Pavcnik 2002) and produce relatively low-quality products that would otherwise have not been produced in a competitive environment. In this paper, I explore the impact of low-wage import competition emanating from China on plant revenue productivity, product scope and reallocation of products within-plant in India using factory-level data from the Annual Survey of Industries (ASI). In particular, I exploit China's WTO accession in December 2001 and the ensuing rise in import competition in India as the key identification strategy.

To guide my empirical framework, I draw on the recent theoretical models of multi-product heterogeneous firms. In single-product models of firm heterogeneity (Melitz 2003; Melitz and Ottaviano 2008), trade liberalization increases aggregate productivity by inducing reallocation of resources across firms, as a decline in trade cost encourages the less-productive firms to exit and the more-productive firms to enter the export market. In this setup, the entry and the exit of products and their corresponding firms occur simultaneously. The multi-product extension of the single-product heterogeneous firms literature predicts that trade liberalization improves firm performance as firms drop their least attractive products and reallocate resources toward core competence (Eckel and Neary 2010; Bernard, Redding, and Schott 2011; Mayer, Melitz, and

Ottaviano 2014). Using detailed U.S. firm-level census data Bernard, Redding, and Schott (hereafter BRS, 2010) document that firms churn products frequently; and BRS (2011) show that firms reduce their product scope in response to trade liberalization. In a developing-country context, however, Goldberg, Khandelwal, Pavcnik, and Topalova (henceforth GKPT 2010a) find that firms in India rarely drop products and that the reduction in output tariffs does not affect firms' product-rationalization decisions.[1]

The lack of "creative destruction" in India during the 1990s is difficult to reconcile with the fact that the Indian economy went through an extensive tariff liberalization and a substantial structural reform over the same period.[2] One reasonable explanation is that the United States and India differ from one another both in terms of internal economic environment (e.g. labor market rigidities) and level of economic development (GKPT 2010a). Instead, GKPT (2010b) show that trade liberalization can lead to an increase in firms' product scope as a decline in input tariffs paves the way for firms to use new intermediate inputs, which help to create new varieties. One particular feature of the 1990s reform regime in India is that high-wage countries dominated the share of India's imports. For example, during 1996-2000, the European Union (EU-25), Japan and the United States jointly (EJU hereafter) accounted for more than 49 percent of India's non-oil imports

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[1] GKPT (2010a) report that while 22 percent of the firms in the Prowess database add at least one product, over a five-year period, only 4 percent of the firms drop a product and only 2 percent both add and drop a product.

[2] The term "creative destruction" is a concept of Joseph Schumpeter—defined as a process in which innovations not only create new products but also drive out products generated by preceding innovations.

on average, while all the low-wage countries (including China) comprised just around 10 percent of imports over the same period. The scenario changed drastically after 2001: the average share of EJU dropped to 32 percent, while that of all the low-wage countries increased to 22 percent in 2006-10, where the average share of imports from China alone increased by 12 percent.

This staggering change in the composition of India's imports, in a short period, has important implications for firm dynamics. The change in the origin of trade also alters the nature of the product market competition faced by the firms. More specifically, product market competition between low-wage and high-wage countries is distinct from the competition that occurs between different low-wage countries. The current evidence shows that within a particular product category, varieties originating in high-wage countries are of superior quality than those originating in low-wage countries (Schott 2004; Hummels and Klenow 2005). More recent studies document that import competition leads to product quality upgrading (Amiti and Khandelwal 2013; Fernandes and Paunov 2013; Martin and Mejean 2014). Taken together, this may affect firms' product selection decision and thereby productivity. For instance, Iacovone, Rauch, and Winters (2013) and Liu (2010) find that there is heterogeneity across products within-plant in the way plants adjust their product mix in response to import competition.

In the 2000s, the Indian economy experienced a new wave of trade shocks in the aftermath of China's accession to the WTO in December 2001. Guided by the theoretical predictions of multi-product firm models of trade, this study explores a set of questions in this context. Have Indian plants managed to improve their revenue productivity in the face of intensified import competition from China? Has import competition shock from China affected the process of creative destruction in India's manufacturing industry? Is the within-plant adjustment mechanism consistent with the theoretical prediction of the multi-product models? The sharp rise in China's share of India's manufacturing imports provides an ideal setting for identifying the impact of import competition originating from China. I primarily exploit the variation in the changes of China's share in India's import across industries and over time as a source of low-wage import competition shock in India. In the main regression specifications, I use a five-year difference of the outcome and trade shocks variables to control for plant fixed effects. To control for concurrent changes in the import share of other sources, I allow the import share of high-wage countries and other low-wage countries to affect plant performance. However, there are reasons to worry about the strength of such an identification scheme. For instance, the measure of exposure to Chinese imports may be correlated with different unobserved demand or supply side shocks to Indian industries. Another concern is the measurement errors in the import competition variables. I address these identification challenges by exploring alternative identification strategies. First, I exploit an instrumental variables (IV) approach to identify the effects of Chinese import competition shock. In line with recent literature on import competition, I use the lagged change in China's share of imports of a large low-wage country, Indonesia, as an instrument for the change in China's share of India's imports. A second alternative specification examines robustness of the primary identification scheme by including sector-specific trends as additional control variables.

I separate the empirical analysis of the paper into three stages: in the first part of the paper, I explore the characteristics of the multi-product plants in the ASI dataset and evaluate the findings in comparison to GKPT (2010a) and BRS (2010). I observe that the cross-sectional features of the multi-product plants in the ASI dataset are consistent with the earlier studies. First, I find that approximately 50 percent of the plants produce multiple products that account for 75 percent of manufacturing output. Second, multi-product plants are significantly larger than the single-product plants in the same industry. Third, in contrast to GKPT (2010), I find that about 63 percent of the

ASI plants change their product mix over a five-year period; interestingly, this rate of change is even higher than that of U.S. firms (54 percent) during 1987-1997.

In the second part of the paper, I investigate the impact of the rising Chinese import competition on plant revenue productivity. Based on plant-level data from 1998 to 2009, I document that the increase in exposure to Chinese imports leads to an improvement in plant revenue productivity. Overall, I find that a 10 percentage point increase in exposure to Chinese imports leads to a 3.8 percent increase in plant Total Factor Productivity (TFP) for large plants in the OLS regression. The relationship between plant performance and Chinese imports remains consistent in the IV regressions and the OLS regressions with 2-digit sector fixed effects. Using product-level data from 2000 to 2009, I find that plants rationalize their product scope in the face of heightened import competition from China. In case of OLS, a 10 percentage point increase in share of India's imports from China leads to a 1 percent decrease in the number of products produced by the plants.

In the final section, I find that the higher the level of exposure to imports from China on a particular product of a plant in the initial period, the more likely it is that the plant drops the product in the current period. But the chance of dropping the product decreases with the proximity of the product to the core competence of the plant.

The remainder of the paper is organized as follows. Section 2 briefly reviews related literature and Section 3 discusses China's integration into WTO and its economic implications. Section 4 describes the data and Section 5 shows some stylized facts about the multi-product plants in India. Section 6 presents the methodology for productivity estimation. Section 7 discusses the link between competition, productivity and product scope, and presents the results. Section 8 presents the results on plant-product level adjustment, and section 9 concludes.

2. The literature on Trade Competition and Firm Performance

Recent studies based on firm-level data from developed economies document several margins of adjustment at the firm-level in response to low-wage country trade competition. Bloom, Draca and Van Reenen (hereafter BDVR, 2016) find a significant within-firm effect of Chinese trade shock on various measures of technical change: patents, IT intensity, R&D, management practices and TFP in European firms. Bernard, Jensen and Schott (2006) show that on an average 7.8 percent of the surviving plants in U.S. switch industries over a five-year period. These switches are inclined towards skill- and capital-intensive industries, and probability of switching rises with low-wage country import exposure. Martin and Mejean (2014) explore the impact of low-wage competition on product quality using the dataset of French exporters from 1995 to 2005. They find that product quality upgrading is more pronounced in sectors and destinations where firms face more intense competition from low-wage countries. De Loecker (2011) explore the impact of trade reform (removal of quota protection) on firm productivity in the Belgian textile industry. Utar and Ruiz (2013) investigate the performance of Mexican export processing plants in response to rising export growth from China in the U.S. market. Bugamelli, Fabiani, and Sette (2015) examine the price adjustment at the firm-level in Italy in response to intensified growth of imports from China, while Auer and Fischer (2010), and Auer, Degen, and Fischer (2013) explore the impact of low-wage import competition on industry-level producer prices in the United States and selected European countries, respectively.

These studies add new insights to the trade literature, particularly in understanding the impact of the low-wage country trade exposure on advanced economies. However, there is little evidence on the impact of such trade shock on the low-wage countries' manufacturing sector. In this paper, I explore the impact of trade shock originating from a large low-wage country, China, on several margins of adjustment at the plant-level in another large low-wage developing country, India.

In addition to the studies mentioned above, this paper relates to two main strands of the literature. First, this paper relates to the studies that explore the channels through which trade liberalization can improve firm performance. The major channels can be classified into three main groups: by greater utilization of imported inputs (Amiti and Konings 2007; Topalova and Khandelwal 2011; Kasahara and Rodrigue 2008; Halpern, Koren, and Szeidl 2015), by encouraging firms in technology adoption (Bustos 2011; Lileeva and Trefler 2010) and by inducing reallocation of resources within firms (BRS 2011; Eckel and Neary 2010; Mayer, Melitz, and Ottaviano 2014; Alfaro and Chen 2017). This paper is more closely related to the last channel, particularly to studies that explore the impact of trade on firm productivity by highlighting the role of product churning within firms. Second, this study also relates to the literature that examines the impact of economic reforms in general and trade liberalization in particular on productivity and other measures of firm performance. Using data from India's organized manufacturing sector, the majority of these studies confirm that trade reforms played an important role in driving productivity growth in India, and the effects of input tariff liberalization is substantially greater than that of output tariff (Pavcnik 2002; Harrison, Martin, and Nataraj 2012; Nataraj 2011; Topalova and Khandelwal 2011; Sivadasan 2009). But the underlying within-firm adjustment mechanism of such productivity improvement remains unknown. In a related study, De Loecker et al (2016) showed that during the trade liberalization period in India, the reduction in the cost of imported inputs induced by decline in input tariff resulted in increased markups as the decline in marginal cost was greater than the corresponding decline in price.

This paper differs from the above studies in a number of dimensions. First, in previous studies, such productivity gains to developing countries' manufacturing sectors are explored in the era when north-north and north-south trade dominated the trade flows of the home country. In contrast, this paper explores plant-level productivity dynamics in the context of the booming south-south trade. Second, in previous studies, the identification of the impact of reform was based on domestic policy changes, which embeds an element of selection across industries (see Topalova and Khandelwal 2011, for a discussion on this issue). This study examines the impact of an important international event, the rise of China in the aftermath of WTO accession that has been affecting the economic environment across countries. Third, the identification of trade shock by source countries allows this paper to draw a line between competition emanating from low-wage and that originating from high-wage countries.

3. China's Integration into WTO and its Economic Implications

On December 11, 2001, China became the 143rd member of WTO. One of the key implications of China's accession to the WTO is that it has been granted "the most favored nation (MFN)" status permanently, like all other member countries. Literally, this means that no nation can discriminate against imports from China (e.g. by imposing higher tariff), which has significantly lowered the cost of trade for Chinese products to other member countries. Prior to China's WTO accession any WTO member country could, in principle, raise the tariff rate unilaterally or resort to any of the non-tariff barriers (antidumping) to restrain Chinese imports (Bown 2010).

A key reason why China sought WTO membership —and agreed to extensive liberalization of its trade and investment regimes in the process —was to gain unfettered market access for its exports to other member nations. WTO inclusion enables Chinese exporters to resort to the WTO dispute settlement system whenever they consider any other member country's actions regarding

Chinese exports to be discriminatory. Thus, accession to WTO has been crucial in ensuring stability in markets for Chinese exporters, particularly in WTO member countries.[3]

3.1 China's WTO accession from India's Perspective:

The pattern of India's foreign trade has undergone significant changes over the last three decades, with China playing an increasingly large role. Before the beginning of trade liberalization in India, China averaged just 0.3 percent of Indian imports during 1987 to 1991 period. In the first five years of liberalization, 1992-1996, China's average share climbed to 2 percent, which increased to around 3 percent in the 1997-2001 period. However, things changed dramatically after China's accession to WTO in December 2001, China became one of India's major trading partners with an average share of about 11 percent of imports during the 2007-2011 period. A clearer picture emerges from the analysis of UN Comtrade product-level data. After excluding imports of oil, it appears that India's imports from China increased to 16 percent in 2007-2011 from 3.5 percent in 1997-2000 (left panel of Figure 1). A much sharper rise in competition is observed by calculating the import ratios for each type of product. Increase in exposure to Chinese imports is highest in capital goods where it increases from 3.3 in 1997-2000 to 26.1 percent in 2007-2011, followed by consumer goods from 2.5 to 18.6 percent (right panel of Figure 1). This scenario suggests that India's manufacturing industry faced a sudden rise in competition from China within a short period of time.

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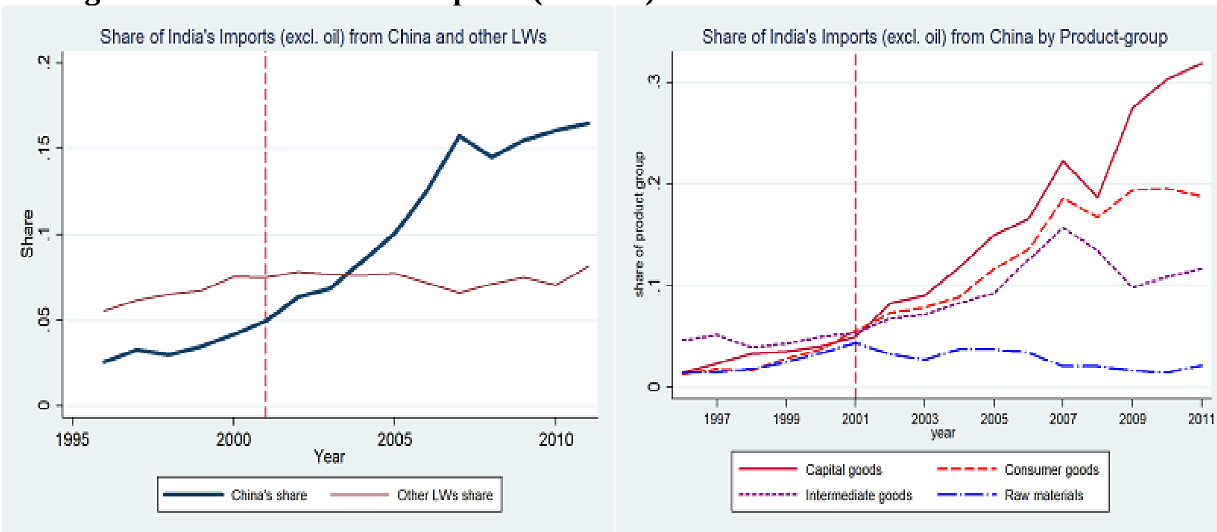
[3] In the pre-accession era, China's MFN status in the United States was subject to an annual approval by the US Congress. Because the United States accounts for a large share of China's exports, even in the pre accession era, this raised a major uncertainty about Chinese exports in the U.S. market.

Figure 1–Share of India's Imports (excl. oil) from China and Other LW countries



3.2 Measures of import Competition:

In this study, I follow the "value share" approach proposed by Schott (2002), and Bernard and Jensen (2002), which allows us to differentiate the trade shocks by origin countries. BDVR (2016) also use this approach as the main measure of Chinese import competition. The degree of import competition in industry *j* is defined as $I^S_{IN},_{jt} = \frac{\sum_k V_{kjt,S}}{\sum_k V_{kjt,W}}$, where $V_{kjt,S}$ is the import value of product *k* in industry *j* at time *t* from source *S* (e.g. China) and $V_{kjt,w}$ is the import value of product *k* in industry *j* at time *t* from all countries. *k* represents a particular HS 6-digit product category that corresponds to industry *j* (ISIC 4-digit industry). $I^S_{IN},_{jt}$ is the ratio of the sum of the values of all products imported from source *S* to the sum of the values of all products imported from all countries (*W*). However, industry-level aggregation of product codes (HS 6-digit) includes consumer goods, capital goods, intermediate goods and raw materials, which may underestimate competitive impact of increasing import exposure. To address this problem, in the main specification, I modify the measure of import exposure by excluding all the raw materials (RM) from the numerator of $I^S_{IN},_{jt}$. Therefore, the degree of import competition in industry *j*, $M^S_{IN},_{jt}$, is defined as $M_{IN,jt}^{S} = \frac{\sum_{k,k \neq RM} V_{kjt,S}}{\sum_{k} V_{kjt,W}}$. As a robustness test we show that our main results are not affected by removing RM from both numerator and denominator of the import exposure measure.

4. Data

4.1 Plant -Level Data: I use the plant-level ASI panel data from 1998 to 2009 (or financial year 1998-1999 to 2009-2010) and combine that with the UN Comtrade's country level bi-lateral commodity trade data from 1996 to 2009 (details in the online appendix). Based on National Industrial Classification (NIC), I use only manufacturing units for analysis: sectors 15 to 36 of NIC-2004. The ASI categorizes plants into 'census' or 'sample' sector on the basis of employment threshold. The main regression results of the paper are based on 'census plants', which are surveyed every year. In 1998 and 1999, 'census plants' include entities with at least 200 workers and from 2001 onwards this sector covers the units with at least 100 workers. Since a plant can switch between census and sample sectors based on its employment level in a given year, I use plants with initial employment of at least 20 workers (i.e. total number of employees reported by a plant in the year of first appearance in the ASI data) for productivity estimation to cover all possible appearances of a particular plant. Based on the availability of key plant-level variables (e.g. output, capital), I obtain 235,186 plant-year observations for 74,162 plants with at least 20 employees. The sample of plants that have at least 20 workers in the initial year is defined as LF20 plants. Likewise, I use LF100 and LF200 for the sample of plants with at least 100 and 200 workers in the initial year respectively.

For estimating plant productivity, I construct the key variables in line with existing literature. The real value added is computed as the difference between real output and real values of intermediate inputs. Total output includes the values of all products- and by-products, the increase in the stock of semi-finished goods and the other income.[4] Real output of a plant is obtained by deflating total output by the corresponding WPI (1993-94) of the 3-digit NIC industry. Inputs include the costs of materials and fuels. The values of materials are deflated by the materials price deflator of the corresponding NIC 3-digit industry constructed by combining WPIs with India's Input-Output Transaction Table (IOTT) 1993-94. The values of fuels are deflated by the WPI for fuel price. The number of blue-collar workers is calculated as the average number of production workers employed in the plant in a given year; and the number of white-collar workers (e.g. supervisors, managers and other non-production employees) is calculated as the difference between the average number of total employees and the average number of blue-collar workers. Plants report the opening and closing book values of fixed capital (net of depreciation) for each financial year. I measure capital as the average of opening and closing net book values of fixed capital in each year and deflate by the WPI of machinery. All the key inputs and output variables are winsorized at 1st and 99th percentiles by NIC 2-digit sector.

4.2 Plant-Product-Level Data: The ASI dataset contain detailed product-level information for all the ASI plants from 2000 to 2009. The ASI survey questionnaire requires plants to identify their products by specific ASI Commodity Classification (ASICC) codes. Factories report product-specific information such as quantity manufactured, quantity sold, gross sale value, taxes, per unit net sale value, and ex-factory value for each manufactured product. In order to directly relate the plant-product level adjustment with the product-specific measure of import competition by source country, I map the ASICC product-level data from the ASI to the Central Product Classification

[4] I follow the ASI tabulation manuals to construct the plant-level value of output and input measures.

(CPC-version 2, hereafter CPC).[5] I use a concordance published by the Central Statistics Office (CSO) of India to map the ASICC codes to the CPC level (details in the online appendix). Throughout the paper, I use the CPC codes as the main product classification system and define the number of unique CPC-product codes as the number of products produced by the plants.

As in the case of plant-level analysis, the product-level analysis is also based on manufacturing sector plants with at least 20 employees for which data on key plant level variables are available. Further, I exclude the plants that do not report detailed product codes or any manufacturing sector products. The final sample for the plant-product-level dataset consists of 68,986 manufacturing plants from the 2000 to 2009 ASI sample. In this sample, all the plants jointly report 5,546 distinct ASICC-2008-09 product codes that correspond to 945 unique CPC 5-digit product codes. Defining products by the CPC five-digit classification system, therefore, provides a more conservative estimate of product level adjustment within plants. For the sake of comparison, I also report additional results based on ASICC product codes.

5. Multi-Product Plants in India: Some Stylized Facts

Theoretical models of multi-product firms present several predictions about the distribution and the characteristics of firms in the cross-section. This section explores some stylized facts about the multiproduct plants in India through the lens of the theoretical multi-product models developed by BRS (2010), Eckel et al. (2015), and Eckel and Neary (2010). Table 1 reports the proportion of

[5] The commodity trade data are observed at HS 6-digit level, which have been converted to CPC by using HS to CPC concordance provided by the United Nations. Both HS 1996 and CPC are the official product classification systems of the United Nations.

single and multi-product plants in India's formal manufacturing sector and their respective output share in the total manufacturing output in 2000.[6]

Table 1–Proportion of Plants Producing Multiple Products in 2000

	Percent of Plants	Percent of Output	Average No. of 5-digit, 4-digit or 2-digit Products
	(1)	(2)	(3)
Multiple Product (MpC)	0.50	0.76	2.8
Multiple Class (MpI)	0.38	0.65	2.6
Multiple Division (MpS)	0.28	0.48	2.3
Multiple ASICC Product (MpA)	0.52	0.78	3.0

Notes: Table 1 reports the distribution of multi-product plants by classifying them in terms of their production of multiple 5-digit CPC, 4-digit CPC, 2-digit CPC and ASICC product categories. Sampling weights for the plants are used to create the tabulated statistics. This table is based on the LF20 sample excluding the plants that do not report detailed product codes.

A single-product plant (SpC) is considered as one whose set of products can be aggregated to a single CPC 5-digit code. Therefore, if a plant produces single or multiple ASICC product categories that fall within a single CPC 5-digit code, it is considered as a single-product plant. Similarly, a multi-product plant (MpC) is one that produces multiple CPC 5-digit categories. In addition, I also categorize plants by 4-digit CPC class and 2-digit CPC division, i.e. whether the plants produce more than one CPC class or division. Table 1 shows that around 50 percent of the plants in the ASI data are multi-product plants that account for 76 percent of the manufacturing output (additional details in the online appendix). These ratios are quite close to the Prowess firm

[6] I show that the characteristics of the multi-product ASI plants are consistent with the inferences of theoretical models and resemble the cross-sectional feature of India's Prowess dataset and U.S. census studied by GKPT (2010) and BRS (2010), respectively. Since classification of products varies across studies, such comparisons should be considered with this caveat in mind.

sample, where 47 percent of the plants produce multiple products and contribute 80 percent of manufacturing output (GKPT 2010a). For the sake of comparison, 39 percent of the firms in the U.S. produce multiple products and share 87 percent of total output.

In the online appendix (Table A.3), I show that the multi-product plants are significantly larger than the single-product plants in the same industry. The former group outperforms the latter both in terms of revenue based TFP and labor productivity—the MpC plants have 9 percent higher TFP than the SpC plants in the same industry. Additionally, in line with the theoretical models of multi-product firms (BRS 2010; Eckel and Neary 2010), I find evidence of product heterogeneity within plants. Consistent with the findings of BRS (2010) and GKPT (2010a), the distribution of product-level ASI data also shows high skewness (Table A.4).

I also observe that Indian plants were shrinking their product range in the second half of 2000s—the proportion of MpC plants decreased from 51 percent on average in 2000-04 to 46 percent in 2005-09 period and the mean number of products sold by the plants decreased from 1.92 in 2000-04 to 1.84 in 2005-09 period (Table A.5). In order to understand the within-plant adjustment mechanism behind the observed decline in the proportion of multi-product plants and the reduction in product scope, it is important to investigate how plants changed their product mix over the same period. In Table 2, I find that Indian plants change their product mix quite frequently between 2000 and 2009. The table portrays product switching activity of the plants over a five-year horizon, based on the CPC 5-digit classification. Each column shows the distribution of a particular type (all, single-product and multi-product) of plants according to their activity. Columns (1) to (3) present the results for the LF20 sample and (4) to (6) show the results for the LF200 sample. In Column (1), I find that more than 63 percent of the ASI plants change their product mix over a five-year period on average in the 2000s—10 percent of the plants only add ("A") and 11 percent only drop ("D") products, while 42 percent of the plants both add and drop products ("AD").

Table 2–Product Switching Activity of the Plants

	LF20			LF200		
	(1)	(2)	(3)	(4)	(5)	(6)
Activity	All	Single-Product	Multi-product	All	Single-Product	Multi-product
No Activity	37.5	61.4	20.8	34.8	64.5	21.8
Only Add	9.7	9.6	9.8	10.6	11.4	10.3
Only Drop	11.0	-	18.6	12.5	-	18.0
Both Add & Drop	41.8	29.0	50.7	42.1	24.1	49.9

Notes: The table presents the classification of the plants in terms of four mutually exclusive product-switching activities: No Activity, only add, only drop and both add and drop. Columns (1) to (3) show the results for the LF20 sample and (4) to (6) show the results for the LF200 sample. Each column of this table is based on five-year average of the activities. A product is considered as added in year *t* if it was not produced in *t-5* and a product is dropped in year *t* if it was produced in *t*-5 but not in year *t*.

These figures are remarkably different than those reported in GKPT (2010a): 22 percent only add, 4 percent only drop and 2 percent both add and drop products in the 1990s. Though the product switching pattern observed here is much different from the GKPT (2010a) for India, this pattern is reasonably similar to activity of U.S. firms between 1987 and 1997 reported by BRS (2010): 14 percent only add, 15 percent only drop and 25 percent both add and drop products. Therefore, the results provide new insights about the behavior of the plants in India in the 2000s.

The key difference between the present study and GKPT (2010a) is that, this study investigates the plant-product level dynamics in the 2000s, while GKPT explore firm-product level dynamics in the 1990s. The difference between these two periods in the context of India is that during the 1990s, India's imports and exports were dominated by developed countries. In contrast, during the 2000s, India experienced a sharp rise in growth of imports from low-wage sources in general and

China in particular. The difference in the plant-product level dynamics between the two studies, therefore, may arise from the distinction in product market competition that emanates from developed countries and that originates from low-wage countries. The main objective of this paper is to investigate whether intensified import competition from China is an important contributing factor in driving this "creative destruction" phenomenon in Indian economy.

6. Measuring Productivity

I estimate productivity at the plant-level by implementing Wooldridge's (2009) production function estimation approach, which modifies the control function methodologies developed by Olley and Pakes (hereafter OP, 1996) and Levinsohn and Petrin (hereafter LP 2003). The modified estimation strategy is known as the Wooldridge-Levinsohn-Petrin (WLP) approach and it is robust to the Ackerberg, Caves, and Frazer (hereafter ACF, 2006, 2015) criticism of the OP and the LP approaches. One of the key advantages of the WLP approach is that it is a system GMM based approach that makes efficient use of the moment conditions of the OP and the LP methods. It is also easy to obtain robust standard errors in system GMM estimation taking into account of both serial correlation and heteroskedasticity (Wooldridge's 2009). I assume a Cobb-Douglas production function,

$$y_{it} = \alpha + \beta_b l_{b,it} + \beta_w l_{w,it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it}, \qquad (1)$$

where y_{it} is the log of value added of plant *i* at year *t*. $l_{b,it}$ is the log of blue-collar labor input, $l_{w,it}$ is the log of white-collar labor input, and k_{it} is the log of the capital stock. ω_{it} represents shocks to productivity that are observed by plants while choosing their inputs but unobservable to the econometrician. ε_{it} represents all other shocks to productivity that are not known to the plants before taking decision regarding input at time t. However, given that ω_{it} (assumed to be a state variable) is observable to the plant at time t, it can potentially influence optimal choice of inputs, leading to correlation between predictable component of productivity shocks, ω_{it} and input levels. Intuitively, a positive productivity shock will encourage plants to use more inputs and *vice versa*. As a result, the OLS estimates of the production function coefficients will be biased and inconsistent, leading to biased productivity estimates.

In order to solve the problem of simultaneity of productivity and variable inputs, OP and LP provide conditions under which unobserved productivity shocks can be controlled for by inverting investment (OP) or intermediate input demand (LP) functions. The methodologies OP and LP are based on a set of assumptions.

First, ω_{it} follows a first order markov process: $p(\omega_{it}|\Omega_{it-1}) = p(\omega_{it}|\omega_{it-1})$, where Ω_{it} is the set of available information to plant i at time t. In other words, a firm's expectation about future productivity depends only on ω_{it-1}.

Second, labor inputs are assumed to be non-dynamic (variable inputs) and can depend on realization of ω in the current period.

Third, capital is considered as a state variable—capital stock (k_t) at time t was determined at period $t-1$, following $k_t = (1-\delta)k_{t-1} + i_{t-1}$, therefore, it is not correlated with the innovation term (ξ_{it}) of productivity ($i.e. E(\xi_{it}|k_{it}) = 0$), which is defined as $\xi_{it} = \omega_{it} - E(\omega_{it}|\Omega_{it-1})$.

Fourth, in the OP framework, investment (i_{it}) evolves according to $i_{it} = h(k_{it}, \omega_{it})$ resulting from the firm's dynamic optimization problem, and i_{it} is a strictly monotonic function of ω_{it}.[7] In

[7] LP argue that the strict monotonicity assumption does not hold, in practice, as investment appears to be zero (potentially due to high adjustment costs) for a large fraction of plants. To circumvent this problem, LP suggest using intermediate inputs as proxy variables to solve this zero-investment problem.

this context, LP assume that there exists an intermediate input demand function $m_{it} = h(k_{it}, \omega_{it})$, satisfying strict monotonicity assumption. Based on this assumption, the investment policy function or the intermediate input demand function can be inverted to represent unobservable productivity shocks as a function of observables:

$$\omega_{it} = h^{-1}(k_{it}, m_{it}), \qquad (2)$$

I can rewrite (1) by using (2),

$$y_{it} = \beta_b l_{b,it} + \beta_w l_{w,it} + \varphi_t(k_{it}, m_{it}) + \varepsilon_{it}, \qquad (3)$$

where $\varphi_t(k_{it}, m_{it}) = \alpha + \beta_k k_{it} + h^{-1}(k_{it}, m_{it})$. The estimation follows a two-stage procedure in both the OP and the LP approaches. In the first stage, the labor input coefficients can be estimated by applying OLS on equation (3), where higher order polynomials of k_{it} and m_{it} can be used to approximate $\varphi_t(k_{it}, m_{it})$. Since k_{it} appears both as a variable and in the function $h^{-1}(\cdot,\cdot)$, it is not identifiable in this equation. Therefore, the purpose of the first stage is to obtain estimates of β_b, β_w and φ_t using the condition:

$$E\left(\varepsilon_{it} \middle| l_{b,it}, l_{w,it}, k_{it}, m_{it}\right) = 0, \qquad (4)$$

In the second stage, productivity (ω_{it}) is decomposed into its conditional expectation and an innovation component (ξ_{it}),

$$\omega_{it} = E(\omega_{it}|\Omega_{it-1}) + \xi_{it} = g(\omega_{it-1}) + \xi_{it}.$$

Using this decomposition, I can rewrite equation (1),

$$y_{it} = \alpha + \beta_b l_{b,it} + \beta_w l_{w,it} + \beta_k k_{it} + g(\omega_{it-1}) + \xi_{it} + \varepsilon_{it},$$

$$y_{it} = \alpha + \beta_b l_{b,it} + \beta_w l_{w,it} + \beta_k k_{it} + g(\varphi_{t-1}(k_{it-1}, m_{it-1}) - \alpha - \beta_k k_{it-1}) + \xi_{it} + \varepsilon_{it} \qquad (5)$$

where the last line is obtained by using equation (2) and the definition of $\varphi_t(k_{it}, m_{it})$.

The second stage identifies the capital coefficient (β_k) by plugging in the estimates of β_b, β_w, and φ_t (i.e. $\widehat{\beta_b}$, $\widehat{\beta_w}$, and $\widehat{\varphi_t}$) from the first stage and applying the orthogonality condition:

$$E(\xi_{it} + \varepsilon_{it} | k_{it}) = 0. \qquad (6)$$

The above two-step estimation algorithm, (in particular the LP approach), suffers from an identification problem in the first stage. ACF (2006, 2015) show that if intermediate inputs and labor inputs are determined simultaneously then the labor coefficients are not identifiable in the first stage. To circumvent this identification issue, Wooldridge (2009) suggests a one-step GMM framework, where the moment conditions of the OP and the LP techniques are modified to estimate β_b, β_w and β_k jointly. The method is based on a two-equation system GMM approach, with the same dependent variable on both equations, but with different sets of orthogonality conditions. Wooldridge (2009) modifies the orthogonality conditions in Eq. (4) to

$$E\left(\varepsilon_{it} \middle| l_{b,it}, l_{w,it}, k_{it}, m_{it}, l_{b,it-1}, l_{w,it-1}, k_{it-1}, m_{it-1}, \ldots\ldots l_{b,i1}, l_{w,i1}, k_{i1}, m_{i1}\right) = 0, \quad (7)$$

and in Eq. (6) to

$$E\left(\xi_{it} + \varepsilon_{it} \middle| k_{it}, l_{b,it-1}, l_{w,it-1}, k_{it-1}, m_{it-1}, \ldots\ldots l_{b,i1}, l_{w,i1}, k_{i1}, m_{i1}\right) = 0 \qquad (8)$$

The moment conditions in equations (7) and (8) imply that the current value of capital stock and the lagged values of any inputs and their functions can be used as instruments for equations (3) and (5). These two sets of orthogonality conditions can be used to estimate β_b, β_w, β_k and other parameters of the model simultaneously. Wooldridge (2009) suggests that if the coefficients of variable inputs are not identified in equation (3), they can still be identified by using the moments in equation (8).

The next stage estimates (log) plant-level productivity as

$$lnPr_{it} = y_{it} - \left(\hat{\beta}_b^s l_{b,it} + \hat{\beta}_w^s l_{w,it} + \hat{\beta}_k^s k_{it}\right), \qquad (9)$$

where the superscript s on the coefficients of inputs represents a sector and $\hat{\beta}_m^s$ represents estimated elasticity of value-added in sector s with respect to input m $(l_b, l_w \; or \; k)$. I use fuel consumption at the plant level as a proxy variable and estimate the production function coefficients for each sector (ISIC/NIC 2-digit) separately. The estimated coefficients of the production function are reported in the online appendix (Table A.2B).[8]

7. The Link between Competition, Productivity and Product Scope

The incorporation of multi-product firms into the international trade models of firm heterogeneity highlights a new channel of within-firm adjustment in response to trade competition in addition to the across firm selection (entry-exit) effect that arises in the single-product models with heterogeneous firms. The main prediction from these models is that firms change their product mix or drop the least performing products in the face of trade competition in a way that results in productivity gains within the firm (BRS 2011; Eckel and Neary 2010).

BRS (2011) develop a multi-product extension of the single-product heterogeneous firm model of Meltiz (2003) with constant elasticity of substitution preferences and monopolistic competition. The key implication of combining these two assumptions is that the markup is fixed and unaffected by a trade shock. In this model, opening up to trade increases product market competition by encouraging entry of domestic firms, which leads to a reduction in average prices. Surviving firms drop their least successful products in the domestic market but derive more revenue from the export market for their higher quality products. Productivity of firms increases as firms focus on their higher quality products.

Eckel and Neary (2010) build a model of multi-product firms by combining the supply side connection between the varieties through flexible manufacturing and the demand side linkage

[8] I use a slightly modified version of the Stata program for production function estimation used by Petrin and Levinsohn (2012). These codes are available on the website of Amil Petrin: https://sites.google.com/a/umn.edu/amil-petrin/home/Available-Programs.

through a cannibalization effect. Under flexible manufacturing marginal cost differs across varieties. Marginal cost is lowest for the core competence variety, which the firm can produce most efficiently. On the other hand, the cannibalization effect arises when a large firm in a particular market faces declining demand for its existing varieties when it introduces a new variety. A rise in competition increases the productivity as firms focus on their core competence products and drop the high marginal cost varieties.

Bloom, Romer, Terry, and Van Reenen (2013, 2014) build a new theoretical framework that shows how low-wage (southern) import competition can induce firms in high-wage (northern) countries to innovate more.[9] Though the underlying mechanism is different, this model also predicts reallocation of resources within firms in the face of import competition, in line with the multi-product firm models above.

Based on the mechanism prescribed by the firm heterogeneity and trade literature in the context of trade liberalization, we can postulate that the pro-competitive effect of China's WTO accession unfolds through the inward shift of the demand curve of the firms operating in the industries that experience a rise in Chinese imports. Firms respond to this change in competitive environment by changing their product mix, which in turn leads to an increase in (revenue) productivity.

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[9] They argue that some factors of production are firm-product specific. These can be used either to produce an existing good or to innovate a new good. An increase in low-wage import competition that lowers the profitability of an existing firm product, by driving down its price, also lowers the opportunity cost of the trapped factors for innovating relative to producing the old good. This is a north-south model where only the northern firms innovate.

7.1 Import Competition and Plant Performance

The primary empirical strategy of this paper draws upon the framework adopted in the earlier studies that explore the impact of low-wage (Chinese) import competition shocks on the productivity of manufacturing establishments. The main left-hand side variable is a particular measure of productivity for the manufacturing plant *i*, in industry *j*, at time *t*:

$$lnPr_{ijt} = \rho_i + \tau_{st} + \beta_1 (M_{IN}^{CH})_{jt-l} + \epsilon_{ijt} \qquad (10)$$

The key coefficient of interest in equation (10) is β_1 corresponding to $(M_{IN}^{CH})_{jt-l}$ that measures China's share of India's imports in industry *j*.[10] The term ρ_i denotes plant fixed effects that account for time-invariant unobserved heterogeneity, which are likely to be correlated with the plant productivity and the plant's exposure to trade shocks. The term τ_{st} represents the set of state-year fixed effects that control for state-level macroeconomic shocks and changes in state-level policies over time. The last term, ϵ_{ijt} is an idiosyncratic error assumed to be uncorrelated with the measures of trade shocks and other right-hand side variables.

I take a five-year difference of the key variables of interest to control for plant fixed effects:

$$\Delta_5 lnPr_{ijt} = \Delta_5 \tau_{st} + \beta_1 \Delta_5 (M_{IN}^{CH})_{jt-l} + \Delta_5 \epsilon_{ijt}, \qquad (11)$$

where $\Delta_5 lnPr_{ijt}$ represents the change in productivity of plant *i* at time *t* compared to *t-5*. $\Delta_5 (M_{IN}^{CH})_{jt-l}$ indicates the lagged change (five-year difference) in the value share of import from China in industry *j* in period *t-l*. In order to control for other factors that may influence productivity, I also include a vector ($\boldsymbol{X_i}$) of control variables, in the main specification:

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[10] To have a more precise measure of import exposure at industry level, in the baseline specification, I exclude all the products that are categorized as raw materials from the numerator of the measure of import exposure, M_{IN}^{CH}.

$$\Delta_5 lnPr_{ijt} = \Delta_5\tau_{st} + \boldsymbol{\mu X_i} + \beta_1\Delta_5(M_{IN}^{CH})_{jt-l} + \Delta_5\epsilon_{ijt}, \qquad (12)$$

where $\boldsymbol{X_i}$ includes a set of initial technology classification (based on R&D intensity) dummies and a location (rural) dummy and an intercept (α).[11] In this difference form specification, the inclusion of the initial technology dummies addresses the possibility that the productivity growth may differ across different technology intensity groups. Similarly, the rural dummy (which equals 1 if a plant was located in a rural location in the initial year or 0 otherwise) controls for differential trend in productivity growth rate between plants located in rural areas and those located in urban areas.[12] Since I measure the trade shocks at the industry (NIC 4-digit) level, I cluster the standard errors at the level of the plant's main industry in all the regressions. I use the first lag (i.e. lag length $l = 1$) of the change in import value shares for all regression specifications.[13]

[11] I use OECD (2011) technology classification of the industries based on R&D intensities to categorize the ASI plants by technology groups: High-tech., Medium-high-tech., Medium-low-tech., and Low-tech. industries.

[12] To the extent that production environment in a rural area may be different from that of an urban area; dynamics of plant growth can also differ between the two areas. Another important observation in the context of this paper is that the average age of rural plants in the ASI data is significantly smaller than the average age of urban plants. This evidence suggests that formation of new plants is higher in rural than in urban locations. Therefore, the inclusion of a rural dummy is expected to capture the differences in patterns of plant growth dynamics.

[13] UN Comtrade records trade data in calendar years whereas the ASI data are available in financial years. For example, 1998-99 ASI data and 1998 trade data in Comtrade are considered in the same year.

According to the theory of multi-product firms, β_1 would be positive if an increase in Chinese import competition leads to an improvement in plant performance as plants reallocate resources towards their core competence and drop their higher marginal cost products. Alternatively, β_1 can be positive if competition induces plants to increase efficiency by adopting advanced technology or better management practices.[14]

In the above specification (12), I do not control for import competition from other sources, which may bias the coefficient β_1. One possibility is that an increase in imports from China in a particular industry drives out the imports from other sources (e.g. developed economies) in that industry. Another possibility is that an industry which is not exposed to Chinese competition may nonetheless face competition from developed countries. As a result, there would be a negative correlation between the measure of competition from China and developed countries. If competition from developed countries also has a positive effect on plant performance measure, omission of this alternative source of shock can cause a downward bias in the estimate of β_1. However, the estimated coefficient may overestimate the impact of Chinese competition if it is positively correlated with a simultaneous rise in import share from other sources, where the latter itself is also positively correlated with the productivity measure. Similarly, the omission of import shocks from other low-wage countries (excluding China) can also lead to biased estimate of β_1.

To address these issues, I also show the results for two additional specifications: first, by adding the lagged change in the share of India's combined imports from EU, Japan and U.S. ($\Delta_5(M_{IN}^{EJU})_{jt-l}$) with (12):

[14] β_1 can also be positive if plants invest in innovating high-quality products in the face of competition.

$$\Delta_5 lnPr_{ijt} = \Delta_5\tau_{st} + \boldsymbol{\mu X_i} + \beta_1\Delta_5(M_{IN}^{CH})_{jt-l} + \beta_2\Delta_5(M_{IN}^{EJU})_{jt-l} + \Delta_5\epsilon_{ijt}, \quad (13)$$

and second by including India's imports from other low-wage countries ($\Delta_5(M_{IN}^{LW})_{jt-l}$) in (13)

$$\Delta_5 lnPr_{ijt} = \Delta_5\tau_{st} + \boldsymbol{\mu X_i} + \beta_1\Delta_5(M_{IN}^{CH})_{jt-l} + \beta_2\Delta_5(M_{IN}^{EJU})_{jt-l} + \beta_3\Delta_5(M_{IN}^{LW})_{jt-l} + \Delta_5\epsilon_{ijt}, \quad (14)$$

For notational simplicity, in the discussion that follows, I use ΔCHN_t for $\Delta_5(M_{IN}^{CH})_{jt}$, ΔEJU_t for $\Delta_5(M_{IN}^{EJU})_{jt}$ and ΔLW_t for $\Delta_5(M_{IN}^{LW})_{jt}$.

Endogeneity emanating from unobserved Shocks: Our baseline estimation strategy is not free from endogeneity concerns, such as biases emanating from unobserved demand and supply shocks. One possibility is that industry-specific unobserved technology shocks are partly correlated with the change in import demand from China and productivity growth of the industry. An unobserved positive technology shock that raises aggregate productivity of an industry may discourage growth of imports from China in that Industry. As a result, the OLS estimate of the coefficient β_1 would be biased downward. Similar bias can also arise from other supply side shocks such as fall in input prices. Another potential source of endogeneity lies in the fact that industry-level import competition variables could be measured with error. Such measurement error would cause attenuation bias in our estimate of interest. In contrast, positive demand shocks will generate an upward bias in the OLS estimate of β_1. Therefore, whether OLS leads us to underestimate or overestimate the impact of import competition on productivity is an empirical issue.

In order to address the endogeneity concern in the relationship between Chinese import exposure and India's manufacturing performance, I employ an instrumental variable (IV) strategy. Since, I am interested in estimating China's contribution to the improvement of plant performance in India, the best way to identify that mechanism is to find an instrument that can capture China's supply-side driven component of its growth of exports to low-wage countries, but uncorrelated with the demand- and supply-side shocks in India. For this purpose, we need another low-wage country that is comparable to India in terms of economic conditions and that faces an increase in import competition from China within the period under consideration. In the spirit of the recent studies of Autor, Dorn, and Hanson (2013), and Acemoglu et al. (2016), I use the lagged change in the Chinese import share in Indonesia, a large low-wage country, as an instrument for the change in the Chinese import share in India. Particularly, I use the *l*-1'th lagged change in the Chinese import share in Indonesia $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ as an instrument for the *l*'th lagged change in the Chinese import share in India $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. The legitimacy of this identification strategy relies on the assumption that the growth of China's exports to India and Indonesia share a common component, which is mainly driven by China's rising competitiveness and falling barriers to trade.

7.2 Results: Impact on productivity

Table 3 shows the OLS and the IV regression results of the change in plant productivity (revenue based) measured by the WLP approach on the changes in import competition from different sources measured at the industry (NIC 4-digit) level. Panel-A reports the OLS estimates, Panel-B reports the two-stage least square (2SLS) estimates and Panel-C reports some key results from the corresponding first stages. Since the ASI dataset contains both census and sample plants and the impact of import competition may differ by plant size, I perform regressions by different size thresholds of plants.

In Table 3, Block-A reports the results for the LF200 sample (plants with at least 200 employees in the initial year) and Block-B reports the results for the LF100 sample (at least 100 employees). Columns (1) and (4) show the results when only ΔCHN_{t-1} (the lagged change in the Chinese import ratio) is included in the regression. Columns (2) and (4) add the lagged change in EJU's (i.e. Europe, Japan and U.S.) import share (ΔEJU_{t-1}); and Columns (3) and (6) add the lagged changes in both EJU's and other LW's (ΔLW_{t-1}) import shares with the changes in China's share.

Table 3–Impact of Import Competition from China on Plant Productivity (OLS and IV)

	Block-A (LF200)			Block-B (LF100)		
Panel-A	**OLS** Dep. Variable: $\Delta_5 lnPr_{ijt}$ (WLP approach)					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_5CHN_{t-1}	0.379**	0.414**	0.443**	0.399**	0.427**	0.451**
	(0.186)	(0.206)	(0.200)	(0.191)	(0.213)	(0.213)
Δ_5EJU_{t-1}		0.103	0.149		0.080	0.119
		(0.139)	(0.138)		(0.137)	(0.149)
Δ_5LW_{t-1}			0.132			0.109
			(0.094)			(0.108)
R-squared	0.035	0.036	0.036	0.032	0.033	0.033
Panel-B	**2SLS** Dep. Variable: $\Delta_5 lnPr_{ijt}$ (WLP approach)					
Δ_5CHN_{t-1}	0.865**	0.917**	0.948**	0.761*	0.794*	0.817*
	(0.428)	(0.442)	(0.438)	(0.442)	(0.456)	(0.455)
Δ_5EJU_{t-1}		0.218	0.285		0.166	0.221
		(0.170)	(0.174)		(0.175)	(0.192)
Δ_5LW_{t-1}			0.198**			0.160
			(0.093)			(0.115)
R-squared	0.033	0.033	0.033	0.031	0.031	0.031
Obs. (n)	22569	22569	22569	31842	31842	31842
Plants (n)	4961	4961	4961	7874	7874	7874
Panel-C	**First Stage** Dep. Var.: $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$					
$\Delta_5(CHN_{IDN})_{(t-1)-1}$	0.555***	0.530***	0.522***	0.518***	0.498***	0.489***
	(0.076)	(0.083)	(0.089)	(0.069)	(0.072)	(0.077)
First stage F-stat	53.44	40.90	34.29	56.79	47.72	39.96

Notes: Table 3 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in TFP) on the lagged changes in China's, EJU's and other LW's import shares in India. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. Columns (1)–(3) in Block-A include only the LF200 and Columns (4)–(6) in Block-B include only the LF100 sample. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) indicates the number of plants included in the regression. All the regressions include 118 industries or clusters (NIC 4-digit). ** and * indicate significant at 5% and 10% level, respectively.

The regressions in Table 3 include the plants that are sampled and non-missing (for which data on key variables are available) at the starting and end points of the five-year interval. In all tables, standard errors are clustered at the 4-digit industry level and reported in parentheses below the estimated coefficients.

Of particular interest is β_1, the coefficient of the change in the Chinese import share (ΔCHN_{t-1}) across various regression specifications. The estimates are economically and statistically significant. In Column (1) of Panel-A, the estimated β_1 coefficient is 0.379 with a standard error of 0.186, which indicates that a 10 percentage point increase in the share of India's imports from China causes a 3.8 percent increase in plant TFP. Across all the specifications in Panel-A, the sign of the estimated β_1 remains positive and statistically significant at 5 percent level.

In Columns (2) and (5), I introduce a control for other sources of import competition by including the first lag of ΔEJU_t. In both cases, the magnitude of the coefficient of Chinese imports (β_1) increases after including ΔEJU_{t-1}. The estimated β_1 increases further in Columns (3) and (6) after including the first lag of the change in other LW's import share (ΔLW_{t-1}) in addition to ΔEJU_{t-1}. In Panel-A of the table, both the import shocks of high-wage countries (EJUs) and other low-wage (LWs) countries are positive but remain statistically insignificant under OLS. Taken together, the results suggest that the coefficient of ΔCHN_{t-1} is slightly biased downward when I do not control for the import shocks from high-wage and other low-wage countries. As discussed above, this downward bias is plausibly arising from a negative correlation between the Chinese import share and the high-wage (or other low-wage) import share, where the latter is also positively associated with plant productivity. The estimated β_1 coefficients across all the columns in Block-B of Panel-A (for LF100) are also slightly larger than their corresponding estimates in Block-A of Panel-A (for LF200).

Panel-B of Table 3 reports the 2SLS estimates and Panel-C shows some key results from the corresponding first stage regressions (detailed results in Table A.6). In Column (1) of Panel-C, the first-stage coefficient (standard error) of (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ is 0.555 (0.076) and the first stage F-statistics is 53.44 for the 2SLS regression in Column (1) of Panel-B. The results show that there is a positive and a statistically significant relationship between the lagged change in Indonesia's imports from China and the change in India's imports from China. The corresponding 2SLS estimate of the coefficient of interest β_1 is 0.865, which is statistically significant at 5% level (Column 1, Panel-B).

As in the case of OLS, the magnitude of the estimated coefficient of Chinese import competition increases after adding the changes in EJU's (Column 2), and both EJUs and other LW's import shares (Column 3). The 2SLS estimates of the change in Chinese imports (Block-A), based on the LF200 sample, are significantly larger than their corresponding OLS estimates and the estimates are statistically significant at 5 percent level. A similar pattern is observed for the LF100 sample (Block-B), and the estimates are statistically significant at 10 percent level in all the columns. Therefore, it appears that the OLS coefficient of Chinese competition shock is biased downward. The results are consistent with the findings of earlier studies. For example, BDVR (2016) find that the 2SLS estimates are generally larger than their OLS counterparts. As discussed earlier, unobserved technology shocks coupled with error in measurement of import exposure variables may cause OLS to underestimate the competition effects of China. One interesting change in the 2SLS regression for the LF200 sample is that the coefficient of other LW import exposure appears to be positive and statistically significant at 5% level in Column (3) of Panel-B. On the other hand, the coefficient of EJU import exposure remains positive and statistically insignificant.

Table 4–Impact of Import Competition from China on Plant Productivity (robustness tests)

Panel-A	Dep. Variable: $\Delta_5 lnPr_{ijt}$ (WLP)							
	Balanced Sample				OLS with Sector Fixed Effects			
	OLS		IV		OLS-LF200		OLS-LF100	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_5 CHN_{t-1}$	0.466***	0.487***	1.063***	1.124***	0.297*	0.326**	0.356**	0.375**
	(0.151)	(0.171)	(0.387)	(0.403)	(0.152)	(0.150)	(0.171)	(0.163)
$\Delta_5 EJU_{t-1}$		0.014		0.203		0.028		0.012
		(0.134)		(0.183)		(0.132)		(0.133)
$\Delta_5 LW_{t-1}$		0.207***		0.282***		0.082		0.073
		(0.072)		(0.080)		(0.106)		(0.109)
R-sq.	0.036	0.037	0.030	0.031	0.053	0.053	0.051	0.051
Obs. (n)	12110	12110	12110	12110	22569	22569	31842	31842
Panel-B	Dep. Variable: $\Delta_5 lnPr_{ijt}$ (LP)				Dep. Variable: $\Delta_5 lnPr_{ijt}$ (WLP)			
	Productivity based on LP				Import Ratios excluding RMs			
	OLS-LF200		IV-LF200		OLS-LF200		IV-LF200	
$\Delta_5 CHN_{t-1}$	0.335*	0.411**	0.796*	0.886**	0.377**	0.438**	0.863**	0.985**
	(0.194)	(0.206)	(0.433)	(0.441)	(0.181)	(0.199)	(0.420)	(0.459)
$\Delta_5 EJU_{t-1}$		0.185		0.312*		0.117		0.292
		(0.139)		(0.177)		(0.132)		(0.190)
$\Delta_5 LW_{t-1}$		0.140		0.202**		0.106		0.206*
		(0.093)		(0.092)		(0.100)		(0.110)
R-sq.	0.034	0.035	0.031	0.032	0.036	0.036	0.033	0.033
Obs. (n)	22569	22569	22569	22569	22569	22569	22569	22569

Notes: In Table 4, Panel-A reports the OLS and the IV estimates for the balanced sample (Columns 1-4) and the OLS with initial sector fixed effects estimates for the LF200 (Columns 5-6) and the LF100 (Columns 7-8) plants. In Panel-B, Columns 1-4 show the results for the LP based TFP and Columns 5-8 present the results for the WLP based TFP using an alternative measure of import exposure (excluding RM both from numerator and denominator). In the IV regressions, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. ** and * indicate significant at 5% and 10% level, respectively.

7.3 Robustness of the results on Productivity:

In this section, I investigate the robustness of the regression results for productivity. Table 4 shows the robustness test results for the two main specifications (equations 12 and 14) and the detailed results for all the specifications are presented in the online appendix. First, in order to address the concern that the results are not driven by plant entry and exit or missing data problem, I re-estimate the model with a balanced sample of plants (i.e. for which data are available for all the years from 1998 to 2009). In Panel-A of Table 4, Columns (1)–(2) show the OLS and Columns (3)–(4) show the IV estimates for the balanced sample (detailed results in Table A.7). Both the OLS and the IV estimates for the balanced sample are larger than their corresponding estimates for the LF200 and the LF100 plants reported in Table 3. For instance, in Panel-A of Table 4, the OLS coefficient of Chinese imports in Column (1) is 0.466 with a standard error of 0.151, whereas for the same specification, the baseline coefficient is 0.379 with a standard error of 0.186 (Column (1) Table 3).

Second, there is a concern that the change in import competition from China is likely to be correlated with the technological progress within sectors. To address this issue, Columns (5)–(8) show the results with sector (NIC 2-digit) fixed effects (detailed results in Table A.8). Given that our regressions are in difference form, incorporation of these fixed effects is equivalent to allowing for sector-specific differential trends in level form. In these specifications, I exclude the initial technology intensity dummies and replace them with the initial sector dummies. These specifications exploit the variations in import exposure across industries within sectors to identify the plant-level impacts of import competition shocks. It is observed that the magnitude of the estimated coefficients reduces in regressions with sector fixed effects compared to their corresponding estimates reported in Table 3. This is not surprising—if the industry-level import exposure is measured with error, inclusion of these sector-specific dummy variables may exacerbate attenuation bias in the import exposure coefficients. Moreover, as Acemoglu et al. (2016) point out, a rise in import competition in a particular industry within a sector may induce plants in other industries in the same sector to adjust to this shock in anticipation of a rise in competition.

In Panel-B of Table 4, Columns (1)-(4) show the results for plant productivity measured by the LP approach using the LF200 sample (detailed results in Table A.9). The coefficient (standard error) on exposure to Chinese imports is 0.335 (0.194) in case of specification 12 and is 0.411 (0.206) in case of specification 14. However, across all the specifications the estimated coefficient of ΔCHN_{t-1} is slightly smaller than their corresponding estimates for the WLP regressions.

In Panel-B, Columns (5)-(8) report the results for the alternative measure of import competition where raw materials are excluded from both numerator and denominator of the import exposure measure (Table A.10). In Column (5) of Panel-B, the coefficient (standard error) of Chinese import ratio is 0.377 (0.181), which is close to the baseline estimate (standard error) of 0.379 (0.186). In all cases, the estimates are very close to their corresponding estimates in Table 3.

Therefore, the baseline results are robust to a range of tests: the balanced sample specifications, the inclusion of initial sector specific fixed effects, the LP based productivity and the alternative measure of import competition. In the appendix (Table A.11) as an additional robustness check, I show that the four-year difference form regression results remain similar to Table 3. In order to check the sensitivity of the results to outliers in TFP, I report the regression results for the winsorized TFP series (Table A.12), where the β_1 coefficients are slightly larger than their corresponding estimates in Table 3. Thus, the presence of outliers in baseline TFP slightly underestimates the impact of Chinese competition on plant TFP. I also report the results for the LF20 sample that covers both the census and the sample plants of ASI (Table A.13). The coefficient (standard error) of ΔCHN_{t-1} is 0.366 (0.184) under OLS and is 0.840 (0.444) under IV for the baseline TFP series, and is 0.382 (0.182) under OLS and is 0.877 (0.435) under IV for the winsorized TFP series. Therefore, the main results hold even after the inclusion of the small plants in ASI, which are sampled randomly.

One important question that deserves special consideration is the effects of import competition on the productivity of multi-product plants. In Section 7.7, I show the results for both productivity and product scope based on the sample of the multi-product plants over the 2000-2005 period. In Table A.14, I report the productivity regression results for the multi-product plants over the 2000-2009 period.

7.4 Import Competition and Product Scope

The empirical results in the previous section provide evidence that Chinese import competition played an important role in increasing the revenue productivity of plants in India. The ensuing question is how plants have managed to improve their productivity in the face of heightened import competition. The theoretical models of multi-product firms suggest that in the face of changing trade costs firms can increase their productivity through rationalization of product scope. In this section, I investigate the impact of rising import competition from China on product scope of plants by replacing the dependent variable of the specification (14) with $\Delta_5 lnNp_{ijt}$,

$$\Delta_5 lnNp_{ijt} = \Delta_5\tau_{st} + \boldsymbol{\mu X_i} + \beta_1\Delta_5(M_{IN}^{CH})_{jt-l} + \beta_2\Delta_5(M_{IN}^{EJU})_{jt-l} + \beta_3\Delta_5(M_{IN}^{LW})_{jt-l} + \Delta_5\epsilon_{ijt}, \qquad (15)$$

where $\Delta_5 lnNp_{ijt}$ is the change in the log of number of products of plant *i* at time *t* compared to *t-5* and the rest of the variables are as defined earlier.

Endogeneity and Negative Supply Shocks: Plants may drop products for reasons unrelated to import competition but the decision may coincide with the rise in the Chinese import share in India in that particular industry. One such source of endogeneity is a negative supply shock.

Table 5–Impact of Import Competition from China on Plant Product Scope

	Block-A (LF200)						Block-B (LF100)	
	Baseline Specification			MP	Scope+1	ASICC	All	MP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel-A	**OLS Dep. Var.:** $\Delta_5 lnNp_{ijt}$							
$\Delta_5 CHN_{t-1}$	-0.101***	-0.100**	-0.097**	-0.115**	-0.070***	-0.097**	-0.049	-0.062
	(0.036)	(0.038)	(0.041)	(0.053)	(0.025)	(0.040)	(0.031)	(0.050)
$\Delta_5 EJU_{t-1}$		0.003	0.007					
		(0.050)	(0.054)					
$\Delta_5 LW_{t-1}$			0.013					
			(0.028)					
R-sq.	0.013	0.013	0.013	0.023	0.014	0.014	0.012	0.025
Panel-B	**2SLS Dep. Var.:** $\Delta_5 lnNp_{ijt}$							
$\Delta_5 CHN_{t-1}$	-0.145**	-0.146**	-0.145*	-0.242**	-0.098**	-0.166**	-0.061	-0.229**
	(0.069)	(0.072)	(0.076)	(0.108)	(0.048)	(0.074)	(0.075)	(0.104)
$\Delta_5 EJU_{t-1}$		-0.008	-0.007					
		(0.052)	(0.057)					
$\Delta_5 LW_{t-1}$			0.006					
			(0.032)					
R-sq.	0.013	0.013	0.013	0.022	0.013	0.014	0.012	0.024
Obs. (n)	18200	18200	18200	12670	18200	18200	26900	17193
Plants (n)	4807	4807	4807	3247	4807	4807	7640	4717
Indus. (n)	117	117	117	112	117	117	117	115
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$							
$F(1, cl^n)$	41.07	38.96	31.91	51.87	41.07	41.07	42.11	52.50

Notes: Table 5 reports the results for the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnNp_{ijt}$ on the lagged changes in China's, EJU's and other LW's import shares in India. In Panel-C, $\Delta_5 (M_{IDN}^{CH})_{jt-1-1}$ is used as an instrument for $\Delta_5 (M_{IN}^{CH})_{jt-1}$. Columns (1)–(6) include the LF200 and Columns (7)–(8) the LF100 plants, where Columns (4) and (8) show the results for the multi-product plants, Column (5) uses change in the log of product scope plus one and (6) uses product scope based on ASICC classification. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state-year fixed effects. Sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC industries included in the regression. ***, ** and * indicate significant at 1%, 5% and 10% level, respectively. $F(1, cl^n)$ denotes first stage F-stat and cl^n df (cluster-1).

For example, a negative supply shock may increase the marginal cost of producing a particular product, thereby causing the product to be unprofitable to produce. As a result, plants may drop the product. The reduction in supply by the domestic producers as a result of this negative supply shock can be replaced by increasing the supply of similar products from China.

7.5 Results: Impact on Product Scope

Table 5 shows the OLS and the IV regression results on product scope (i.e. the number of unique CPC-product codes). In Block-A of Panel-A, based on the LF200 sample, I observe that an increase in Chinese import exposure is associated with a decrease in the number of products. In Column (1), the coefficient of ΔCHN_{t-1} is -0.101 with a standard error of 0.036, which indicates that a 10 percentage point increase in exposure to Chinese import competition leads to a 1 percent decrease in the number of products sold by plants. Column (2) shows the results after adding ΔEJU_{t-1} and Column (3) shows the results after controlling for both ΔEJU_{t-1} and ΔLW_{t-1}. The inclusion of these other sources of import shocks has minimal effect on the estimated β_1 coefficient. The coefficients of both ΔEJU_{t-1} and ΔLW_{t-1} are not statistically significantly different from zero in all cases. Interestingly, after reducing the initial employment threshold to 100, in Block-B of Panel-A, the magnitude of the coefficient of Chinese import exposure diminishes in Column (7) compared to its corresponding estimate in Column (1) and appears to be statistically insignificant.

Panel-B of Table 5 presents the 2SLS estimates for product scope and Panel-C reports the F-statistics from the corresponding first stage regressions. Panel-C suggests that there is a strong first stage in all cases. For instance, the coefficient (standard error) of $\Delta_5(M_{IDN}^{CH})_{jt-1-1}$ is 0.560 (0.087) (showed in Table A.16) and the first stage F-statistics is 41.07 (Column 1 of Panel-C in Table 5). As observed in cases of productivity regressions, the coefficient of Chinese import exposure in each specification under 2SLS (Panel-B) appears to be larger than its OLS counterpart (Panel-A).

The estimated coefficient of Chinese imports is -0.145 with a standard error of 0.069 in Column (1) of Panel-B. The magnitude of this coefficient remains similar in regressions after controlling for other import shocks. However, similar to the OLS results, the coefficient of exposure to Chinese competition remains insignificant in Panel-B (Column 7) for the LF100 sample (details in Table A.16). Therefore, the IV results confirm the impact of Chinese competition on product scope of the LF200 or large plants only.

Overall, the results suggest that Chinese import competition induces plants to rationalize their product scope. But the impact is statistically significant only for the plants with at least 200 employees in the initial period. One plausible explanation for this finding is that a significant proportion of large plants in the ASI data were producing multiple products in the initial year. For instance, in 2000, approximately 68 percent of the large plants (with at least 200 employees) were producing more than one product (averaging 2.44 products per plant), whereas 48 percent of the small- and medium-sized plants (employing between 20 and less than 200 workers) were producing multiple products (averaging 1.83 products per plant). As a result, product level adjustment is more significant in the case of the large plants (LF200). On the other hand, the estimated relationship between the number of products and exposure to import competition from high-wage countries is statistically insignificant in all specifications under the OLS and the IV estimation. Similarly, there is no significant relationship between product scope and competition from other low-wage countries.

7.6 Robustness of the Results on Product Scope

To explore the robustness of the effects of Chinese import competition on the number of products sold by the plants, I test a series of alternative specifications (details in the online appendix). In Column (4) of Table 5, I restrict the sample to only those LF200 plants that are identified as multi-product plants (hereafter LF200MP) in their first appearance (between 2000 and 2009) in the ASI data. The estimated coefficient (standard error) of Chinese import exposure for the LF200MP sample is -0.115 (0.053) under OLS and -0.242 (0.108) under 2SLS (Column 4), where the latter is much larger in magnitude than that of the LF200 sample (Column 1 of Panel-B). Interestingly, in Column (8) of Panel-B, the magnitude of the 2SLS estimate (-0.229) for the LF100 multi-product plants (hereafter LF100MP) is more than three times larger than that of the sample of LF100 plants (Column 7 of Panel-B) and the coefficient is significant at 5% level (detailed results in Table A.17). In Column (5), the product scope is measured as the log of number of CPC products plus one (i.e. $\ln(Np_{ijt} + 1)$) and in Column (6) it is defined as the log of number of unique ASICC product codes. The main results are robust to alternative measures of product scope (Table A.18).

In the online appendix, I also show product scope results for the balanced sample (Table A.19), the specifications with the alternative measure of import exposure (Table A.20) and the LF20 sample (Table A.21). The results for these alternative specifications remain qualitatively similar to results obtained for the LF200 plants.

7.7 Productivity and Product Scope of Multi-product (MP) Plants

To further investigate the relevance of the main findings of this study in the context of the theoretical models of multiproduct firms, I show the results for the sample of LF200MP plants that are available in both 2000 and 2005 (i.e. periods before and after China's accession to WTO). Table 6 shows the OLS and the IV regression results for the changes in product scope (Columns 1-4) and productivity (Columns 5-8). The estimated coefficients (standard errors) of Chinese import exposure for the CPC and the ASICC based measures of product scope are -0.142 (0.085) and -0.212 (0.080) respectively under OLS and -0.374 (0.179) and -0.487 (0.195) respectively under IV. Similarly, the coefficients (standard errors) of exposure to Chinese imports for the WLP and the LP based measures of productivity are 0.867 (0.319) and 0.820 (0.324) respectively under OLS and 1.041 (0.433) and 0.901 (0.417) respectively under IV.

Table 6–Impact of Import Competition on Productivity and Product Scope (MP 2000-2005)

	Product Scope				Productivity			
	CPC-5 digit		ASICC		WLP		LP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(4)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
$\Delta_5 CHN_{t-1}$	-0.142*	-0.374**	-0.212***	-0.487**	0.867***	1.041**	0.820**	0.901**
	(0.085)	(0.179)	(0.080)	(0.195)	(0.319)	(0.433)	(0.324)	(0.417)
R-sq.	0.03	0.03	0.03	0.03	0.04	0.04	0.04	0.04
N	2395	2395	2395	2395	2395	2395	2395	2395

Notes: Table 6 shows the results for the OLS and the IV regressions of $\Delta_5 lnNp_{ijt}$ on $\Delta_5(M_{IN}^{CH})_{jt-1}$. In the IV regressions, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. All the regressions include a rural dummy, technology intensity dummies and state fixed effects. Plant specific sampling weights are applied in all regressions. ****, ** and * indicate significant at 1%, 5% and 10% level, respectively.

Interestingly, the magnitude of the coefficients of exposure to Chinese import increases considerably for the 2000-2005 period compared to their corresponding full sample results that are reported in tables (3)-(5). Overall, the results suggest that an intensification of import competition from China following its WTO accession has led to both a rationalization of product scope and an increase in productivity of multi-product plants over the 2000-2005 period.

8. Import Competition and Plant-product Level Adjustment

In the plant-level analysis, I find that a rise in import competition from China leads to both an improvement in revenue productivity and a rationalization of product range within plants. Together these two margins of adjustment at the plant-level suggest that reallocation of resources across products within-plant may be a potential channel of improvement in plant performance as predicted by the literature of multi-product firms. In order to test this channel, I investigate the impact of Chinese competition at the plant-product level.

8.1 Import Competition and Decision to Drop a Product:

In this section, I present an empirical framework of within-plant product selection mechanism guided by the theoretical models of multi-product firms. I relate a plant's decision to drop a product with the level of import competition in that particular product in the initial period. I construct a product-level measure of import competition by aggregating HS 6-digit product codes to their corresponding CPC 5-digit product categories. In the case of plant-product level response to trade shocks, product-specific measure of import competition provides a more direct measure of exposure to import competition than an industry-specific measure. The specification (16) given below jointly tests whether the probability of decision to drop a product increases due to an increase in Chinese import competition in that product and whether the chance of eliminating the product because of this trade shock is even higher for the one further away from a plant's core competence. This specification is broadly in line with previous studies on plant-product level adjustment (Iacovone, Rauch, and Winters, 2013 and Liu, 2010). For the purpose of analysis, the share of a product in total revenue from all products is used as a measure of distance from core competence: the higher the revenue share of a product the closer the product is to a plant's core competence (Eckel et al. 2015 and Eckel and Neary 2010).

$$D_{ikt} = \alpha + \tau_{st} + \rho_i + \beta_1 (M_{IN}^{CH})_{kt-5} + \beta_2 \left(M_{IN}^{EJU}\right)_{kt-5} + \gamma S_{ikt-5}$$

$$+\delta_1 (S_{ikt-5} \times (M_{IN}^{CH})_{kt-5}) + \delta_2 \left(S_{ikt-5} \times \left(M_{IN}^{EJU}\right)_{kt-5}\right) + \xi_{ikt} \qquad (16)$$

The dependent variable, D_{ikt}, is a dummy variable that equals 1 when a plant *i* produces a product *k* in period *t*-5 but does not produce it in period *t*, and 0 if the product is still in production in period *t*. To test whether a plant is less likely to drop a product that is close to its core competence, I add the variable S_{ikt-5}, the revenue share of product *k* of plant *i* in period *t*-5, in the main specification. The expected sign of the coefficient γ is negative, implying that a plant is less likely to drop a product, which is nearer to its core competence. The term ρ_i represents plant fixed effects and τ_{st} indicates state-year fixed effects. As the regression is based on pooled plant-product data, plant fixed effects control for any plant specific attributes that are constant across products within a given plant. I hypothesize that the sign of the coefficient of product-specific Chinese import $(M_{IN}^{CH})_{kt-5}$ exposure, β_1, is positive: the higher a product's (*k*'s) exposure to import competition from China, the greater is the likelihood that the plant drops the product in the subsequent period.

In order to explore whether import competition disproportionately affects products that are further away from the core competence, the revenue share of each product, S_{ikt-5} is interacted with the measures of import competition. The theoretical models of multi-product firms suggest that the coefficient of interaction terms, δ_1 and δ_2, are negative: while import competition increases the probability of dropping a product, a plant is less likely to drop the product if it is close to its core competence. For simplicity, I use CHN_t for $(M_{IN}^{CH})_{kt}$, EJU_t for $(M_{IN}^{EJU})_{kt}$ and LW_t for $(M_{IN}^{LW})_{kt}$.

8.2 Results: Impact on Decision to Drop a Product

Table 7 reports the plant-product level regression results based on the LF200 sample, where a plant's (*i*'s) decision to drop a product *k* in year *t* depends on the level of import competition at period *t*-5 and its interaction with the share of that product in total revenue at *t*-5. Columns (1)–(3) in Block-A show the OLS and Columns (4)–(6) in Block-B show the IV estimates. In the first stage, $(M_{IN}^{CH})_{kt-5}$ and $S_{ikt-5} \times (M_{IN}^{CH})_{kt-5}$ are instrumented by $(M_{IDN}^{CH})_{kt-5-1}$ and $S_{ikt-5} \times (M_{IDN}^{CH})_{kt-5-1}$, where $(M_{IDN}^{CH})_{kt-5-1}$ is (*t*-5)-1 lag of the Chinese import share in Indonesia for a particular product k and $(M_{IN}^{CH})_{kt-5}$ is t-5 lag of the Chinese import share for the product k in India. Panel-B reports the first stage F-statistics for the IV estimates in Block-B. All the regressions include plant fixed effects and state-year fixed effects. Standard errors are clustered by product codes. Results for the LF100 and the LF20 plants are presented in the online appendix. The first row shows the coefficients of the share of a product in period t-5, γ, in different specifications.

In Columns (1)-(3), the estimates of γ are negative and remain statistically significant in Columns (1) and (2) but turns insignificant in Column (3), after controlling for the trade shocks from other low-wage countries. The result implies that everything else constant, the higher the share of a product or the closer the product is to the core competence in the initial period (t-5), the less likely it is for the plant to drop the product in the current period (t).

The second row of Table 7 shows that the Chinese import share coefficient, β_1, is positive and statistically significant at least at 5 percent level in all the specifications. The third row reports the coefficient of the interaction term (δ_1) between the five-year lagged level of Chinese import competition and the share of the product in that period, which is negative in all the specifications. In Column (2) of Block-A, the baseline specification for the LF200 sample, the coefficient (standard error) of Chinese import ratio (β_1) is 0.224 (0.088) and the coefficient (standard error) of the interaction between the Chinese import share and the initial share of a product, δ_1 is -0.299 (0.159). Together these two coefficients imply that the impact of Chinese import exposure on the selection of a product depends on the position of the product within the portfolio of the plants.

Table 7–Impact of Import Competition on Decision to Drop a product (LF200)

	Block-A **OLS**			Block-B **IV**		
	Dependent Variable: Dropped (1 if dropped or 0 otherwise)					
	(1)	(2)	(3)	(4)	(5)	(6)
$S_{(ikt\text{-}5)}$	-0.215***	-0.129*	-0.105	-0.125**	0.005	0.061
	(0.050)	(0.070)	(0.067)	(0.062)	(0.095)	(0.106)
$CHN_{t\text{-}5}$	0.219**	0.224**	0.213**	0.787**	0.681**	0.788***
	(0.092)	(0.088)	(0.090)	(0.334)	(0.296)	(0.297)
$S_{(ikt\text{-}5)}\times CHN_{t\text{-}5}$	-0.243	-0.299*	-0.326**	-1.453***	-1.638***	-1.638***
	(0.151)	(0.159)	(0.134)	(0.422)	(0.495)	(0.463)
$EJU_{t\text{-}5}$		0.151**	0.149**		0.160**	0.166**
		(0.067)	(0.072)		(0.066)	(0.069)
$S_{(ikt\text{-}5)}\times EJU_{t\text{-}5}$		-0.261***	-0.301***		-0.338***	-0.413***
		(0.088)	(0.094)		(0.104)	(0.122)
$LW_{t\text{-}5}$			-0.112			-0.075
			(0.109)			(0.100)
$S_{(ikt\text{-}5)}\times LW_{t\text{-}5}$			0.022			-0.122
			(0.135)			(0.149)
Plant FE	Yes	Yes	yes	yes	yes	yes
R-squared	0.32	0.32	0.32	0.02	0.02	0.02
Obs.—36088, No. of Plants—4452, No. of Plant-product—14546, No of Product (cluster)—680						
Panel-B						
First Stage	Dep. Var (s): $(M_{IN}^{CH})_{kt-5}$ *and* $S_{ikt-5}\times(M_{IN}^{CH})_{kt-5}$ Instrument(s): $(M_{IDN}^{CH})_{kt-5-1}$ and $S_{ikt-5}\times(M_{IDN}^{CH})_{kt-5-1}$					
$(M_{IN}^{CH})_{kt-5}$	F (2, 679			8.9 (0.0)	8.5 (0.0)	11.0 (0.0)
$S_{ikt-5}\times(M_{IN}^{CH})_{kt-5}$	p-value)			8.4 (0.0)	6.0 (0.0)	7.3 (0.0)

Notes: Table 7 reports the OLS and the IV results from the regression of a dummy variable indicating whether a plant *i* drops a product *k* in year *t* on the level of China's, EJU's and LW's import shares in India in *t*-5 and their interactions with the share of that product in total revenue at *t*-5 using plant-product level data from 2000 to 2009 for the LF200 sample. Columns (1)–(3) show the OLS and Columns (4)–(6) the IV results. Standard errors (in parentheses) are clustered at product level (5-digit CPC product) level. All the regressions include plant fixed effects and state-year fixed effects. Plant specific sampling weights are applied in all regressions. In the first stage, $(M_{IN}^{CH})_{kt-5}$ and $S_{ikt-5}\times(M_{IN}^{CH})_{kt-5}$ are instrumented by $(M_{IDN}^{CH})_{kt-5-1}$ and $S_{ikt-5}\times(M_{IDN}^{CH})_{kt-5-1}$.

For example, a 10 percentage point increase in exposure to Chinese imports in a particular product increases the probability that the plant drops the product by 1.94 percentage point if the product holds only 10 percent share of plant revenue in the initial period (*t*-5). However, the same amount of increase in import exposure reduces the probability to drop a product by 0.45 percentage point for a product that holds 90 percent share of plant revenue. The results suggest that the impact of Chinese import competition is asymmetric across products. One remarkable feature of these results is that the asymmetry in plant-product level margin of adjustment to Chinese import competition remains robust both for the LF100 and the LF20 plants (Table A.24 and Table A.25).

In Block-B, I observed that the sign of the coefficients of the product level measure of Chinese import competition (β_1) and that of the associated coefficients of interaction (δ_1) remain unchanged but the magnitudes are much larger than their corresponding OLS coefficients. Therefore, the IV estimates magnify the asymmetric impact of import competition shocks. For example, in Column (5), for the sample of plants with at least 200 employees, the 2SLS estimate of β_1 is 0.681 and δ_1 is -1.638, implying that an increase in import competition from China in a particular product by 10 percentage point raises the probability of dropping the product by 5.2 percentage point if it holds only 10 percent share of revenue in the initial period. In contrast, the same amount of change causes 7.9 percentage point reduction in the probability to drop a product that contributes 90 percent share of total revenue from all products.

Another interesting observation is that import competition from EJU also has a similar impact on selection of products within-plant. The coefficient of EJU and its interaction with the share of a product in the initial period remains statistically significant at least at 5 percent level in all the specifications. In contrast, the sign of the coefficient of other LW import shock is negative and statistically insignificant in all cases. In the online appendix, I test sensitivity of the main results by performing plant-product fixed effects regression for the sample of LF200 plants (Table A.26). Although the magnitude and statistical significance of the coefficients weaken by the inclusion of plant-product fixed effects, the coefficient of exposure to Chinese import competition still remains significant at 10% level. The results for the OLS and the IV regressions with plant fixed effects for same sample of plants remain similar to baseline results. Overall, the findings suggest that the reallocation of resources across products within-plant may be a potential channel through which plants improve their performance in response to import competition as predicted by the literature of multi-product firms.

9. Concluding Remarks

In this study, I examine the impact of import competition from China on the performance of India's manufacturing plants through the lens of the theoretical framework of the multi-product firm models of trade (Eckel and Neary 2010; Bernard, Redding, and Schott 2011; Mayer, Melitz, and Ottaviano 2014). I use the ASI data on India's formal manufacturing sector plants from 1998 to 2009 survey, which contain detailed product level data from 2000 onwards. First, I document that the ASI data resemble the general cross-sectional features of multi-product firms predicted by the theoretical literature and are consistent with the characteristics of India's Prowess database (publicly listed firms) studied by GKPT (2010a) and U.S. census firms studied by BRS (2010). Next, I show that the Indian formal sector plants exhibit significant amount of creative destruction in the 2000s. The fact that India's manufacturing sector experienced a sharp rise in import competition from China in the 2000s provide a primary motivation to examine the role of this trade shock in the creative destruction process.

Using 1998-2009 ASI plant-level data, I find that the increase in Chinese imports exposure leads to an increase in plant revenue productivity measured by the WLP approach. In the next step, I explore the relationship between Chinese import competition and plant product scope using product-level data from 2000-2009. The results suggest that the plants reduce their product range in response to import competition from China. A further examination of the impact of Chinese competition on selection of products within plants finds that plants are more likely to drop a product that faces a heightened import competition from China but the closer the product is to the core competence of the plants the less likely it is to drop the product.

Overall, the findings in the paper suggest that trade with a low-wage country played an important role in the process of creative destruction in India. This process of creative destruction coincides with an improvement in the productivity (revenue based) of manufacturing firms in response to import competition shock from China. One interesting extension of the study is to investigate the role import competition in product quality upgrading. Another possible area of investigation is to explore the effects of intermediate input imports from China on plant performance.

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Online Appendix to

“Effects of Chinese Import Competition on Plant Productivity and Product Scope: Evidence from India”

Shubhasish Barua

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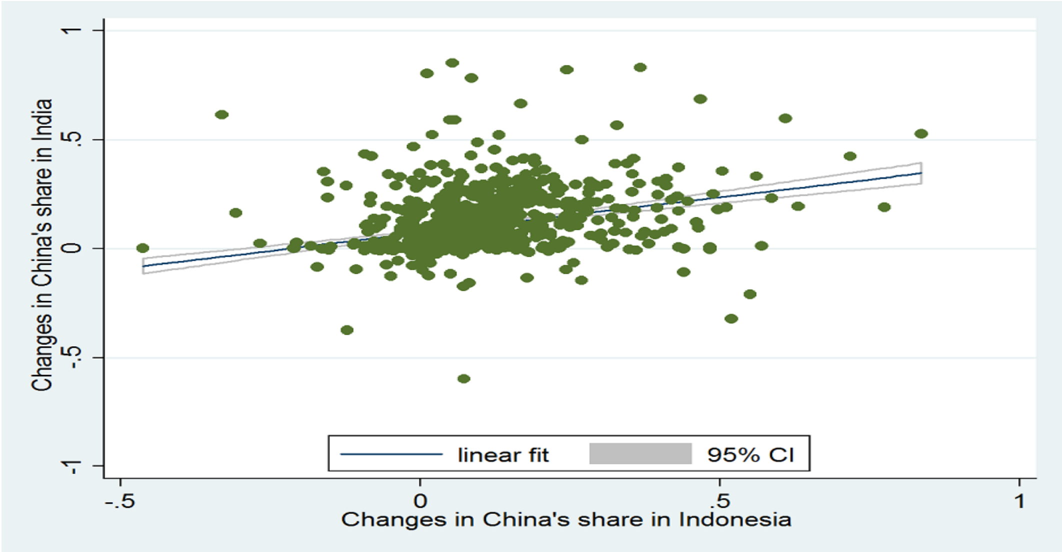
Figure A.1–Scatter Plot of Changes in Chinese Import Exposure in India and Indonesia



Note: The graph is a scatter plot of the five-year changes in China's share of India's imports and the lagged five-year changes in China's share of Indonesia's imports by industry from 2002 to 2009. Each dot represents a particular NIC 4-digit industry in a particular year. The line represents fitted values from the OLS regression.

A.1 Plant-level Data

In order to explore the impact of a low-wage country trade shock, I combine plant-level micro data from India with the country level bi-lateral commodity trade data from UN Comtrade. The source of plant-level data is the Annual Survey of Industries (ASI), a survey of formal sector manufacturing plants in India conducted by Central Statistical Office (CSO), a division of the National Statistical Office (NSO) under the Ministry of Statistics and Programme Implementation, Government of India.

The ASI sampling frame includes all the plants registered under Sections 2m(i) and 2m(ii) of the Factories Act, 1948: (i) factories that use power for manufacturing activities and employ more than 10 employees (ii) those that conduct manufacturing without power and employ more than 20 workers. The ASI also includes bidi and cigar factories satisfying one of the two criteria above and all the electricity generation plants. The sampling frame is based on the list of registered entities maintained by chief inspector of factories in each state. The frame is regularly updated on a periodic basis to include newly registered plants and exclude the de-registered ones.

Though the ASI is the principal source of statistics for the Indian manufacturing sector, and is increasingly popular among the applied micro researchers, there are important caveats of this dataset that need careful consideration. In general, the unit of the ASI survey is a plant in the case of manufacturing entities. However, plants owned by the same company can submit the return jointly if they operate in the same state and belong to same industry and sampling frame (census or sample). The ASI sampling frame is divided into census and sample sectors. I label these two categories as “census plants” and “sample plants”. Factories with employment above a given threshold are considered to be “census plants”, and they are surveyed each year. In addition, all the factories in less industrially developed states are always surveyed. The sample plants are randomly selected. I utilize the ASI sampling weight (inverse of the sampling frequency) for each plant in each year in all regression analysis. The employment threshold for the Census plants was 200 or more workers per plant for the year 1998 and 1999, which was reduced to 100 or more workers from the year 2000 onwards. The ASI reports the year of initial production for each plant and hence I can identify entrants and survivors. The ASI also provides information about the current status of the plant (open or closed or others) but this information is not enough to identify plant closure exactly. Identification of plant exit is also constrained by the fact that only a fraction of the sample plants is surveyed in each year.

The ASI plant data are available on the basis of the financial year. For example, the 1998-99 survey reports plant data for the financial year that starts on April 1998 and ends on March 1999. Throughout the paper, I refer the survey year 1998-99 as year 1998 and so on.

I use the plant-level ASI panel data from 1998-1999 to 2009-2010 period. The choice of period is based on following considerations. First, the main identification strategy set out in this paper is based on the sharp increase in bi-lateral trade between China and India, following China's WTO accession in December 2001. To evaluate the impact of this bi-lateral trade shock, I need plant-level panel data from India that cover the periods both before and after this event. Second, a common factory identifier for the ASI sample is available from 1998-1999 onwards, which allows me to use the panel data directly. Third, previous studies report that 1996-97 and 1997-98 data are not comparable with the rest of the sample owing to differences in sampling methodology and survey instrument; in addition, the 1995-96 survey was not conducted.[15]

[15] Few recent studies use this dataset for exploring the impact of various liberalization changes on firm performance see Sivadasan (2009); Harrison, Martin and Nataraj (2012); and Bollard, Klenow, and Sharma (2013) for recent works. Earlier studies used some form of matching method

I use only manufacturing units for the analysis, i.e. sectors 15 to 36 of NIC-2004 industry codes. I refer the full ASI manufacturing sample “ASI-all”, which includes all the “census plants” and “sample plants” after excluding non-manufacturing industries and the electricity generation and distribution sector. Plants report information about output, labor, capital, materials, fuels, and investment in each financial year. A large percentage of the plants (43 percent) belong to low-technology intensive industries, while only a small proportion of the plants (6 percent) belong to the high-technology category.

Table A.1A shows the distribution of “ASI-all” plants by usability across years. The table shows that plant-level variables such as output, labor, capital, materials, and fuels are missing for a significant proportion of plants. I treat a plant as missing in a given year if at least one of these variables is missing in the data. There are 417,006 plant-year observations in the “ASI-all” sample, of which around 14 percent of observations are coded as missing. The non-missing “ASI-all” sample includes 135,581 individual plants and 357,097 plant year observations, where 57,274 plants appear only once, and 2,160 plants appear in all the years (Table A.1B).

In addition to information about key plant-level variables, the ASI also reports plant location (state and rural/urban) and other characteristics such as type of organization, ownership and firm (multi plant or single plant). Plants report the opening and closing book values of fixed capital (net of depreciation) for each financial year. I measure capital as the average of opening and closing net book values of fixed capital in each year. Plants also report gross additions to fixed capital,

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to construct an imperfect panel of survey data prior to 1998-1999 (excluding the years mentioned above), which is then added with the panel dataset with common factory codes from 1998-1999 onwards.

which I use as the main measure of investment. Both capital and investment are deflated by the WPI of machinery.

Table A.1A–Distribution of ASI plants

Year	ASI-all	Useable	Missing (percent)
1998	22799	19129	16.1
1999	23541	19988	15.1
2000	29680	25546	13.9
2001	31929	27744	13.1
2002	32234	28105	12.8
2003	43265	37251	13.9
2004	37863	32163	15.1
2005	41540	35259	15.1
2006	41533	35604	14.3
2007	36827	31627	14.1
2008	36110	30850	14.6
2009	39685	33831	14.8
Total	417006	357097	14.4

Only open plants are considered in the ASI-all Sample. In addition, a small fraction of plants with non-missing observations is also treated as open. Plants are coded as missing if at least one of the key variables (i.e. output, labor, capital, materials, and fuels) is missing. Only manufacturing sector plants (NIC 2-digit sector 15 to 36) are included.

Table A.1B–Frequency Distribution of Non-missing ASI-all plants

Frequency	Observations	Plants	Percent
(1)	(2)	(3)	(4)
1	57274	57274	42.24
2	65960	32980	24.32
3	53223	17741	13.09
4	35956	8989	6.63
5	23800	4760	3.51
6	17532	2922	2.16
7	14147	2021	1.49
8	14744	1843	1.36
9	15489	1721	1.27
10	18180	1818	1.34
11	14872	1352	1.00
12	25920	2160	1.59
Total	357097	135581	100.00

The table shows the distribution of non-missing ASI plants by frequency of appearance. Each row in Column (3) shows the number of plants against their corresponding frequency in Column (1).

The real value added is computed as the difference between real output and real values of intermediate inputs. Total output includes the values of all products- and by-products, the increase in the stock of semi-finished goods and the other income.[16] Real output of a plant is obtained by deflating total output with the corresponding WPI of the 3-digit NIC industry. Inputs include the costs of materials and fuels. The value of materials is deflated by the materials price deflator of the corresponding NIC 3-digit industry constructed by combining WPIs with India's Input-Output Table transaction table. The value of fuels is deflated by the WPI for fuel price.

Labor employed by the plant is categorized into blue-collar or production employees and white-collar or non-production employees. The ASI further classifies blue-collar labor into regular and contractual workers. The number of blue-collar workers is calculated as the average number of production workers employed in the plant in a given year; and the number of white-collar workers is the difference between the average number of total employees and the average number of blue-collar workers. In the ASI data, white-collar workers are comprised of supervisors, managers and all other non-production employees.

In terms of initial employment (LF), a significant percentage of the ASI-all (non-missing) sample plants are small: around 34 percent of the plants employ less than 20 employees in the initial year.[17] Therefore, about 66 percent of the plants report at least 20 employees, where only around 20 percent of the plants employ more than 200 employees in the beginning year. In this paper, I am primarily interested in the impact of Chinese competition on medium and large plants.

[16] I follow the ASI tabulation manuals to construct the plant-level value of output and input measures.

[17] I consider initial employment as the total number employees reported by a plant when it is observed for the first time in the ASI data (1998-2009).

Therefore, I exclude all small-sized plants from the baseline sample. All the key inputs and output variables are winsorized at 1st and 99th percentiles by NIC 2-digit sector.

Table A.2A–Distribution of Plants by NIC 2-digit Sector and Technology Intensity

NIC 2-digit	Sector Name	Technology				
		High-tech.	Medium-high-tech.	Medium-low-tech.	Low-tech.	Total
15	Food products & beverages				62500	62500
16	Tobacco products				6778	6778
17	Textiles				33106	33106
18	Wearing apparel; dressing & dyeing				10531	10531
19	Leather, luggage, footwear				6532	6532
20	Wood & wood products				7301	7301
21	Paper & paper products				10878	10878
22	Publishing, printing				7184	7184
23	Coke, refined petroleum prod.			3496		3496
24	Chemicals & chemical prod.	9649	25481			35130
25	Rubber & plastic prod.			17471		17471
26	Other non-metallic mineral prod.			36193		36193
27	Basic metals			22564		22564
28	Fabricated metal prod.			19580		19580
29	Machinery & equipment n.e.c.		27418			27418
30	Office, acc. & comp. machinery	937				937
31	Electrical machinery & appa. n.e.c.		14279			14279
32	Radio, TV & comm. Equipment	4616				4616
33	Medical, precision & optical instr.	4881				4881
34	Motor vehicles, trailers & semi-trail		10450			10450
35	Other transport equipment	152	6142	564		6858
36	Furniture, manufacturing n.e.c.				8414	8414
		20235	83770	99868	153224	357097

Notes: Table A.2B shows the distribution of non-missing ASI-all plants by sector (NIC 2-digit) and technology (R&D) intensity. Technology classification of industries is based on OECD (2011) definition.

Table A.2B– Coefficients of the Production Function (WLP) by NIC 2-digit Sector

		Estimated Coefficients		
NIC 2-digit	Sector Name	log of blue-collar labor input $\hat{\beta}_b^s$	log of white-collar labor input $\hat{\beta}_w^s$	log of the capital stock $\hat{\beta}_k^s$
15	Food products & beverages	0.291	0.337	0.394
16	Tobacco products	0.317	0.352	0.124
17	Textiles	0.120	0.218	0.479
18	Wearing apparel; dressing & dyeing	0.007	0.441	0.368
19	Leather, luggage, footwear	0.416	0.146	0.417
20	Wood & wood products	0.288	0.488	0.432
21	Paper & paper products	0.218	0.322	0.508
22	Publishing, printing	0.100	0.531	0.352
23	Coke, refined petroleum prod.	0.316	0.279	0.299
24	Chemicals & chemical prod.	0.202	0.368	0.472
25	Rubber & plastic prod.	0.184	0.354	0.416
26	Other non-metallic mineral prod.	0.144	0.352	0.280
27	Basic metals	0.258	0.223	0.378
28	Fabricated metal prod.	0.191	0.304	0.502
29	Machinery & equipment n.e.c.	0.226	0.432	0.570
30	Office, acc. & comp. machinery	0.208	0.215	0.673
31	Electrical machinery & appa. n.e.c.	0.395	0.359	0.449
32	Radio, TV & comm. Equipment	0.332	0.689	0.541
33	Medical, precision & optical instr.	0.056	0.536	0.625
34	Motor vehicles, trailers & semi-trail	0.216	0.360	0.524
35	Other transport equipment	0.256	0.259	0.444
36	Furniture, manufacturing n.e.c.	0.305	0.562	0.464

Notes: Table A.2B reports estimated coefficients of the production function for each NIC 2-digit sector based on the Wooldridge-Levinsohn-Petrin (WLP) approach.

A.2 Plant-Product-level Data

In the ASI survey, products are identified by the ASI Commodity Classification (ASICC) system. Plants report values of products and by-products produced in a given financial year against specific ASICC product codes.[18] Based on the information, I construct plant-product level panel data from 2000 to 2009 to investigate the product level adjustment within plants in response to trade shocks. Though the ASICC is a very detailed product classification scheme, it is developed independently of the other internationally recognized product and industrial (NIC) classification systems. As a result, under the ASICC scheme it is not possible to establish a one-to-one relationship between these two variables.

There are two main versions of ASICC classification: ASICC-1998 and ASICC-2008-09. In the ASI data all product-specific information are coded by ASICC-1998 from 1998 to 2009 and ASICC-2008-09 from 2008 to 2009. The Central Statistics Office (CSO) of India introduced a new 7-digit product classification system to record all input and output items of the plants from 2010-11 survey onwards. This new classification system is known as National Product Classification for Manufacturing Sector-2011 (NPCMS). The NPCMS-2011 is a 7-digit extension of the 5-digit the Central Product Classification (CPC), a reference classification of the United Nations. In order to analyze the product switching decision in light of the existing literature and in the context of international trade, it is useful to convert the ASICC codes into an internationally recognized product classification system. Fortunately, ASICC 2008-09 product codes can be mapped to CPC version-2 codes. Since I can also measure trade shock at CPC product level, redefining ASICC products into CPC level allows me to directly relate product switching decisions at the factory level with product level trade exposure.

[18] ASICC is a 5-digit product classification system.

I aggregate the ASICC products to CPC products in two steps. First, I map all the ASICC-1998 product codes into their corresponding ASICC-2009 counterpart to identify the products under a unique ASICC version. In the second stage, I collapse all the ASICC products to CPC products by using the concordance from ASICC-2009 to NPCMS-2011 published by CSO.

Moreover, in some cases a plant uses same ASICC code to report multiple rows of data.[19] Perhaps these products are identifiable at lower level of aggregation, hence different from one another in terms of their prices and quality, nonetheless falls within the same ASICC product category. So, I aggregate multiple rows of same ASICC codes and keep a single ASICC codes per plant per year.

[19] Some plants report a fraction of their output under other-products and by-products category (ASICC-99). Thus, I treat the products under this category as a single ASICC product. However, I exclude other-products and by-products category from the product-switching analysis as this code cannot be matched to a unique CPC product code.

A.3 Proportion of Multiple Products Plants (in 2000):

In the main text, Table 1 shows that around 50 percent of the ASI plants produce more than one product (CPC 5-digit). Rows (2) and (3) of Table 1, indicate that 38 percent and 28 percent (Column 1) of the ASI plants manufacture products that fall into more than one class (i.e. 4-digit CPC) and division (i.e. 2-digit CPC) of CPC products, contributing 65 percent and 48 percent (Column 2) of total manufacturing output, respectively.[20] These figures are also consistent with GKPT (2010a), where 33 percent and 24 percent of the plants produce multiple-industry and multiple-sector products and account for 62 percent and 54 percent of output shares, respectively. In contrast, only 10 percent of U.S. firms operate in multiple sectors but they produce 66 percent of total output. Therefore, both the ASI and the Prowess data show that plants/firms in India are more likely to operate in more than one segments but these multiple division plants account for relatively lower share of output compared to firms in U.S.

A.4 Comparison between Multi-Product and Single-Product Plants

One of the key predictions of multiproduct model is that higher productivity firms produce a larger range of products than the lower productivity firms. In BRS (2010) higher productivity firms derive higher revenues per product, therefore can manage the fixed costs of a larger range of products. Table A.3 shows a comparison between multi-product and single-product plants in India using the ASI data in 2000.[21] The table suggests that within the same industry, the multi-product plants are significantly larger than the single-product plants in terms of all the measures of plant

[20] Based on ASICC product classification, 52 percent of the plants in the ASI data produce more than one product and 77 percent of the output.

[21] Results for the other years are similar. The year 2000 is selected for reporting purposes to compare the results with GKPT (2010a) and BRS (2010).

size. In the same industry, multi-product plants produce 95 percent higher output and employ 54 percent more labor than single-product plants.

Table A.3–Comparison Between Multi-Product and Single-Product Plants

	(1)	(2)	(3)
Variable	MpC	MpI	MpS
Output (Y)	0.95	0.70	0.54
Value Added (RVA)	0.99	0.77	0.60
Employment (L)	0.54	0.48	0.40
Labor Productivity (L_P)	0.30	0.20	0.14
TFP	0.09	0.03	0.01

Notes: Each row in this table reports the results from regression of a plant-level outcome measure on a dummy variable indicating whether the plant produces multiple CPC 5-digit (MpC), CPC 4-digit (MpI) and CPC 2-digit (MpS) products respectively while controlling for plants' main industry fixed effects. Numbers reported in each cell are in percent form. Robust standard errors are clustered at the level of plants' main industry. The ASI data for 2000 is used in this Table. TFP is estimated by Wooldridge-Levinsohn-Petrin approach. All the coefficients are significant at 1 percent level, except the log of L_P in MpS, which is significant at 5 percent and TFP in MpI and MpS, which are insignificant.

Table A.3 also indicates that MpC plants outperform their single-product counterparts both in terms of revenue based TFP and labor productivity. In the same industry MpC plants have 9 percent higher TFP than SpC plants. The TFP coefficient is much larger than the corresponding estimates in GKPT (2010a) and BRS (2010), where it is reported as 1 percent and 2 percent, respectively. The results are similar for plants producing multiple class (MpI) and division (MpS) of CPC products. Although the TFP difference is relatively smaller for MpI and MpS plants and statistically insignificant, they are greater than GKPT (2010a) and BRS (2010) estimates.[22]

Table A.4–Distribution of Product Outputs Within-plant

		Number of CPC 5-digit products produced by the plant									
		1	2	3	4	5	6	7	8	9	10
Average share of a product in total sales	1	100	92	80	73	67	61	57	53	49	46
	2		8	16	18	20	21	21	20	20	19
	3			3	6	8	10	11	11	12	12
	4				2	4	5	6	7	7	8
	5					1	2	3	4	5	5
	6						1	2	2	3	4
	7							1	1	2	3
	8								1	1	2
	9									1	1
	10										1

Notes: Table shows the heterogeneity in distribution of products within-plant in the sample (2000-2009) comprising plants that produce up to 10 products (CPC 5-digit). Columns indicate the number of products produced by the plants. Rows indicate the share of the products in total sale of the plants. Each cell is the average share of a product within the set of products produced by the plant.

Another key prediction of multi-product firm model (BRS 2010; Eckel and Neary 2010) is that the firm's output is skewed towards its core competence. Table A.4 represents the average share of a product in total sales of the plants, where products are sorted in terms of their output share in descending order. I show the results for the plants producing up to ten products (CPC 5-digit). These plants represent 99.89 percent of the LF20 sample. The table portrays the evidence of product heterogeneity within plants in line with the prediction of multi-product firm models. As in BRS (2010) and GKPT (2010a), distribution of the ASI product-level data also shows high

[22] The TFP coefficient for MpI plants ranges from 4 percent to 9 percent from 2001 to 2009 and remains statistically significant in most cases. For MpS plants it ranges from 0 percent to 8 percent from 2001 to 2008 but turns negative (1 percent) in 2009 though statistically insignificant.

skewness. The average share of the largest product declines gradually as the number of product increases: starting from 92 percent for plants producing two products to 46 percent for plants producing 10 products. These figures are close to the corresponding figures reported in GKPT (2010a): 86 and 46 percent, respectively.

Table A.5–Proportion of Multi-product Plants in the Sample

	Percentage of Plants			Average CPC Products			Average
Year	MpC	MpI	MpS	5-digit	4-digit	2-digit	ASICC Product
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2000	50	38	28	1.91	1.61	1.37	2.09
2001	51	40	31	1.93	1.65	1.41	2.14
2002	51	41	32	1.90	1.66	1.42	2.12
2003	51	41	33	1.94	1.69	1.44	2.13
2004	51	41	33	1.92	1.68	1.44	2.13
2005	49	38	30	1.88	1.62	1.39	2.07
2006	47	37	30	1.85	1.61	1.39	2.02
2007	46	36	29	1.87	1.61	1.39	2.00
2008	46	36	28	1.82	1.59	1.38	1.98
2009	44	34	27	1.78	1.55	1.35	1.93
2000-2004	51	40	31	1.92	1.66	1.41	2.12
2005-2009	46	36	29	1.84	1.60	1.38	2.00

Notes: In this table, MpC, MpI and MpS respectively denote the plants producing multiple CPC 5-digit products, 4-digit class and 2-digit division. The first three columns show the share of MpC, MpI and MpS plants in the ASI data. The final column shows the average number ASICC products produced by the plants. Figures in the Table are adjusted for sampling weights. The patterns of unweighted figures are similar.

Table A.5 looks at the time series pattern of the proportion of multi-product plants and the mean number of products from 2000 to 2009. The last two rows show that the proportion of multi-product plants in the ASI data decreased from 51 percent on average in 2000-04 to 46 percent in 2005-09 period.[23] This pattern is also reflected in the percentage of multiple CPC-class and

[23] This pattern is also consistent with the un-weighted mean of the sample.

division plants. In a similar pattern, the average number of 5-digit, 4-digit and 2-digit products decline from 2004 onwards though the changes are marginal. Column (4) shows that the mean number of CPC 5-digit products produced by the plants decreased from 1.92 in 2000-04 to 1.84 in 2005-09 period. The observed downward trends in the proportion of multi-product plants and the mean number of products suggest that, overall, Indian plants were shrinking their product range in the second half of 2000s. GKPT (2010a) report that the average number of products increased from 1.4 in 1989 to around 2.3 in 2003. The question of interest is what has caused this turnaround at the aggregate level. In this paper, I find that changes in competitive environment in India driven by the rising share of Chinese imports induced plants to shrink their product range.

A.5 Construction of Product Switching Activity Variables

The product switching analysis is based on the plants for which data are available both in the beginning and end point of a period. I categorize the plants into four mutually exclusive activities: N, A, D and AD. The group "N" only includes the plants that keep their product mix unaltered over time or take "no action". The group "A" contains plants that "only add" products and "D" includes plants that "only drop" products. The "AD" group comprises plants that "both add and drop" products at the same time. A plant is considered as belonging to group "A" if it adds at least one product in period t that is not produced in period $t - \tau$ and it does not drop any product over the same time. Similarly, a plant is considered as belonging to group "D" if it drops at least one product in period t that is produced in $t - \tau$ and it does not add any product in the same period. In all cases τ represents a lag time period (e.g. 1, 5).

A.6 UN Comtrade Data:

I use country level bi-lateral imports data from the UN Comtrade database, which records various trade statistics at the HS 6-digit product level. The primary measure of import competition is constructed from bi-lateral import data for India (as a reporter country), which are available by HS 1996 classification. Country level HS 6-digit data are combined to construct the country-group level trade data. I use yearly sample from 1996 to 2009 to construct the value share of import by different source region: China, EU-Japan-US and other low-wage countries. Bi-lateral imports data for Indonesia are also available at HS 1996 level and therefore the same procedure is followed to construct the share of China in Indonesia's industry-specific imports. Trade data for all the EU member countries, Japan and U.S. are available in HS 1996 classification.

The product level trade data is then aggregated to industry-level by using HS 6-digit to ISIC review 3.1 concordance file provided by World Integrated Trade Solution, WITS. HS 6-digit products are classified into raw materials, intermediate goods, consumer goods and capital goods using the HS-standard product group classification provided by WITS.[24]

A.7 Concordance between Industry and Trade data:

In the ASI data industrial classification of the plants are reported according to 5-digit National Industrial Classification NIC-2004 from 1998-99 to 2007-08 and NIC-2008 from 2008-09 onwards. NIC follows International Standard Industrial Classification (ISIC) up to 4-digit level. Specifically, NIC-2004 is the 5-digit extension of the 4-digit ISIC-3.1 and similarly NIC-2008 is that of 4-digit ISIC-4.1. To obtain a unique 4-digit industry coding for the full sample, I convert the NIC-2008 codes for 2008 and 2009 sample to their NIC-2004 counterparts using the ISIC-4 to

[24] WITS tables are available at http://wits.worldbank.org/referencedata.html

ISIC-3.1 concordance provided by the United Nations Statistics Division.[25] Therefore, all the plants are identified by a unique NIC 4-digit (2004) industry code.

[25] http://unstats.un.org/unsd/cr/registry/regdnld.asp?Lg=1

Table A.6–Impact of Import Competition on Plant Productivity (IV with First Stage)

	LF200 Sample					
	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage	IV	First Stage	IV	First Stage	IV
$\Delta_5(CHN_{IDN})_{(t-1)-1}$	0.555***		0.530***		0.522***	
	(0.076)		(0.083)		(0.089)	
$\Delta_5 CHN_{t-1}$		0.865**		0.917**		0.948**
		(0.428)		(0.442)		(0.438)
$\Delta_5 EJU_{t-1}$			-0.185***	0.218	-0.218***	0.285
			(0.057)	(0.170)	(0.063)	(0.174)
$\Delta_5 LW_{t-1}$					-0.105***	0.198**
					(0.037)	(0.093)
R-squared	0.399	0.033	0.441	0.033	0.455	0.033
N	22569	22569	22569	22569	22569	22569
	LF100 Sample					
$\Delta_5(CHN_{IDN})_{(t-1)-1}$	0.518***		0.498***		0.489***	
	(0.069)		(0.072)		(0.077)	
$\Delta_5 CHN_{t-1}$		0.761*		0.794*		0.817*
		(0.442)		(0.456)		(0.455)
$\Delta_5 EJU_{t-1}$			-0.201***	0.166	-0.237***	0.221
			(0.059)	(0.175)	(0.066)	(0.192)
$\Delta_5 LW_{t-1}$					-0.113***	0.160
					(0.038)	(0.115)
R-squared	0.380	0.031	0.431	0.031	0.447	0.031
N	31842	31842	31842	31842	31842	31842

Notes: Columns (1), (3) and (5) of Table A.6 show first stage estimates for the 2SLS regression results presented in Panel-B of Table 3 in the main text. Results for the 2SLS regressions are also repeated here for comparison in Columns (2), (4) and (6). Panel-A and Panel-B respectively present the results for the LF200 and the LF100 plants. The main right-hand side variables in Columns (1), (3) and (5) is $(t-1)-1$ lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ and the dependent variable is $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. Columns (2), (4) and (6) report the results for the 2SLS regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in TFP) on the lagged changes in China's, EJU's and other LW's import shares in India. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. ** and * indicate significant at 5% and 10% level, respectively.

Table A.7–Impact of Import Competition on Plant Productivity (Balanced)

Panel-A	**Block-A**			**Block-B**		
OLS Dep. Var:	$\Delta_5 lnPr_{ijt}$ (WLP approach)			$\Delta_5 lnPr_{ijt}$ (LP approach)		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_5CHN$_{t-1}$	0.466***	0.446**	0.487***	0.419***	0.405**	0.448**
	(0.151)	(0.181)	(0.171)	(0.153)	(0.184)	(0.175)
Δ_5EJU$_{t-1}$		-0.054	0.014		-0.037	0.035
		(0.134)	(0.134)		(0.136)	(0.137)
Δ_5LW$_{t-1}$			0.207***			0.217***
			(0.072)			(0.068)
R-squared	0.036	0.036	0.037	0.034	0.034	0.035
Panel-B	**IV (2SLS)**					
2SLS	$\Delta_5 lnPr_{ijt}$ (WLP approach)			$\Delta_5 lnPr_{ijt}$ (LP approach)		
Δ_5CHN$_{t-1}$	1.063***	1.091***	1.124***	0.953**	0.981**	1.014**
	(0.387)	(0.417)	(0.403)	(0.398)	(0.429)	(0.415)
Δ_5EJU$_{t-1}$		0.115	0.203		0.114	0.202
		(0.183)	(0.183)		(0.187)	(0.189)
Δ_5LW$_{t-1}$			0.282***			0.284***
			(0.080)			(0.079)
R-squared	0.030	0.030	0.031	0.030	0.030	0.031
Obs. (n)	12110	12110	12110	12110	12110	12110
Plants (n)	1730	1730	1730	1730	1730	1730
Indus. (n)	112	112	112	112	112	112
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$					
Ad. R-sq.	0.40	0.46	0.47	0.40	0.46	0.47
F (1,111)	63.10	44.06	38.28	63.10	44.06	38.28

Notes: Table A.7 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in TFP) on the lagged changes in China's, EJU's and other LW's import shares in India based on the balanced sample. Columns (1)–(3) in Block-A report the results for the WLP and Columns (4)–(6) in Block-B report the results for the LP based productivity. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. F (1,111) indicates first stage F-stat. ***, ** and * indicate significant at 1%, 5% and 10% level, respectively.

Table A.8–Impact of Import Competition on Plant Productivity (Sector Fixed Effects)

	Block-A (LF200)			Block-B (LF100)		
Panel-A	**OLS** Dep. Variable: $\Delta_5 lnPr_{ijt}$ (WLP approach)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 CHN_{t-1}$	0.297*	0.295*	0.326**	0.356**	0.348**	0.375**
	(0.152)	(0.159)	(0.150)	(0.171)	(0.169)	(0.163)
$\Delta_5 EJU_{t-1}$		-0.005	0.028		-0.018	0.012
		(0.139)	(0.132)		(0.135)	(0.133)
$\Delta_5 LW_{t-1}$			0.082			0.073
			(0.106)			(0.109)
R-squared	0.045	0.044	0.045	0.045	0.044	0.045
Panel-B	**2SLS** Dep. Variable: $\Delta_5 lnPr_{ijt}$ (WLP approach)					
Obs. (n)	22569	22569	22569	31842	31842	31842
Plants (n)	4961	4961	4961	7874	7874	7874
Indus. (n)	118	118	118	118	118	118

Notes: Table A.8 reports the results from the OLS (Panel-A) regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in TFP) on the lagged changes in China's, EJU's and other LW's import shares in India with 2-digit initial sector specific fixed effects. Columns (1)–(3) in Block-A include only the LF200 and Columns (4)–(6) in Block-B include the LF100 plants. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, NIC 2-digit (initial sector) dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. ** and * indicate significant at 5% and 10% level, respectively.

Table A.9–Impact of Import Competition on Plant Productivity (LP approach)

	Block-A (LF200)			Block-B (LF100)		
Panel-A	**OLS** Dep. Variable: $\Delta_5 lnPr_{ijt}$ (LP approach)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 CHN_{t-1}$	0.335*	0.381*	0.411**	0.324	0.362	0.390*
	(0.194)	(0.212)	(0.206)	(0.200)	(0.220)	(0.221)
$\Delta_5 EJU_{t-1}$		0.135	0.185		0.109	0.155
		(0.140)	(0.139)		(0.137)	(0.153)
$\Delta_5 LW_{t-1}$			0.140			0.129
			(0.093)			(0.112)
R-squared	0.034	0.034	0.035	0.030	0.030	0.030
Panel-B	**2SLS** Dep. Variable: $\Delta_5 lnPr_{ijt}$ (LP approach)					
$\Delta_5 CHN_{t-1}$	0.796*	0.855*	0.886**	0.669	0.706	0.732
	(0.433)	(0.445)	(0.441)	(0.448)	(0.459)	(0.459)
$\Delta_5 EJU_{t-1}$		0.244	0.312*		0.189	0.250
		(0.173)	(0.177)		(0.175)	(0.196)
$\Delta_5 LW_{t-1}$			0.202**			0.176
			(0.092)			(0.122)
R-squared	0.031	0.032	0.032	0.029	0.029	0.029
Obs. (n)	22569	22569	22569	31842	31842	31842
Plants (n)	4961	4961	4961	7874	7874	7874
Indus. (n)	118	118	118	118	118	118
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$					
Ad. R-sq.	0.39	0.44	0.45	0.38	0.43	0.44
F (1,117)	53.44	40.90	34.29	56.79	47.72	39.96

Notes: Table A.9 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in TFP based on the LP approach) on the lagged changes in China's, EJU's and other LW's import shares in India. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$. Columns (1)–(3) in Block-A include only the LF200 and Columns (4)–(6) in Block-B include the LF100 sample. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. F (1,117) indicates first stage F-stat. ** and * indicate significant at 5% and 10% level, respectively.

Table A.10–Impact of Import Competition on Plant Productivity (alternative import ratio)

	Block-A (LF200)			Block-B (LF100)		
Panel-A	**OLS** Dep. Variable: $\Delta_5 lnPr_{ijt}$ (WLP approach)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 CHN_{t-1}$	0.377**	0.405**	0.438**	0.399**	0.418**	0.441**
	(0.181)	(0.204)	(0.199)	(0.187)	(0.209)	(0.213)
$\Delta_5 EJU_{t-1}$		0.075	0.117		0.049	0.080
		(0.133)	(0.132)		(0.130)	(0.142)
$\Delta_5 LW_{t-1}$			0.106			0.078
			(0.100)			(0.113)
R-squared	0.036	0.036	0.036	0.032	0.033	0.033
Panel-B	**2SLS OLS** Dep. Variable: $\Delta_5 lnPr_{ijt}$ (WLP approach)					
$\Delta_5 CHN_{t-1}$	0.863**	0.930**	0.985**	0.768*	0.808*	0.845*
	(0.420)	(0.450)	(0.459)	(0.435)	(0.464)	(0.476)
$\Delta_5 EJU_{t-1}$		0.213	0.292		0.152	0.212
		(0.176)	(0.190)		(0.178)	(0.206)
$\Delta_5 LW_{t-1}$			0.206*			0.154
			(0.110)			(0.132)
R-squared	0.033	0.032	0.033	0.031	0.031	0.031
Obs. (n)	22569	22569	22569	31842	31842	31842
Plants (n)	4961	4961	4961	7874	7874	7874
Indus. (n)	118	118	118	118	118	118
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$					
Ad. R-sq.	0.39	0.44	0.46	0.37	0.43	0.46
F (1,117)	51.03	39.33	31.93	54.55	46.84	38.99

Notes: Table A.10 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in TFP) on the lagged changes in China's, EJU's and other LW's import shares in India based on the alternative measure of import competition, where raw materials are excluded from both numerator and denominator of import exposure measure. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$. Columns (1)–(3) in Block-A include only LF200 and Columns (4)–(6) in Block-B include LF100 plants. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. F (1,117) indicates first stage F-stat. ** and * indicate significant at 5% and 10% level, respectively.

Table A.11–Impact of Import Competition on Plant Productivity (four-year difference)

	Block-A (LF200)			**Block-B (LF100)**		
Panel-A	**OLS** Dep. Variable: $\Delta_4 lnPr_{ijt}$ (WLP approach)					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_4CHN$_{t-1}$	0.361**	0.409**	0.415**	0.387**	0.405**	0.413**
	(0.175)	(0.185)	(0.181)	(0.176)	(0.194)	(0.193)
Δ_4EJU $_{t-1}$		0.112	0.118		0.041	0.050
		(0.122)	(0.119)		(0.117)	(0.118)
Δ_4LW$_{t-1}$			0.032			0.038
			(0.055)			(0.068)
R-squared	0.034	0.035	0.035	0.031	0.031	0.031
Panel-B	**2SLS OLS** Dep. Variable: $\Delta_4 lnPr_{ijt}$ (WLP approach)					
Δ_4CHN$_{t-1}$	0.771*	0.837*	0.857*	0.735*	0.767	0.786*
	(0.433)	(0.460)	(0.462)	(0.445)	(0.467)	(0.471)
Δ_4EJU$_{t-1}$		0.228	0.241		0.138	0.156
		(0.163)	(0.164)		(0.155)	(0.159)
Δ_4LW$_{t-1}$			0.060			0.070
			(0.061)			(0.069)
R-squared	0.033	0.033	0.033	0.029	0.029	0.029
Obs. (n)	27412	27412	27412	39572	39572	39572
Plants (n)	5514	5514	5514	9015	9015	9015
Indus. (n)	118	118	118	118	118	118
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_4 (M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_4 (M_{IDN}^{CH})_{jt-1-1}\right)$					
Ad. R-sq.	0.31	0.39	0.39	0.30	0.38	0.39
F (1,117)	35.15	28.20	24.77	37.66	34.65	30.25

Notes: Table A.11 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_4 lnPr_{ijt}$ (four-year change in TFP) on the lagged four-year changes in China's, EJU's and other LW's import shares in India. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_4 (M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_4 (M_{IN}^{CH})_{jt-1}\right)$. Columns (1)–(3) in Block-A include only the LF200 and Columns (4)–(6) in Block-B include the LF100 plants. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. F (1,117) indicates first stage F-stat. ** and * indicate significant at 5% and 10% level, respectively.

Table A.12–Impact of Import Competition on Plant Productivity (Winsorized)

	Block-A (LF200)			Block-B (LF100)		
Panel-A	**OLS** Dep. Variable: $\Delta_5 lnPr_{ijt}$ (WLP Winsorized)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 CHN_{t-1}$	0.395**	0.430**	0.450**	0.419**	0.446**	0.459**
	(0.183)	(0.201)	(0.196)	(0.189)	(0.210)	(0.210)
$\Delta_5 EJU_{t-1}$		0.103	0.136		0.077	0.100
		(0.132)	(0.132)		(0.133)	(0.142)
$\Delta_5 LW_{t-1}$			0.092			0.062
			(0.097)			(0.110)
R-squared	0.037	0.037	0.037	0.034	0.034	0.034
Panel-B	**2SLS** Dep. Variable: $\Delta_5 lnPr_{ijt}$ (WLP Winsorized)					
$\Delta_5 CHN_{t-1}$	0.918**	0.972**	0.998**	0.808*	0.841*	0.858*
	(0.420)	(0.432)	(0.431)	(0.433)	(0.445)	(0.446)
$\Delta_5 EJU_{t-1}$		0.227	0.282*		0.170	0.210
		(0.163)	(0.167)		(0.170)	(0.185)
$\Delta_5 LW_{t-1}$			0.164*			0.117
			(0.087)			(0.110)
R-squared	0.033	0.034	0.034	0.032	0.032	0.033
Obs. (n)	22569	22569	22569	31842	31842	31842
Plants (n)	4961	4961	4961	7874	7874	7874
Indus. (n)	118	118	118	118	118	118
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$					
Ad. R-sq.	0.39	0.44	0.45	0.38	0.43	0.44
F (1,117)	53.44	40.90	34.29	56.79	47.72	39.96

Notes: Table A.12 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in winsorized TFP) on the lagged changes in China's, EJU's and other LW's import shares in India. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$. The baseline TFP series is winsorized at 1st and 99th percentiles before taking the five-year difference. Columns (1)–(3) in Block-A include only LF200 and Columns (4)–(6) in Block-B include LF100 plants. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. F (1,117) indicates first stage F-stat. ** and * indicate significant at 5% and 10% level, respectively.

Table A.13–Impact of Import Competition on Plant Productivity (LF20)

	Block-A (LF20)			Block-B (LF20)		
Panel-A	**OLS** Dep. Var.: $\Delta_5 lnPr_{ijt}$ (WLP)			$\Delta_5 lnPr_{ijt}$ (WLP Winsorized)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 CHN_{t-1}$	0.366**	0.363*	0.381*	0.382**	0.378*	0.388*
	(0.184)	(0.211)	(0.216)	(0.182)	(0.208)	(0.214)
$\Delta_5 EJU_{t-1}$		-0.007	0.022		-0.010	0.006
		(0.123)	(0.138)		(0.120)	(0.133)
$\Delta_5 LW_{t-1}$			0.088			0.047
			(0.109)			(0.109)
R-squared	0.029	0.029	0.029	0.031	0.031	0.031
Panel-B	**2SLS** Dep. Var.: $\Delta_5 lnPr_{ijt}$ (WLP)			$\Delta_5 lnPr_{ijt}$ (WLP Winsorized)		
$\Delta_5 CHN_{t-1}$	0.840*	0.862*	0.883*	0.877**	0.899**	0.915**
	(0.444)	(0.458)	(0.458)	(0.435)	(0.447)	(0.449)
$\Delta_5 EJU_{t-1}$		0.109	0.159		0.111	0.150
		(0.156)	(0.175)		(0.151)	(0.169)
$\Delta_5 LW_{t-1}$			0.161			0.124
			(0.118)			(0.112)
R-squared	0.027	0.027	0.027	0.028	0.028	0.028
Obs. (n)	40198	40198	40198	40198	40198	40198
Plants (n)	11561	11561	11561	11561	11561	11561
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$					
Ad. R-sq.	0.35	0.40	0.42	0.35	0.40	0.42
F (1,117)	54.17	46.92	39.63	54.17	46.92	39.63

Notes: Table A.13 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in TFP) on the lagged changes in China's, EJU's and other LW's import shares in India based on the LF20 sample. Block-A shows the results for the baseline WLP based TFP series and Block-B shows the results after correcting for outliers in estimated TFP, where the baseline TFP series is winsorized at 1st and 99th percentiles before taking the five-year difference. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. F (1,117) indicates first stage F-stat. ** and * indicate significant at 5% and 10% level, respectively.

Table A.14–Impact of Import Competition on Plant Productivity (MP Plants)

	Block-A (LF200)			Block-B (LF100)		
Panel-A	**OLS** Dep. Var.: $\Delta_5 lnPr_{ijt}$ (WLP)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 CHN_{t-1}$	0.294**	0.344**	0.370**	0.332**	0.377**	0.403**
	(0.147)	(0.167)	(0.162)	(0.161)	(0.184)	(0.182)
$\Delta_5 EJU_{t-1}$		0.144	0.182		0.125	0.165
		(0.142)	(0.137)		(0.142)	(0.142)
$\Delta_5 LW_{t-1}$			0.148*			0.148
			(0.081)			(0.094)
R-squared	0.040	0.040	0.040	0.036	0.036	0.037
Panel-B	**2SLS** Dep. Var.: $\Delta_5 lnPr_{ijt}$ (WLP)					
$\Delta_5 CHN_{t-1}$	0.747**	0.814**	0.839**	0.844**	0.908**	0.932**
	(0.374)	(0.403)	(0.405)	(0.423)	(0.442)	(0.442)
$\Delta_5 EJU_{t-1}$		0.286	0.336		0.289	0.343
		(0.206)	(0.209)		(0.211)	(0.221)
$\Delta_5 LW_{t-1}$			0.204***			0.216**
			(0.079)			(0.103)
R-squared	0.036	0.036	0.037	0.031	0.032	0.033
Obs. (n)	12069	12069	12069	16280	16280	16280
Plants (n)	3181	3181	3181	4580	4580	4580
Indus. (n)	111	111	111	115	115	115
Panel-C	**First Stage** Dep. Variable: $(\Delta_5(M_{IN}^{CH})_{jt-1})$ Instrument: $(\Delta_5(M_{IDN}^{CH})_{jt-1-1})$					
Ad. R-sq.	0.39	0.44	0.46	0.37	0.43	0.45
$F(1, cl^n)$	51.9	37.02	33.07	51.82	40.32	35.84

Notes: Table A.14 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in TFP) on the lagged changes in China's, EJU's and other LW's import shares in India based on the units that are identified as multi-product plants in their first appearance (between 2000 and 2009) in the ASI data. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $(\Delta_5(M_{IDN}^{CH})_{jt-1-1})$ is used as an instrument for $(\Delta_5(M_{IN}^{CH})_{jt-1})$. Columns (1)–(3) in Block-A include only LF200 and Columns (4)–(6) in Block-B include LF100 plants. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. $F(1, cl^n)$ indicates first stage F-stat and cl^n indicates df (cluster-1). ** and * indicate significant at 5% and 10% level, respectively.

Table A.15–Impact of Import Competition on Plant Productivity (2000-2005, LF200)

	Block-A (LF200)			Block-B (LF200)		
Panel-A	**OLS** Dep. Var.: $\Delta_5 lnPr_{ijt}$ (WLP)			$\Delta_5 lnPr_{ijt}$ (LP)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 CHN_{t-1}$	0.808**	0.816**	0.796**	0.778**	0.788**	0.764**
	(0.343)	(0.327)	(0.325)	(0.356)	(0.334)	(0.330)
$\Delta_5 EJU_{t-1}$		0.151	0.131		0.209	0.183
		(0.213)	(0.237)		(0.213)	(0.238)
$\Delta_5 LW_{t-1}$			-0.108			-0.138
			(0.330)			(0.309)
R-squared	0.027	0.027	0.027	0.024	0.025	0.025
Panel-B	**2SLS** Dep. Var.: $\Delta_5 lnPr_{ijt}$ (WLP)			$\Delta_5 lnPr_{ijt}$ (LP)		
$\Delta_5 CHN_{t-1}$	0.797*	0.808**	0.792*	0.693*	0.708*	0.685*
	(0.408)	(0.398)	(0.406)	(0.421)	(0.408)	(0.415)
$\Delta_5 EJU_{t-1}$		0.151	0.130		0.207	0.176
		(0.213)	(0.241)		(0.215)	(0.245)
$\Delta_5 LW_{t-1}$			-0.109			-0.163
			(0.341)			(0.320)
R-squared	0.027	0.027	0.027	0.024	0.025	0.025
Obs. (n)	3318	3318	3318	3318	3318	3318
Indus. (n)	107	107	107	107	107	107
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$					
Ad. R-sq.	0.57	0.57	0.58	0.57	0.57	0.58
F (1,106)	23.24	22.64	24.09	23.24	22.64	24.09

Notes: Table A.15 reports the productivity regression results for the 2000-2005 period (i.e. periods before and after China's WTO accession) based on the LF200 sample. Panel-A shows the OLS and Panel-B the 2SLS results from the regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in TFP) on the lagged changes in China's, EJU's and other LW's import shares in India. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$. Block-A shows the results for the WLP based TFP and Block-B the LP based TFP. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state fixed effects. Plant specific sampling weights are applied in all regressions. Indus. (n) shows the number of plants and the number of NIC 4-digit industries included in the regression. F (1,106) indicates first stage F-stat. ** and * indicate significant at 5% and 10% level, respectively.

Table A.16–Impact of Import Competition on Product Scope (IV with First Stage)

			LF200 Sample			
	(1)	(2)	(3)	(4)	(5)	(6)
	First Stage	IV	First Stage	IV	First Stage	IV
$\Delta_5(CHN_{IDN})_{(t-1)-1}$	0.560***		0.546***		0.533***	
	(0.087)		(0.087)		(0.094)	
$\Delta_5 CHN_{t-1}$		-0.145**		-0.146**		-0.145*
		(0.069)		(0.072)		(0.076)
$\Delta_5 EJU_{t-1}$			-0.213***	-0.008	-0.242***	-0.007
			(0.067)	(0.052)	(0.073)	(0.057)
$\Delta_5 LW_{t-1}$					-0.106***	0.006
					(0.038)	(0.032)
R-squared	0.352	0.013	0.403	0.013	0.417	0.013
N	18200	18200	18200	18200	18200	18200
			LF100 Sample			
$\Delta_5(CHN_{IDN})_{(t-1)-1}$	0.517***		0.508***		0.496***	
	(0.080)		(0.076)		(0.082)	
$\Delta_5 CHN_{t-1}$		-0.061		-0.060		-0.065
		(0.075)		(0.077)		(0.079)
$\Delta_5 EJU_{t-1}$			-0.221***	0.011	-0.255***	0.002
			(0.067)	(0.046)	(0.074)	(0.050)
$\Delta_5 LW_{t-1}$					-0.116***	-0.024
					(0.039)	(0.028)
R-squared	0.336	0.012	0.393	0.012	0.409	0.013
N	26900	26900	26900	26900	26900	26900

Notes: Columns (1), (3) and (5) of Table A.16 show the first stage estimates for the 2SLS regression results presented in Panel-B of Table 5 in the main text. Results for the 2SLS regressions are also repeated here for comparison in Columns (2), (4) and (6). Panel-A and Panel-B respectively present the results for the LF200 and the LF100 plants. The main right-hand side variables in Columns (1), (3) and (5) is $(t-1)-1$ lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ and the dependent variable is $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. Columns (2), (4) and (6) report the results for the 2SLS regressions of $\Delta_5 lnNp_{ijt}$ (five-year change in the log of number of products) on the lagged changes in China's, EJU's and other LW's import shares in India. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. ***, ** and * indicate significant at 1%, 5% and 10% level, respectively.

Table A.17–Impact of Import Competition on Plant Product Scope (MP Plants)

Panel-A	**Block-A (LF200MP)**			**Block-B (LF100MP)**		
	OLS Dep. Var.: $\Delta_5 lnNp_{ijt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 CHN_{t-1}$	-0.115**	-0.093*	-0.084	-0.062	-0.036	-0.030
	(0.053)	(0.052)	(0.052)	(0.050)	(0.049)	(0.051)
$\Delta_5 EJU_{t-1}$		0.063	0.076		0.073	0.081
		(0.056)	(0.054)		(0.055)	(0.054)
$\Delta_5 LW_{t-1}$			0.050			0.030
			(0.043)			(0.050)
R-sq.	0.023	0.024	0.024	0.025	0.026	0.026
Panel-B	**2SLS Dep. Var.:** $\Delta_5 lnNp_{ijt}$					
$\Delta_5 CHN_{t-1}$	-0.242**	-0.238**	-0.233**	-0.229**	-0.225**	-0.225**
	(0.108)	(0.114)	(0.115)	(0.104)	(0.109)	(0.112)
$\Delta_5 EJU_{t-1}$		0.020	0.028		0.015	0.016
		(0.066)	(0.066)		(0.066)	(0.067)
$\Delta_5 LW_{t-1}$			0.030			0.002
						(0.052)
R-sq.				0.024	0.024	0.024
Obs. (n)	12670	12670	12670	17193	17193	17193
Plants (n)	3247	3247	3247	4717	4717	4717
Indus. (n)	112	112	112	115	115	115
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$					
R-sq.	0.39	0.44	0.46	0.37	0.43	0.45
$F(1, cl^n)$	51.87	37.29	32.38	52.50	40.68	34.81

Notes: Table A.17 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnNp_{ijt}$ (five-year change in the log of number of products) on the lagged changes in China's, EJU's and other LW's import shares in India, based on the units that are identified as multi-product plants in their first appearance (between 2000 and 2009). In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$. Columns (1)–(3) include the LF200MP and Columns (4)–(6) include the LF100MP plants. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. ** and * indicate significant at 5% and 10% level, respectively. $F(1, cl^n)$ indicates first stage F-stat and cl^n indicates df (cluster-1).

Table A.18–Impact of Import Competition on Plant Product Scope (Altern. Prod. Scope)

Panel-A: OLS	**Block-A (LF200)**			**Block-B (LF200)**		
OLS	$\Delta_5 \ln(Np_{ijt}+1)$ (based on CPC)			$\Delta_5 lnNp_{ijt}$ (based on ASICC)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 CHN_{t-1}$	-0.070***	-0.069***	-0.067**	-0.097**	-0.096**	-0.099**
	(0.025)	(0.026)	(0.028)	(0.040)	(0.043)	(0.046)
$\Delta_5 EJU_{t-1}$		0.004	0.006		0.004	-0.000
		(0.035)	(0.037)		(0.056)	(0.059)
$\Delta_5 LW_{t-1}$			0.007			-0.016
			(0.019)			(0.036)
R-sq.	0.014	0.014	0.014	0.014	0.014	0.014
Panel-B: 2SLS						
$\Delta_5 CHN_{t-1}$	-0.098**	-0.098**	-0.097*	-0.166**	-0.168**	-0.174**
	(0.048)	(0.050)	(0.052)	(0.074)	(0.077)	(0.081)
$\Delta_5 EJU_{t-1}$		-0.003	-0.002		-0.013	-0.021
		(0.036)	(0.040)		(0.059)	(0.064)
$\Delta_5 LW_{t-1}$			0.003			-0.027
			(0.022)			(0.041)
R-sq.	0.013	0.013	0.013	0.014	0.014	0.014
Obs. (n)	18200	18200	18200	18200	18200	18200
Plants (n)	4807	4807	4807	4807	4807	4807
Indus. (n)	117	117	117	117	117	117
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$					
R-sq.	0.35	0.40	0.41	0.35	0.40	0.41
F(1,116)	41.07	38.96	31.91	41.07	39.0	31.91

Notes: Table A.18 reports the regression results using two alternative measures of product scope based on the LF200 sample. In Block-A, the dependent variable is defined as the change in the log of number of CPC products plus one (i.e. $\ln(Np_{ijt}+1)$) and in Block-B it is defined as the change in the log of number of unique ASICC products. Panel-A shows the results from the OLS and Panel-B shows the IV regressions of the change in product scope on the lagged changes in China's, EJU's and other LW's import shares in India. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. F(1, 116) indicates first stage F-stat. ***, ** and * indicate significant at 1%, 5% and 10% level, respectively.

Table A.19–Impact of Import Competition on Plant Product Scope (Balanced)

Panel-A	**Block-A (LF200 Balanced)**			**Block-B (LF100 Balanced)**		
	OLS Dep. Var.: $\Delta_5 lnNp_{ijt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5 CHN_{t-1}$	-0.142***	-0.125***	-0.125***	-0.117***	-0.104**	-0.105**
	(0.040)	(0.042)	(0.042)	(0.038)	(0.040)	(0.040)
$\Delta_5 EJU_{t-1}$		0.055	0.055		0.040	0.039
		(0.064)	(0.066)		(0.059)	(0.061)
$\Delta_5 LW_{t-1}$			0.002			-0.005
			(0.025)			(0.023)
R-sq.	0.023	0.023	0.023	0.022	0.022	0.022
Panel-B	**2SLS Dep. Var.:** $\Delta_5 lnNp_{ijt}$					
$\Delta_5 CHN_{t-1}$	-0.152*	-0.147*	-0.147*	-0.138	-0.134	-0.136
	(0.080)	(0.084)	(0.085)	(0.085)	(0.089)	(0.090)
$\Delta_5 EJU_{t-1}$		0.049	0.049		0.032	0.030
		(0.068)	(0.070)		(0.065)	(0.068)
$\Delta_5 LW_{t-1}$			-0.001			-0.009
			(0.025)			(0.024)
R-sq.	0.023	0.023	0.023	0.022	0.022	0.022
Obs. (n)	8405	8405	8405	8965	8965	8965
Plants (n)	1681	1681	1681	1793	1793	1793
Indus. (n)	103	103	103	109	109	109
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$					
R-sq.	0.39	0.45	0.46	0.38	0.44	0.45
$F(1, cl^n)$	46.17	41.34	35.62	48. 94	43.01	37.35

Notes: Table A.19 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnNp_{ijt}$ (five-year change in the log of number of products) on the lagged changes in China's, EJU's and other LW's import shares in India based on both the LF200 balanced sample and the LF100 balanced sample. Columns (1)–(3) in Block-A include only the balanced sample of the LF200 and Columns (4)–(6) in Block-B include only the balanced sample of the LF100 plants. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. ** and * indicate significant at 5% and 10% level, respectively. $F(1, cl^n)$ indicates first stage F-stat and cl^n indicates df (cluster-1).

Table A.20–Impact of Import Competition on Product Scope (alternative import ratio)

	Block-A (LF200)			Block-B (LF100)			Block-C (MP)	
Panel-A	**OLS Dep. Var.:** $\Delta_5 lnNp_{ijt}$						LF200	LF100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta_5 CHN_{t-1}$	-0.101***	-0.099**	-0.094**	-0.049	-0.043	-0.048	-0.114**	-0.061
	(0.035)	(0.039)	(0.043)	(0.031)	(0.034)	(0.034)	(0.053)	(0.050)
$\Delta_5 EJU_{t-1}$		0.007	0.012		0.018	0.011		
		(0.050)	(0.054)		(0.042)	(0.045)		
$\Delta_5 LW_{t-1}$			0.016			-0.018		
			(0.029)			(0.026)		
R-sq.	0.013	0.013	0.013	0.012	0.012	0.013	0.023	0.025
Panel-B	**2SLS Dep. Var.:** $\Delta_5 lnNp_{ijt}$							
$\Delta_5 CHN_{t-1}$	-0.139**	-0.140*	-0.138*	-0.056	-0.054	-0.060	-0.236**	-0.227**
	(0.069)	(0.074)	(0.082)	(0.075)	(0.079)	(0.084)	(0.107)	(0.103)
$\Delta_5 EJU_{t-1}$		-0.005	-0.002		0.015	0.008		
		(0.054)	(0.061)		(0.048)	(0.053)		
$\Delta_5 LW_{t-1}$			0.007			-0.020		
			(0.035)			(0.031)		
R-sq.	0.013	0.013	0.013	0.012	0.012	0.013	0.022	0.024
Obs. (n)	18200	18200	18200	26900	26900	26900	12670	17193
Plants (n)	4807	4807	4807	7640	7640	7640	3247	4717
Indus. (n)	117	117	117	117	117	117	112	115
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$							
R-sq.	0.34	0.41	0.43	0.33	0.40	0.42	0.39	0.37
$F(1, cl^n)$	39.84	38.35	30.22	41.16	44.89	37.00	49.78	52.50
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Table A.20 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnNp_{ijt}$ (five-year change in the log of number of products) on the lagged changes in China's, EJU's and other LW's import shares in India based on the alternative measure of import competition, where raw materials are excluded from both numerator and denominator of import exposure measure. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry *j* $\left(\Delta_5 (M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5 (M_{IN}^{CH})_{jt-1}\right)$. Columns (1)–(6) in Block-A include the LF200 and Columns (7)–(6) in Block-B include the LF100 plants. Columns (4) and (8) report the results for the multi-product plants. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. $F(1, cl^n)$ indicates first stage F-stat and cl^n indicates df (cluster-1). ***, ** and * indicate significant at 1% 5% and 10% level, respectively.

Table A.21–Impact of Import Competition on Plant Product Scope (LF20 plants)

	Block-A (LF20-OLS)			Block-B (LF20-IV)			Block-C (MP)	
Panel-A	**Dep. Var.:** $\Delta_5 lnNp_{ijt}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS			IV			OLS	IV
$\Delta_5 CHN_{t-1}$	-0.077**	-0.077*	-0.085**	-0.145	-0.145	-0.155	-0.077	-0.350**
	(0.035)	(0.040)	(0.041)	(0.100)	(0.100)	(0.103)	(0.056)	(0.140)
$\Delta_5 EJU_{t-1}$		0.000	-0.013		-0.015	-0.031		
		(0.042)	(0.046)		(0.050)	(0.056)		
$\Delta_5 LW_{t-1}$			-0.040			-0.051		
			(0.029)			(0.036)		
R-sq.	0.013	0.013	0.014	0.013	0.013	0.013	0.028	0.023
Obs. (n)	33771	33771	33771	33771	33771	33771	20343	20343
Plants (n)	10711	10711	10711	10711	10711	10711	6097	6097
Indus. (n)	118	118	118	118	118	118	117	117
Panel-B	**First Stage** Dep. Variable: $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$							
R-sq.				0.29	0.36	0.37		0.34
F(1, 117)				36.52	42.85	35.77		49.68

Notes: Table A.21 reports the results from the OLS (Panel-A) and the 2SLS (Panel-B) regressions of $\Delta_5 lnNp_{ijt}$ (five-year change in the log of number of products) on the lagged changes in China's, EJU's and other LW's import shares in India based on the LF20 sample. Columns (1)–(3) in Block-A show the OLS and Columns (4)–(6) in Block-B show the IV results. Column (7) and (8) respectively show the OLS and the IV results based on the LF20 units that are identified as multi-product plants in their first appearance (between 2000 and 2009) in the ASI data. In Panel-B, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. F(1, 117) indicates first stage F-stat. ** and * indicate significant at 5% and 10% level, respectively.

Table A.22–Impact of Import Competition on Plant Product Scope (2000-2005, MP Plants)

Panel-A	Block-A (LF200 CPC)			Block-B (LF200 ASICC)		
	OLS Dep. Var.: $\Delta_5 lnNp_{ijt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_5CHN$_{t-1}$	-0.142*	-0.133*	-0.127	-0.212***	-0.202***	-0.227***
	(0.085)	(0.079)	(0.085)	(0.080)	(0.073)	(0.081)
Δ_5EJU$_{t-1}$		0.099	0.105		0.108	0.080
		(0.087)	(0.094)		(0.107)	(0.116)
Δ_5LW$_{t-1}$			0.031			-0.141
			(0.163)			(0.154)
R-sq.	0.034	0.034	0.034	0.033	0.034	0.034
Panel-B	**2SLS Dep. Var.:** $\Delta_5 lnNp_{ijt}$					
Δ_5CHN$_{t-1}$	-0.374**	-0.358**	-0.371**	-0.487**	-0.470**	-0.515**
	(0.179)	(0.176)	(0.186)	(0.195)	(0.193)	(0.201)
Δ_5EJU$_{t-1}$		0.083	0.067		0.089	0.036
		(0.091)	(0.098)		(0.107)	(0.115)
Δ_5LW$_{t-1}$			-0.077			-0.268*
			(0.162)			(0.161)
R-sq.	0.030	0.031	0.031	0.028	0.029	0.030
Obs. (n)	2395	2395	2395	2395	2395	2395
Indus. (n)	105	105	105	105	105	105
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$					
R-sq.	0.62	0.62	0.64	0.62	0.62	0.64
F(1,104)	21.94	21.09	22.77	21.95	21.10	22.77
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Table A.22 reports the product scope regression results for the 2000-2005 period (i.e. periods before and after China's WTO accession) based on the LF200 sample. Panel-A shows the OLS and Panel-B the 2SLS results from the regressions of $\Delta_5 lnNp_{ijt}$ (five-year change in the log of number of products) on the lagged changes in China's, EJU's and other LW's import shares in India. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. Columns (1)–(3) show the results for the CPC based and Columns (4)–(6) the ASICC based product scope. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. F(1,104) indicates first stage F-stat. ***, ** and * indicate significant at 1%, 5% and 10% level, respectively.

Table A.23–Impact of Import Competition on Plant Productivity (2000-2005, MP Plants)

	Block-A (LF200)			Block-B (LF200)		
Panel-A	**OLS** Dep. Var.: $\Delta_5 lnPr_{ijt}$ (WLP)			$\Delta_5 lnPr_{ijt}$ (LP)		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ_5CHN$_{t-1}$	0.867***	0.878***	0.795**	0.820**	0.839***	0.747**
	(0.319)	(0.310)	(0.309)	(0.324)	(0.313)	(0.309)
Δ_5EJU$_{t-1}$		0.116	0.025		0.202	0.101
		(0.254)	(0.288)		(0.258)	(0.291)
Δ_5LW$_{t-1}$			-0.461			-0.509
			(0.437)			(0.422)
R-squared	0.038	0.038	0.039	0.035	0.036	0.037
Panel-B	**2SLS** Dep. Var.: $\Delta_5 lnPr_{ijt}$ (WLP)			$\Delta_5 lnPr_{ijt}$ (LP)		
Δ_5CHN$_{t-1}$	1.041**	1.066**	1.005**	0.901**	0.941**	0.865**
	(0.433)	(0.422)	(0.423)	(0.417)	(0.403)	(0.404)
Δ_5EJU$_{t-1}$		0.130	0.057		0.210	0.119
		(0.246)	(0.278)		(0.252)	(0.285)
Δ_5LW$_{t-1}$			-0.368			-0.457
			(0.438)			(0.422)
R-squared	0.037	0.038	0.039	0.035	0.036	0.037
Obs. (n)	2395	2395	2395	2395	2395	2395
Indus. (n)	105	105	105	105	105	105
Panel-C	**First Stage** Dep. Variable: $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$ Instrument: $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$					
Ad. R-sq.	0.62	0.62	0.64	0.62	0.62	0.64
F (1,104)	21.95	21.10	22.76	21.94	21.09	22.77

Notes: Table A.23 shows the productivity regression results for the 2000-2005 period (i.e. periods before and after China's WTO accession) based on the sample of LF200 multi-product plants. Panel-A shows the OLS and Panel-B the 2SLS results from the regressions of $\Delta_5 lnPr_{ijt}$ (five-year change in TFP) on the lagged changes in China's, EJU's and other LW's import shares in India. In Panel-C, (t-1)-1 lag of the five-year change in the Chinese import share in Indonesia in industry j $\left(\Delta_5(M_{IDN}^{CH})_{jt-1-1}\right)$ is used as an instrument for $\left(\Delta_5(M_{IN}^{CH})_{jt-1}\right)$. Block-A shows the results for the WLP based TFP and Block-B the LP based TFP. Standard errors (in parentheses) are clustered at the industry level. All the regressions include a rural dummy, technology intensity dummies and state fixed effects. Plant specific sampling weights are applied in all regressions. Plants (n) and Indus. (n) respectively show the number of plants and the number of NIC 4-digit industries included in the regression. F(1,104) indicates first stage F-stat. ** and * indicate significant at 5% and 10% level, respectively.

Table A.24–Impact of Import Competition on Decision to Drop a product (LF100)

	OLS			IV		
	Dependent Variable: Dropped (1 if dropped or 0 otherwise)					
	(1)	(2)	(3)	(4)	(5)	(6)
$S_{(ikt\text{-}5)}$	-0.239***	-0.158**	-0.121*	-0.161***	-0.044	0.021
	(0.045)	(0.066)	(0.065)	(0.055)	(0.085)	(0.092)
$CHN_{t\text{-}5}$	0.195**	0.211***	0.204**	0.739**	0.661***	0.758***
	(0.087)	(0.081)	(0.084)	(0.294)	(0.256)	(0.254)
$S_{(ikt\text{-}5)}\times CHN_{t\text{-}5}$	-0.217*	-0.268*	-0.312***	-1.265***	-1.408***	-1.446***
	(0.130)	(0.139)	(0.120)	(0.345)	(0.403)	(0.391)
$EJU_{t\text{-}5}$		0.174***	0.172**		0.182***	0.190***
		(0.062)	(0.068)		(0.062)	(0.064)
$S_{(ikt\text{-}5)}\times EJU_{t\text{-}5}$		-0.249***	-0.301***		-0.314***	-0.397***
		(0.088)	(0.093)		(0.097)	(0.108)
$LW_{t\text{-}5}$			-0.113			-0.083
			(0.098)			(0.090)
$S_{(ikt\text{-}5)}\times LW_{t\text{-}5}$			-0.002			-0.123
			(0.123)			(0.126)
Plant FE	yes	yes	yes	yes	yes	yes
R-squared	0.35	0.35	0.35	0.03	0.03	0.03
Obs.-49930, No. of Plants-7013, No. of Plant-product-21593, No of Product (cluster) 706						
First Stage	Dep. Var (s): $(M_{IN}^{CH})_{kt-5}$ *and* $S_{ikt-5}\times(M_{IN}^{CH})_{kt-5}$ Instrument(s): $(M_{IDN}^{CH})_{kt-5-1}$ and $S_{ikt-5}\times(M_{IDN}^{CH})_{kt-5-1}$					
$(M_{IN}^{CH})_{kt-5}$	F (2, 705, p-value)			13.2 (0.0)	12.6 (0.0)	15.7 (0.0)
$S_{ikt-5}\times(M_{IN}^{CH})_{kt-5}$				10.8 (0.0)	7.6 (0.0)	8.2 (0.0)

Notes: Table A.24 reports the OLS and the IV results from the regression of a dummy variable indicating whether a plant *i* drops a product *k* in year *t* on the level of China's, EJU's and LW's import shares in India in *t*-5 and their interactions with the share of that product in total revenue at *t*-5 using plant-product level data from 2000 to 2009 for the LF100 sample. Columns (1)–(3) show the OLS and Columns (4)–(6) the IV results. Standard errors (in parentheses) are clustered at product level (5-digit CPC product) level. All the regressions include plant fixed effects and state-year fixed effects. Plant specific sampling weights are applied in all regressions. In the first stage, $(M_{IN}^{CH})_{kt-5}$ *and* $S_{ikt-5}\times(M_{IN}^{CH})_{kt-5}$ are instrumented by $(M_{IDN}^{CH})_{kt-5-1}$ and $S_{ikt-5}\times(M_{IDN}^{CH})_{kt-5-1}$.

Table A.25–Impact of Import Competition on Decision to Drop a product (LF20)

	OLS			IV		
	Dependent Variable: Dropped (1 if dropped or 0 otherwise)					
	(1)	(2)	(3)	(4)	(5)	(6)
$S_{(ikt\text{-}5)}$	-0.226***	-0.144***	-0.112**	-0.165***	-0.062	0.001
	(0.040)	(0.056)	(0.056)	(0.044)	(0.063)	(0.072)
$CHN_{t\text{-}5}$	0.194**	0.212***	0.212**	0.714***	0.635***	0.679***
	(0.088)	(0.081)	(0.083)	(0.232)	(0.196)	(0.195)
$S_{(ikt\text{-}5)} \times CHN_{t\text{-}5}$	-0.286**	-0.327***	-0.367***	-1.180***	-1.249***	-1.300***
	(0.125)	(0.123)	(0.116)	(0.269)	(0.290)	(0.296)
$EJU_{t\text{-}5}$		0.185***	0.188***		0.189***	0.201***
		(0.051)	(0.056)		(0.049)	(0.052)
$S_{(ikt\text{-}5)} \times EJU_{t\text{-}5}$		-0.261***	-0.302***		-0.298***	-0.377***
		(0.074)	(0.077)		(0.076)	(0.086)
$LW_{t\text{-}5}$			-0.047			-0.026
			(0.078)			(0.072)
$S_{(ikt\text{-}5)} \times LW_{t\text{-}5}$			-0.033			-0.134
			(0.101)			(0.104)
Plant FE	yes	yes	yes	yes	yes	yes
R-squared	0.40	0.41	0.41	0.03	0.04	0.04
Obs.- 65017, No. of Plants-10977, No. of Plant-product-31779, No of Product (cluster) 738						
First Stage	Dep. Var (s): $(M_{IN}^{CH})_{kt-5}$ *and* $S_{ikt-5} \times (M_{IN}^{CH})_{kt-5}$ Instrument(s): $(M_{IDN}^{CH})_{kt-5-1}$ and $S_{ikt-5} \times (M_{IDN}^{CH})_{kt-5-1}$					
$(M_{IN}^{CH})_{kt-5}$	F (2, 737			21.6 (0.0)	21.5 (0.0)	25.6 (0.0)
$S_{ikt-5} \times (M_{IN}^{CH})_{kt-5}$	p-value)			18.3 (0.0)	14.5 (0.0)	14.6 (0.0)

Notes: Table A.25 reports the OLS and the IV results from the regression of a dummy variable indicating whether a plant *i* drops a product *k* in year *t* on the level of China's, EJU's and LW's import shares in India in *t*-5 and their interactions with the share of that product in total revenue at *t*-5 using plant-product level data from 2000 to 2009 for the LF20 sample. Columns (1)–(3) show the OLS and Columns (4)–(6) the IV results. Standard errors (in parentheses) are clustered at product level (5-digit CPC product) level. All the regressions include plant fixed effects and state-year fixed effects. Plant specific sampling weights are applied in all regressions. In the first stage, $(M_{IN}^{CH})_{kt-5}$ *and* $S_{ikt-5} \times (M_{IN}^{CH})_{kt-5}$ are instrumented by $(M_{IDN}^{CH})_{kt-5-1}$ and $S_{ikt-5} \times (M_{IDN}^{CH})_{kt-5-1}$.

Table A.26–Impact of Import Competition on Decision to Drop a Product (Plant-Prod. FE)

	MP LF200 plants			All LF200 plants		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	FE	OLS	IV	FE
$S_{(ikt\text{-}5)}$	-0.145***	-0.047	-0.006	-0.149***	-0.052	-0.002
	(0.049)	(0.059)	(0.024)	(0.049)	(0.059)	(0.023)
CHN_{t-5}	0.239**	1.066**	0.151*	0.249***	1.019**	0.158*
	(0.093)	(0.421)	(0.081)	(0.095)	(0.414)	(0.084)
$S_{(ikt\text{-}5)} \times CHN_{t-5}$	-0.234	-1.717***	-0.109	-0.295*	-1.725***	-0.172
	(0.181)	(0.503)	(0.142)	(0.157)	(0.488)	(0.116)
Fixed Effects	Plant	Plant	Plant-Product	Plant	Plant	Plant-Product
N	25740	25740	25740	30283	30283	30283

Notes: The dependent variable indicates whether a plant *i* drops a product *k* in year *t*. The main right-hand side variables are $\beta_1 (M_{IN}^{CH})_{kt-5}$, $\delta_1 (S_{ikt-5} \times (M_{IN}^{CH})_{kt-5})$ *and* γS_{ikt-5}. The regressions include only the LF200 sample for the 2000-2009 period. All the regressions include state-year fixed effects. Columns (1) and (4) show the OLS and Columns (2) and (5) the IV results with plant-fixed effects. Columns (3) and (6) show the results for plant-product fixed effect models. Standard errors (in parentheses) are clustered at product level (5-digit CPC) level. Plant specific sampling weights are applied in all regressions.

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