Essays on Trade, Multi-product Plants, Manufacturing Performance and Labor Market

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Declaration

I declare that the thesis is my own work and has not been submitted for a degree at another university.

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Abstract

The evolution and impact of North-North and North-South trade have been among the main areas of research in the literature of international trade. But how trade shocks emanating from a low-wage southern country affect the manufacturing sector of other low-wage countries has been little researched. In particular, there is a lack of evidence on firm-level adjustment to low-wage trade shock in a low-wage developing country context. The main objective of the thesis is to fill this gap in the literature by empirically examining the impact of import competition shock from China on the evolution of manufacturing sector in India. This thesis combines plant level data from the Annual Survey of Industries (ASI) 1998-2009 with the product level trade data from UN Comtrade database. The thesis contains two main chapters –chapter 2, which explores the impact of a sharp rise in Chinese import exposure on overall plant performance and product reallocation dynamics within-plant, and chapter 3. The latter dwells on wage inequality and employment within-plant.

Chapter 2 finds that increased import competition from China following its WTO accession leads to improvements in revenue productivity and a reduction of product scope at the plant-level. A 10 percentage point increase in Chinese import exposure leads to a 3.7 percent increase in large plants' total-factor productivity. The same amount of increase in exposure to Chinese imports leads to a one percent decrease in the number of products produced by the plant. Plant product-level analysis suggests that the impact on selection of products is not symmetric. Plants drop the product in which Chinese import exposure is higher; however, the closer the product is to the core competence of the plant, the less likely it is to be dropped. 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 both high-wage countries and China have a similar impact on the selection of products within a plant.

Chapter 3 finds that the rise in import competition from China leads to a general increase in within-plant wage inequality between skilled and unskilled workers in large plants. But the overall pattern is driven by much greater adjustment in flexible labor markets or states that have employer friendly industrial relation regulation, while no significant adjustment is evident in the inflexible market. I find that a 10 percentage point increase in Chinese import exposure leads to a 1.35 percent increase in skill premium in the sample of large plants, whereas the same change leads to a 2.65 percent increase in skill premium in the flexible market. It is also observed that increase in import competition from China causes a downsizing of low-productivity plants through employment destruction, and an expansion of high-productivity plants via employment creation. Again, the reallocation of employment is only evident in the flexible labor market.

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Chapter 1

Introduction

In recent times, one of the most significant developments in the world economy is the booming trade between developing countries, termed as South-South trade. The evolution and impact of North-North and North-South trade have been among the main areas of research in both the theoretical and empirical literature of international trade. The expansion of trade between southern countries is a new phenomenon in the history of globalization. In particular, South-South trade has been growing at a spectacular pace in the 2000s, driven by China's rapid integration in the world economy following its accession to WTO in December 2001.[1] In fact, in the 2000s, high-wage northern countries have also been greatly affected by the surge of Chinese imports in domestic market. A few recent studies highlight the importance of low-wage country trade shocks in general and Chinese import competition shocks in particular on the evolution of advanced economies. Bernard, Jensen, and Schott (2006) evaluate the impacts of low-wage country import penetration on various plant-level outcomes (e.g., plant survival, employment growth, product mix etc.) of U.S. manufacturing industry. Acemoglu et al. (2016) and Autor, Dorn, and Hanson (2013) explore the effects of Chinese import growth on the U.S. labor market. Bloom, Draca, and Van Reenen (2016) look at the impact of import competition from China on innovation and productivity dynamics of the firms in a set of EU countries. Martin and Mejean (2014) explore the impact of low-wage competition on the quality content of French exports while Iacovone, Rauch, and Winters (2013) investigate the impact of Chinese import competition on the selection of products within plants. Mion and Zhu (2013), and Utar

[1] Between 2001 and 2011, world merchandise exports increased by 12 trillion US Dollar. Remarkably, trade between southern countries also increased at a spectacular rate -South-South trade alone has increased by USD 3.6 trillion over the same time.

(2014) study the impact of Chinese import competition on skill upgrading in the manufacturing sector of developed countries. These studies provide new insights into the impact of low-wage trade shocks on the evolution of high-wage countries, primarily. The focus of this study centres on identifying the competitive effect of low-wage import exposure on the performance of India's manufacturing plants using China's accession to WTO and subsequent Chinese import escalation in India as the identification strategy.

1.1 Institutional Background

India is the world's largest democracy and a home for about 18 percent of world's population. India became independent in 1947 and largely adhered to an inward-looking, import substitution strategy and enforced state's control on industrial production activity in the first three decades. During the era, entry and production activity in the industrial sector were tightly regulated by licensing requirement under the Industries (Development and Regulation) Act (IDRA), 1951.[2] Between 1980 and 2000, the Government of India undertook major reform initiatives in several phases. Though the steps toward liberalization started in the second-half of 1970s, policy changes were rather ad-hoc. The first major phase of reform was materialized in 1985 with the de-licensing of one-third of the organized industries at the 3-digit level. However, on the external-sector, there was no such development at that time: trade and foreign direct investment restrictions remained abound during the whole 1980s. While, the second phase, compared to the first, was rather drastic and much comprehensive in scope, –prescribed by IMF as pre-conditions for much needed financing at the time of balance of payment crisis that had been gradually building up in the late 1980s. The key elements of 1990s reform program include: de-licensing, FDI liberalization and trade liberalization. Licensing

[2] For a detailed discussion on the License Raj see Aghion, Burgess, Redding, and Zilibotti (2008), Panagariya (2008) and Chamarbagwala and Sharma (2011).

requirement almost abolished in 1991 except for few exceptional cases (Aghion, Burgess, Redding, and Zilibotti 2008). In addition, exchange rates liberalization and abandoning the licensing requirement for the imports of capital and intermediate goods were also initiated (Harrison, Martin, and Nataraj 2012).

India's growth trajectory has changed after it has crossed a decade of significant liberalization in its economic environment both externally and internally. India achieved an amazingly high average growth rate of 8.5 percent during 2003-4 to 2010-11 period. Despite rapid growth acceleration its speed of poverty reduction has been rather slow relative to other faster growing economies. Many believe that the growth process has been largely driven by capital- and skill intensive manufacturing industries rather than unskilled labor-intensive sectors. As a result, the process could not attract a large number of agricultural workers into manufacturing sector. A large proportion of India's huge workforce is employed in small informal enterprises where labor productivity is very low. As a result, the real wage of a large proportion of employed individuals has been trapped at a low-level even though the economy has been growing rapidly. Studies find that even after decades of liberalization changes India's restrictive labor market regime still constrains the growth of the economic establishments in a significant way. Among various labor legislations, Industrial Development Act (IDA) of 1947 is considered the most significant one for the rigidity of India's labor market. One key part of this act requires that a plant with more than 100 workers must obtain permission from the government to retrench any worker or close its operation even while incurring losses. In several studies, it has been argued that the labor market regulations that are created to preserve the well-being of labor are limiting their welfare in reality.

1.2. Pattern of India's International Trade

Direction of India's foreign trade has changed significantly over the last two decades. India's imports and exports have been leaning towards developing countries from its traditional reliance on the EU and North America. This pattern of changes in imports and exports are reflected in Table 1 and Table 2 below.[3] First, total import share of OECD countries declines steadily throughout the period, from 57 percent (row sum of columns 1 to 4) in 1987-1991 to 32 percent 2007-2011, mostly due to fall in EU's share by 18 and North America's share by 5 percentage point. In contrast, share of developing countries increases by 13 percentage point over the same period. Apparently, China's share grows sharply after its WTO accession, which increases from just 3 percent in 1997-2001 to 11 percent in 2007-2011.

Table 1–Share of Different Countries in India's Imports

	EU	North America	Asia and Oceania	All Other OECD	OPEC	Eastern Europe	Developing countries	Others	China
1987-1991	31	12	11	3	15	8	19	0.03	0.3
1992-1996	28	11	10	4	23	3	22	0.01	2
1997-2001	23	8	8	6	15	2	25	13	3
2002-2006	17	7	6	5	15	2	28	20	7
2007-2011	13	7	6	6	33	2	32	1	11

Source: Reserve Bank of India (RBI)

Table 2–Share of Different Countries in India's Exports

	EU	North America	Asia and Oceania	All Other OECD	OPEC	Eastern Europe	Developing countries	Others	China
1987-1991	26	18	11	3	7	16	17	3	0.2
1992-1996	27	20	8	2	10	4	27	2	1
1997-2001	25	22	6	2	11	3	29	2	2
2002-2006	21	18	4	2	15	2	38	0	6
2007-2011	19	12	3	1	20	1	40	4	6

Source: Reserve Bank of India (RBI)

India's exports scenario exhibits some of the long-term patterns we have observed for its imports. Firstly, OECD countries' share of India's exports declines gradually throughout the

[3] Data are reported in financial year basis (For example, period 1987-1991 implies 1987-88 to 1991-1992). Share of China is included in developing countries, hence, the row-sum is 100 excluding China. Columns 1 to 4 are OECD countries.

period, from 58 percent in 1987-1991 to 35 percent in 2007-2011, where the share of EU, North America and Asia and Oceania declines by 7, 6 and 8 percentage points respectively. On the other hand, developing countries' share of India's exports increases by 23 percentage point over the same period. As in the case of imports, there is a spiky increase in China's share of India's exports in 2002-2006 compared to 1997-2001.

1.3 Some Anecdotal Evidence

In India, there is a growing concern among the policy makers and stakeholders regarding the future of India's manufacturing sector in the face of heightened Chinese competition both in the domestic and export markets. Such concerns are documented in different reports and policy statements published by different government institutions in India. One interesting case of Chinese competition faced by Indian producers both at home and abroad is the electrical equipment industry. Recently, the Ministry of Heavy Industries and Public Enterprises (MHIPE), Government of India (2013) published a mission statement (for 2012-22) for electrical equipment sector which documents different dimensions of competitive constraints Indian firms confront including recent intensification of Chinese competition at home and abroad. According to the report, during 2011-12, 45 percent of Indian imports in this sector were contributed by China, which was approximately twice as much of the combined share of Germany (10 percent), Japan (7 percent) and USA (6 percent). In contrast, only 3 percent of India's exports shipped to China. The report claims that Indian manufactures are finding it difficult to compete with foreign suppliers in general, Chinese suppliers in particular, as on the one side they have to pay duties on critical imported materials and taxes that are not applicable to foreign producers, and on the other side, foreign suppliers enjoy lower tariffs on imported inputs. It further claims that Chinese producers benefit from low cost financing, subsidized raw materials and protected domestic market in China. Based on its analysis the report recommends increase in tariff and non-tariff barriers to protect the domestic industry from foreign competition. Another similar report, again by the MHIPE, Automotive Mission Plan 2006-2016, states that mainly because of higher taxes, the cost of manufacturing a passenger vehicle is 23 percent higher in India relative to China. It points out that China has a competitive advantage vis-à-vis India because of relatively higher labor productivity and lower infrastructural costs. The reports like above highlight the concerns of local industries and policy makers about the Chinese competition threat to India's manufacturing sector. Therefore, the empirical evidence presented in the study can be useful for the policymakers and industry stakeholders in formulating future trade policies.

1.4 Related Literature

In addition to studies mentioned above, this paper relates to several strands of the literature. First, there is a growing literature that explores the gains from trade in heterogeneous firm models of trade pioneered by Melitz (2003) and facilitated by increasing availability of firm-level data. The recent literature focuses on three main types of gains from trade (Melitz and Trefler 2012)–owing to increasing availability of varieties with the rise in intra-industry trade ("love-of-variety gains"); reallocation of factors of production from less to more-productive firms ("allocative efficiency gains") and increase in trade induced innovation ("productive efficiency gains"). The first source of gains from trade arises from increased availability of varieties to the consumers. Further, trade liberalization also expands the set of available inputs to firms. Availability of new intermediate inputs facilitates the creation of new varieties, leading to further gains from trade (Goldberg, Khandelwal, Pavcnik, and Topalova 2010b). The second source of gains arises as a result of reallocation of resources between firms (Melitz 2003; Melitz and Ottaviano 2008). In this literature trade does not affect firm productivity but increases aggregate productivity by reallocating market shares from low-productivity firms to high-productivity firms. The third source of gains from trade arises from increase in firm productivity. Trade liberalization can increase firm productivity through several channels (Melitz and Redding 2014): by encouraging firms to invest in technology adoption and innovation activities; by upgrading the organization of production; and by changing the set of products produced. Increased trade can affect innovation by inducing more competition. The endogenous growth theory (Aghion et al. 2001) highlights the relationship between product market competition and productivity growth. Aghion et al. (2005) suggest that competition may encourage innovation via escape competition effect or discourage innovation via Schumpeterian effect. This study suggests that in industries where cost of production is approximately same across firms, competition incentivizes the firms to innovate more (*escape competition effect*) by increasing the incremental profits from innovation. One the other hand, in industries where production costs differ across firms, competition discourages innovation. Economic integration can increase firm productivity by greater utilization of imported inputs, which generally embed modern technology and superior quality (Amiti and Konings 2007; Topalova and Khandelwal 2011; Kasahara and Rodrigue 2008; Halpern, Koren, and Szeidl 2015). Trade liberalization encourages technology adoption by incentivizing firms to enter the export market (Bustos 2011; Lileeva and Trefler 2010). Fall in trade barriers can also increase firm productivity by reallocation of resources within-firm (BRS 2011; Eckel and Neary 2010; Mayer, Melitz, and Ottaviano 2014; Pavcnik 2002). This paper is more closely related to the last channel, particularly studies that explore the impact of trade on firm productivity by highlighting the role of product churning within-firm.

Third, this study also relates to the literature that examines the impact of economic reform in general and trade liberalization in particular on productivity growth in a developing country context. 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 (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. This paper differs from the above studies in a number of dimensions. First, in previous studies, such productivity gains to developing countries' manufacturing sector are explored in the era when North-North and North-South trade dominated the host country trade regime. This paper explores plant-level productivity dynamics in the context of booming South-South trade, a new era of globalization history. Second, in previous studies, the source of identification of the impact of reform is mainly domestic policy changes, which embeds an element of selection across industries (see Topalova and Khandelwal 2011, for a discussion on this issue). In this study, I examine the impact of a large international event, the rise of China in the aftermath of WTO accession that has been affecting the economic environment across countries. Third, the distinction of the trade shock by source country allows me to draw a line between low-wage and high-wage countries.

1.5 Review of Recent Empirical Evidence

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 (2016) find a significant within-firm effect of Chinese trade on various measures of technical change: patents, IT intensity, R&D, management practices and TFP. For example, both OLS and IV estimation for the industries (textiles and clothing) where quotas were applicable, they find that Chinese import growth significantly increases patents, IT intensity and TFP. On the reallocation effect of trade, they find that the rise in the share of import from China negatively affects both employment growth and firm survival: (e.g. a 10 percentage point rise in imports from China is associated with a 3.2 percent fall in employment). Moreover, the industry-level negative effect of China trade is larger than the firm-level, which is consistent with their earlier result that the rise of trade competition leads to exit of less productive firms. Bernard, Jensen, and Schott (2006) show that import penetration from low-wage countries increases the probability of plant death, significantly. Capital-intensive plants are more likely to survive compared to labor-intensive plants, especially in industries with greater exposure to low-wage country imports. Second, low-wage country import penetration is negatively and significantly correlated with employment growth rate at the plant-level. Again, the effect of low-wage import exposure is smaller for more capital-intensive plants. One interesting new result in this paper is that on an average 7.8 percent of the surviving plants 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 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. Iacovone, Rauch, and Winters (2013) and Liu (2010) also find that there are heterogeneity across products within-plant in the way plants adjust their product mix in response to import competition. 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.

Recent research by Autor, Dorn, and Hanson (2013) show that import competition from a low wage country has important implications for the local labor markets in U.S. In this paper differential import exposure of the local labor market stems from their differences in employment concentration in manufacturing relative to non-manufacturing activities, and more importantly, from the variation across manufacturing industries in terms of specialization.

These studies add new insights to the trade literature, particularly in understanding the impact the low-wage country trade exposure on advanced economies. The growth of trade between low-wage countries is a relatively recent phenomenon. Hitherto, how firms in low-wage countries respond to trade shocks from other low-wage countries has been little researched. The goal of this paper is to fill this vacuum in the international trade and plant performance literature in the developing country context in general and low-wage country in particular. 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.

1.6 Outline of Chapter 2

I separate the empirical analysis of the chapter into three stages: in the first part of this chapter, I explore some key stylized facts about the multiple-product vis-à-vis single-product plants in the ASI data with reference to GKPT (2010a) and BRS (2010) and against the cross-sectional predictions of multiple-product models. For this purpose, I use detailed product level data available in the ASI survey from 2000 to 2009. In the Annual Survey of Industries (ASI) data, each product is identified by a unique product code named as ASI commodity classification (ASICC) system. In order to convert the ASI product level information to an internationally recognizable classification system, I reclassify the ASICC products to 5-digit Central Product Classification (CPC) system of the United Nations. In this study, using CPC system a multi-product plant is defined as the plant that produces more than one 5-digit CPC products. Firstly, I find that approximately 50 percent of the plants in the ASI data produce multiple products that account for 75 percent of manufacturing output. Secondly, multi-product plants are significantly larger than the single-product plants in the same industry. But in contrast to GKPT (2010a), I find that plants in India exhibit substantial product churnings in the 2000s, about 63 percent of the ASI plants change their product mix over a five-year period of which 10 percent of plants only add and 11 percent only drop products, while 42 percent of plants both add and drop products.

In the second part of Chapter 2, I first explore the impact of Chinese competition on revenue productivity of the plant. I use Wooldridge-Levinsohn-Petrin approach to estimate plant productivity. I find that increase in Chinese import exposure leads to an improvement of plant productivity. The result is robust to alternative identification schemes. Secondly, I find that large plants rationalize their product range in the face of heightened import competition from China. Again this finding is robust to alternative identification schemes.

In the final part of Chapter 2, I investigate the impact of Chinese competition on selection of products within-plant. First, I examine the impact of Chinese competition on plants' decision to drop a product and whether there is any asymmetry across products within-plant in the response to competitive shocks. The result suggests that the impact of competition on selection of products is not symmetric within-plant, plants drop the product in which Chinese import exposure is greater but the closer the product to the core competence of the plant, the less likely it is to be dropped. Overall, the findings of the paper are consistent with the theoretical models of multiple-product firms. The results are also consistent with the empirical findings of the earlier studies that explore the impact of low-wage import competition shocks in the high-wage country context.

1.7 Outline of Chapter 3

In this chapter, I focus on two core labor market issues in the context of international trade, –wage inequality and employment. I further examine whether the impact of trade shocks differ by the flexibility of labor markets in India. To the extent that labor market inflexibility or restrictions on plants' ability to adjust to shocks is not uniform across Indian states, consequences of trade shocks can also differ across labor regulation regimes. The variation in India's labor market environment presents an ideal setup to test whether there is any difference between plants located in flexible and inflexible states in terms of their response to trade shocks.

In the first part of this chapter, I explore the impact of import competition shocks on wage inequality within-plant. I define wage inequality or skill premium at the plant level as the ratio of average wages of paid to white-collar workers to the average wages of blue-collar workers in the same plant. The set of paid white-collar workers includes supervisors, managers and other employees and that of blue-collar workers include regular and contractual production employees.

In the empirical specification, I examine whether skill premium increases with the increase in import competition from China. In order to understand the underlying forces behind the changes in skill premium, I further investigate how wages of different categories of workers respond to changes in the competitive environment. I observed that the rise in import competition from China leads to a general increase in within-plant wage inequality between skilled and unskilled workers of large plants; a 10 percentage point increase in Chinese import exposure leads to a 1.35 percent increase in skill premium within-plant overall. However, a separate analysis of average wages of white-collar and blue-collar workers suggests that import competition from China induces a significant increase in average wages of white-collar workers only, while there is no such impact on average wages of blue-collar workers. Then I move on to examining whether the impact of competition on wage inequality differs by the flexibility of labor market. Here, I find that the overall pattern is driven by the much larger adjustment of within-plant skill premium in the flexible markets. Again the average wages of white-collar workers rise in the face of import competition in the flexible market only. On the other hand, import competition from China has no significant impact on wage inequality in the inflexible market.

In the final section, I examine the impact of competition from China on employment of different categories of workers. I find that, in the sample of large plants, import competition from China leads to reallocation of labor from less to more productive plants. But consistent with the literature of labor market flexibility, I find that the reallocation occurs only in the flexible labor market suggesting that there is evidence of adjustment costs associated with labor market inflexibility.

Chapter 2

Low-wage Import Competition, Product Switching and Performance of Manufacturing Plants: Evidence from India in the Wake of China Trade Shock

2.1 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 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 less-productive firms to exit and more-productive firms to enter the export market. In this setup, the entry and 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 towards core competent products (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 decision.[4]

The lack of "creative destruction" in India during the 1990s is difficult to reconcile with the fact that the Indian economy went through extensive tariff liberalization and a substantial structural reform over the same period.[5] 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 firm product scope as the decline in input tariffs paves the way for firms to use new intermediate inputs, which helps 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 on average, while all the low-wage countries including China

[4] GKPT (2010a) report that while 22 percent of the firms in 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.
[5] 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.

comprised just around 10 percent of imports over the same period. The scenario has now changed: the average share of EJU dropped to 32 percent, while that of low-wage countries' increased to 22 percent in 2006-10, where the average share of Chinese imports alone increased by 11 percent.

The 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, in a recent paper, Iacovone, Rauch, and Winters (2013) find that Chinese import exposure induced product churning within-firms in Mexico.

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, several questions are explored in this context. Have 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 multiple product model? 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 import share across industries and over time as a source of low-wage import competition shock in India. 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 identification scheme. For instance, the measure of Chinese import exposure may be correlated with different unobserved demand or supply side shocks to Indian industries. Another concern is measurement error in the import competition variables. I address these identification challenges by exploring alternative identification strategies. First, I exploit an instrumental variable approach to identify Chinese import competition shock. In line with recent literature on import competition, I use the lag changes in China’s share of imports of a large low-wage country, Indonesia, as an instrument for changes in China’s share of India’s imports. A second alternative specification examines robustness of the primary identification scheme by allowing 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 data and evaluate the findings in comparison to GKPT (2010a) and BRS (2010). For this purpose, I aggregate ASI product level information to their corresponding internationally recognized Central Product Classification (CPC) codes. I define a multi-product plant as the one that produces more than one 5-digit CPC products. I observe that the cross sectional features of the multi-product plants in ASI data 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; this is even higher rate of change than that of U.S. firms (54 percent) during 1987-1997.

In the second part of the paper, I investigate the impact of rising Chinese import competition on plant revenue-productivity. Based on plant-level data from 1998 to 2009, I document that the increase in Chinese import exposure leads to an improvement in plant revenue productivity. The relationship between plant performance and Chinese import exposure remains consistent in instrumental variable 2SLS regressions and OLS regressions with 2-digit sector fixed effects. Overall, I find that a 10 percentage point increase in Chinese import exposure leads to a 3.7 percent increase in Total Factor Productivity (TFP) for the sample of large plants in the OLS regression. Consistent with the findings with earlier studies, the IV estimates are generally higher than their corresponding OLS counterparts. 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 the 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 investigate the impact of import competition on the selection of products within-plant. I find that the higher the level of import competition 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 deleting the product decreases with the proximity of the product to the core competence of the plants.

The remainder of the paper is organized as follows. Section two discusses China's integration into WTO and its economic implications. Section three presents the data and section four presents some stylized facts about the multi-product plants in India. Section five shows the methodology for productivity estimation. Section six discusses the link between competition, productivity and product scope. Section seven documents the link between import competition and plant-product level adjustment, and section eight concludes.

2.2 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).

Another key implication for developed and developing countries alike is that China also gets the facility of Multi-Fiber Arrangement (MFA) quota relaxation following its incorporation into WTO. In the pre-accession period, China was excluded from the benefits of MFA quota relaxation in the first two phases, which were effective from 1995 and 1998 respectively. The U.S. extended the quota relaxation facility of the first two phases to China simultaneously with the third one, on January 1, 2002, the scheduled the effective date of phase III (Brambilla, Khandelwal, and Schott 2010).[6] Therefore, within a month of China's WTO entry, it gained access to the first three rounds of quota relaxation.

A key reason China sought WTO membership and agreed to extensive liberalization of its trade and investment regimes 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

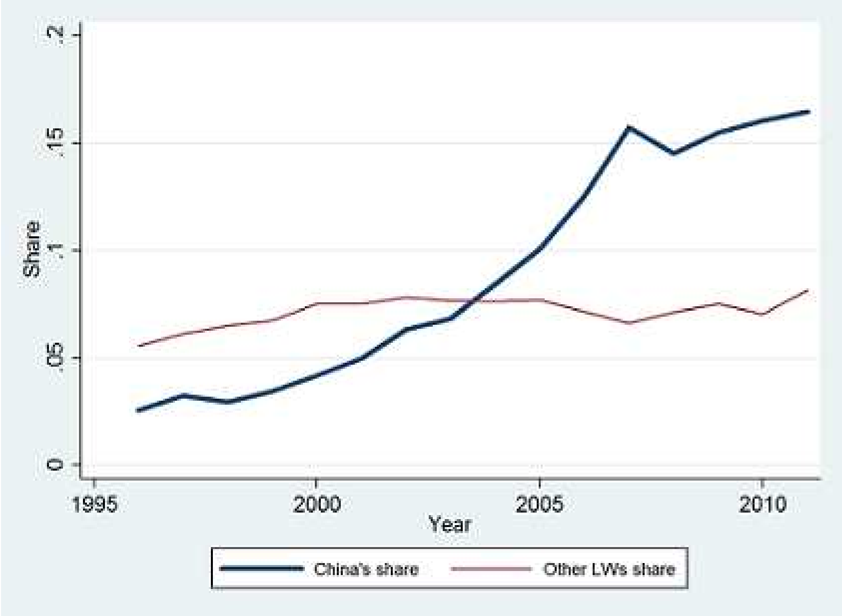
[6] The Agreement on Textile and Clothing (ATC) was signed at the Uruguay Round in 1994 to end the MFA quotas sequentially and to integrate the textiles and clothing products into WTO. The signing of MFA in 1974 protected textiles and clothing products from integration into WTO negotiations. The MFA quotas were scheduled to be withdrawn in four phases: Phase-I, Phase-II, Phase-III, and Phase-IV respectively on 1995, 1998, 2002 and 2005, effective from 1 January of each year.

to be discriminatory. Thus, accession to WTO has been crucial in ensuring stability in markets for Chinese exporters, particularly in WTO member countries.[7] On the other hand, membership obliges China to gradually implement further economic reforms in important areas such as trade liberalization, reducing barriers to foreign direct investment, and adhering to global intellectual property rights standards. As expected, after integration into the WTO, China further reduced barriers (tariffs and non-tariff) to trade and subsidies on exports. As a result of trade liberalization, the cost of imported inputs plummeted, which reduced the cost of production for Chinese firms, and increased the competitiveness of its exports worldwide (Bown, 2010).

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. But things have 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. Consequently, India's manufacturing industry faced a sudden rise in competition from China within a short period of time. Figure 1 shows the overall share of China and other low-wage countries in India's total non-oil imports.[8]

[7] 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 export, even in the pre accession era, this raised a major uncertainty about Chinese exports in the U.S. market.
[8] I exclude HS 1996 commodity codes (270900 and 271000) for petroleum from both imports and exports.

Figure 1–Share of India's (Non-Oil) Imports from China and Other LW countries



Source: UN Comtrade

2.3 Data

2.3.A Plant-level Data: In order to explore the impact of a low-wage country trade shock on the performance of the manufacturing entities of a low-wage country, I combine plant-level micro data from India with the country level bi-lateral commodity trade data. 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 National Statistical Office (NSO) under the Ministry of Statistics and Programme Implementation, Government of India.

I use 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 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.[9]

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 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

[9] 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 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.

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 are 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.

Table A.1 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.2).

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. Table A.3 shows the distribution of ASI plants by initial NIC-2 digit sector and technology intensity.[10] A large percentage of the plants

[10] 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.

(43 percent) belong to low-technology intensive industries, while only a small proportion of the plants (6 percent) belong to the high-technology category.

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 value of fixed capital (net of depreciation) for each financial year. I measure capital as the average of opening and closing net book value of fixed capital in each year. Plants also report gross additions to fixed capital, which I use as the main measure of investment. Both capital and investment are deflated by the Wholesale Price Index (WPI) of machinery.

The real value added is computed as the difference between real output and real values of intermediate inputs. Total output includes the value of all products and by-products, the increase in the stock of semi-finished goods and the other income.[11] Real output of a plant is obtained by deflating total output with the corresponding WPI of the 3-digit NIC industry. Input includes the value of material, fuels and other expenses. The value of material is deflated by the material price deflator of the corresponding NIC 3-digit industry constructed by combining WPIs with India's Input-Output table. The value of fuels is deflated by 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 average number of total employees and blue-collar

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

workers. In the ASI data, white-collar workers are comprised of supervisors, managers and all other non-production employees.

In terms of initial employment (LFirst), a significant percentage of the ASI-all (non-missing) sample are small: around 34 percent of the plants employ less than 20 employees in the initial year.[12] 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. Therefore, I exclude all small-sized plants from the baseline sample. After the cleaning exercise, I end up with 235,186 plant-year observations of 74,162 plants with at least 20 employees. Hereafter, I refer the baseline sample as LFirst20. All the key inputs and output variables are winsorized at 1st and 99th percentiles by NIC 2-digit sector.

2.3.B Plant-Product-Level Data: The ASI data contain detailed product-level information for all ASI plants from 2000 to 2009. Therefore, I use only 2000-2009 survey data for the plant-product level analysis. The ASI survey questionnaire requires plants to identify their products by specific ASI commodity classification (ASICC) codes.[13] 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. 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.

In order to directly relate the plant-product level adjustment with the product-specific measure of import competition by source country, I map ASICC product-level data to the

[12] Initial employment is the total number employees reported when a plant first time observed in the ASI data (1998-2009).
[13] ASICC is a 5-digit product classification system

Central Product Classification (CPC-version 2, hereafter CPC).[14] 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. I use a concordance published by Central Statistics Office (CSO) of India to map the ASICC codes to the CPC level. 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 non-missing manufacturing sector plants with at least 20 employees. 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 non-missing 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.[15]

2.4 Multi-Product Plants in India: Some Stylized Facts

Theoretical models of multi-product firms present several predictions about the distribution and characteristics of the firms in the cross-section. This section explores some stylized facts

[14] The commodity trade data are observed at HS 6-digit level, which is converted at CPC level 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.

[15] Some plants report a fraction of their output under other-products and by-products category (ASICC-99). Thus, I treated the products under this category as a single ASICC product.

about the multiproduct plants in India through the lens of the multi-product models developed by BRS (2010), Eckel and Neary (2010) and Eckel et al. (2015).[16]

I use the CPC codes as the main product classification system to distinguish between multiple- and single-product plants. A single-product plant (SpC) is considered as one whose set of products can be aggregated to a single CPC 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–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
Multiple Product (MpC)	0.50	0.75	2.8
Multiple Class (MpI)	0.38	0.64	2.6
Multiple Division (MpS)	0.28	0.48	2.3
Multiple ASICC Product (MpA)	0.52	0.77	3.0

Notes; Table reports the distribution of multi-product plants classifying them in terms of their production of multiple 5-digit CPC, 4-digit CPC, 2-digit CPC and multiple ASICC product categories. Sampling weights for the plants are used to create the tabulated statistics. This table is based on LFirst20 sample excluding the plants that do not report detailed product codes.

Table 1 reports the proportion of single and multi-product plants in India's formal manufacturing sector and their respective output share in the total manufacturing output in 2000. The table shows that around 50 percent of the plants in the ASI data are multi-product plants that account for 75 percent of manufacturing output. These ratios are quite close to Prowess firm sample, where 47 percent of the plants produce multiple products and contribute

[16] I show that the characteristics of the multi-product ASI plants are consistent with the inferences of theoretical models and resemble the cross-section feature 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.

80 percent of manufacturing output.[17] For the sake of comparison, 39 percent of the firms in the U.S. produce multiple products and share 87 percent of total output. Rows (2) and (3) indicate that 38 percent and 28 percent of ASI plants manufacture products that range more than one class (i.e. 4-digit CPC) and division (i.e. 2-digit CPC) of CPC products, contributing 64 percent and 48 percent of total manufacturing output, respectively.

These figures are also consistent with GKPT (2010a), where 33 percent and 24 percent of 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 ASI and 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.

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 greater range of products. Table 2 provides a comparison between multi-product and single-product plants in India using ASI data in 2000.[18] The table shows that multi-product plants are significantly larger than the single-product plants in the same industry in terms of all the measures of plant size. In the same industry, multi-product plants produce 95 percent higher output and employ 54 percent more labor than single-product plants. The table 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

[17] Based on ASICC product classification 52 percent of the plants in ASI data produce more than one product and 77 percent of output.
[18] 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).

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. Though the TFP difference is relatively smaller for MpI and MpS plants and statistically insignificant, they are greater than GKPT (2010a) and BRS (2010) estimates.[19]

Table 2–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 (LP)	0.30	0.20	0.14
TFP	0.09	0.03	0.01

Notes: Each row in this table reports 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 plant 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. ASI data for 2000 is used in this Table. TFP is estimated by Woolridge-Levinsohn-Petrin approach. All the coefficients are significant at 1 percent level, except log of LP in MpS, which is significant at 5 percent and TFP in MpI and MpS, which are insignificant.

Table A.4 looks at the time series pattern of the proportion of multi-product plants and 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.[20] This pattern is also reflected in the percentage of multiple CPC-class and 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 mean number of CPC 5-digit products produced by the plants decreased from 1.92 in 2000-04 to 1.84

[19] The TFP coefficient for MpI plants ranges from 4 percent to 9 percent from 2001 to 2009 and remain 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.
[20] This pattern is also consistent with the un-weighted mean of the sample.

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 have been shrinking their product range in the second half of 2000s. GKPT (2010a) reports that 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.

Another key prediction of multi-product firm model (BRS 2010; Eckel and Neary 2010) is that firms output is skewed towards its core competence. Table A.5 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 LFirst20 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 show high 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.

In order to understand the within-plant adjustment mechanism behind the observed decline in the proportion of multi-product plants and the fall in product scope in India’s formal manufacturing sector from 2000 to 2009, it is important to investigate how plants change their product mix over the same period. 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 in group "A" if it adds at least one product in period t that is not produced in period t-τ and it does not drop any product over the same time. Similarly, a plant is considered in group "D" if it drops at least one product in period t from a set of products that are produced in t-τ and it does not add any product in the same period. In all cases τ represents lag time period (e.g. 1 or 5).

In Table 3, 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 five-year horizon based on main 5-digit CPC products produced by the plants. Therefore, I exclude "other product and by-products" category from the product-switching analysis as this code cannot be treated as a unique CPC product. 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 LFirst20 sample, and (4) to (6) show the results for the LFirst200 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 plants only add ("A") and 11 percent only drop (D) products, while 42 percent of the plants both add and drop products ("AD").

These figures are strikingly different than those reported in GKPT (2010a): 22 percent only add, 4 percent only drop and 2 percent both add and drop products in 1990s. Though the product switching pattern observed here is much different than 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, 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 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 1990s, India's imports and exports were dominated by developed countries. In contrast, during 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 behind this new "creative destruction" phenomenon in Indian economy.

Table 3–Product Switching Activity of the Plants

	LFirst20			LFirst200		
	(1)	(2)	(3)	(4)	(5)	(6)
Activity	All	Single-Product	Multi-product	All	Single-Product	Multi-product
No Activity	37	61	21	35	64	22
Only Add	10	10	10	11	11	10
Only Drop	11	-	19	12	-	18
Both Add & Drop	42	29	51	42	24	50

Notes: Table presents the classification of the plants in terms of four mutually exclusive product-switching activities: No Activity, only added, only dropped and both added and dropped. Columns (1) to (3) show the results for the LFirst20 sample and (4) to (6) show the results for the LFirst200 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.

The table also shows that plants that produce more than one product are more active than those produce single-product. Only 39 percent of the single-product plants changed their product mix over a five-year period compared to 80 percent of the multi-product plants in LFirst20 sample.

2.5 Measuring Productivity

I estimate productivity at the plant-level by using ASI data over the period 1998 to 2009 and implementing Woolridge's (2009) production function estimation approach, which is a modified version of Levinsohn and Petrin (hereafter LP, 2003). The modified estimation strategy is known as Woolridge-Levinsohn-Petrin (WLP) approach and it is robust to criticism of Ackerberg, Caves, and Frazer (hereafter ACR, 2006).

I assume a Cobb-Douglas production function,

$$\upsilon_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \qquad (1)$$

υ_{it} is the log real value added of plant *i* at year *t*. l_{it} is a vector of variable inputs (log number of blue-collar, $l_{b,it}$ and white-collar employees, $l_{w,it}$) and k_{it} is the log of plant capital. 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 either to the plants or the econometrician. Thus, a plant's input choices are correlated with the predictable component of productivity shocks, ω_{it}. In this case, application of OLS regression leads to bias in the coefficients of the production function and thereby causes bias in the estimated productivity.

In order to solve the problem of simultaneity of productivity and variable inputs, Olley and Pakes (hereafter OP, 1996) propose a proxy variable approach, where investment is used as a proxy variable for productivity, ω_{it}. OP show that if investment is a strictly monotonic function of productivity and capital, then the function can be inverted to obtain the relationship:

$$\omega_{it} = w(k_{it}, m_{it}) \qquad (2)$$

where m_{it} is a vector of proxy variables: investment in OP and intermediate inputs in LP. However, in practice, investment appears to be zero for a large fraction of plants. To circumvent this zero investment problem, Levinsohn and Petrin (2003) suggest using intermediate inputs as proxy variables.

$$v_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + w(k_{it}, m_{it}) + \varepsilon_{it} \qquad (3)$$

Since k_{it} appears both as a variable and in the function $w(\cdot,\cdot)$, it is not identifiable in this equation. ACR (2006) show that if intermediate inputs and labor inputs are determined simultaneously, then β_l is also not identified in equation (3). Woolridge (2009) suggests a one-step GMM framework, where the moment conditions of OP and LP approach are modified to estimate β_l and β_k jointly.

The next stage calculates productivity as the difference between annual value-added (or output) and estimated value-added obtained by adding the factors of production multiplied by their respective elasticity coefficients.

$$\varphi_{it} = v_{it} - \hat{\beta}_b^s l_{b,it} - \hat{\beta}_w^s l_{w,it} - \hat{\beta}_k^s k_{it} \qquad (4)$$

I use fuels consumption at the plant level as a proxy variable and estimate the production function coefficients for each sector (NIC 2-digit) separately. The superscript *s* on the coefficients of input represents a sector.[21]

2.6 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 heterogeneous firm models. 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

[21] I use a slightly modified version of the Stata program for production function estimation available at the website of Amil Petrin: https://sites.google.com/a/umn.edu/amil-petrin/home/Available-Programs.

in a way that results in productivity gains within the firm (BRS 2011; Eckel and Neary 2010; Mayer, Melitz, and Ottaviano 2014).

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 these two assumptions combined 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 of varieties. Surviving firms drop their least successful products in the domestic market but derive more revenue for their higher quality products in the export market. The productivity of firms increases as firms focus on their higher attribute 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 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 productivity as firms focus on core competence products and drop the high marginal cost varieties.

While I emphasize on the role of within-firm product selection mechanism as the main channel of improvement in revenue productivity, there are other important channels through which import-competition can affect firm performance. The endogenous growth theory (Aghion et al. 1997, 2001) highlights the relationship between product market competition and productivity growth. Aghion et al. (2005) suggest that the relationship between product market competition and productivity growth is U-shaped. Competition may encourage innovation via escape competition effect or discourage innovation via Schumpeterian effect. 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 the high-wage (northern) countries to innovate more. They argue that some factors of production are firm-product specific. These can either be used 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. 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 firms above.[22]

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 industries that experience a rise in Chinese imports. Firms respond to this change in competitive environment by reducing prices and markups.

2.6.A 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 (China) import competition shocks on the

[22] Another competition channel of productivity improvement is through inducing better quality management and decentralization in decision making (Van Reenen 2011; Bloom et al. 2010). In a recent study, Bloom et al. (2013) find that low-quality management practices are the major reasons behind low-productivity in India's manufacturing sector. In this case, competition can improve firm productivity by encouraging firms to improve management quality (Van Reenen 2011), and decentralize where both the factors can increase productivity (Bloom et al. 2010).

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*.

$$lnPr_{ijt} = \alpha_i + \beta_1 (M_{IN}^{CH})_{jt-l} + \xi_{ijt} \qquad (5)$$

The key coefficient of interest in equation (5) is β_1 corresponding to $(M_{IN}^{CH})_{jt-l}$ that measures China's share of India's imports in industry *j* in period *t-l*. The term α_i denotes plant fixed effects that account for time-invariant unobserved heterogeneity, which are likely to be correlated with the plant productivity and its exposure to international trade. The last term, ξ_{ijt}, is idiosyncratic error assumed to be uncorrelated with the measures of trade shocks and other right hand side variables.

In this study, the measure of import competition follows the "value share" approach proposed by Schott (2002), and Bernard and Jensen (2002),

$$I_{IN},_{jt}^{S} = \frac{\sum_k V_{kjt,S}}{\sum_k V_{kjt,W}} \qquad (6)$$

where $I_{IN},_{jt}^{S}$ is the ratio of the sum of the value of all products imported from source *S* (China or high-wage countries) and the sum of the value of all products imported from the world (*W*).

$V_{kjt,s}$ is the import value of product *k* in industry *j* at time *t* from source *S* and $V_{kjt,w}$ is the import value of product *k* in industry *j* at time *t* from world. *k* represents a particular HS 6-digit product category that corresponds to industry *j* (ISIC 4-digit industry).[23]

The trade exposure at the industry-level masks the true competition component of trade. Industry-level aggregation of product codes (HS 6-digit) includes four different types of products in general: consumer goods, capital goods, intermediate goods and raw materials

[23] Bloom, Draca, and Van Reenen (2016) use this approach as the main measure of Chinese import competition.

(according to UNCTAD standard product group classification). Aggregating all types of products may underestimate competitive impact of increasing import exposure. In order to obtain a more precise measure of competition at the industry-level, I modify the above measure of import competition by excluding all the raw materials (RM) from the numerator of equation (6). That is, the degree of import competition in industry j, $M^{S}_{IN},_{jt}$, is the ratio of the sum of the value of all products except raw materials imported from China (or high-wage countries) and the sum of the value of all products including raw materials imported from the world. The measure of import competition is as follows:

$$M^{S}_{IN},_{jt} = \frac{\sum_{k,k \neq RM} V_{kjt,S}}{\sum_{k} V_{kjt,W}} \qquad (7)$$

I take the five-year difference of the key variables of interest to control for plant fixed effects and estimate the following equation:

$$\Delta_5 lnPr_{ijt} = \alpha + \tau_{st} + \boldsymbol{\mu} X_i + \beta_1 \Delta_5 (M^{CH}_{IN})_{jt-l} + \xi_{ijt} \qquad (8)$$

where $\Delta_5 lnPr_{ijt}$ represents the change in productivity of plant *i* at time *t* compared to *t-5*. $\Delta_5 (M^{CH}_{IN})_{jt-l}$ indicates the change in the value share of import from China in industry j in period *t-l*. τ_{st} is the set of state-year fixed effects and X_i is a vector of control variables: a set of initial technology classification (based on R&D intensity) dummies and a rural/urban location dummy, which equals 1 if a plant is located in a rural location or 0 otherwise. In this difference form specification, inclusion of the initial technology dummies addresses the issue that the productivity growth may differ across different technology intensity groups. Similarly, the rural/urban dummy controls for differential trend in productivity growth rate between plants located in rural areas and those located in urban areas.[24] Since I measure the trade shock at the

[24] To the extent that production environment in rural area may be different from that of urban area, dynamics of plant growth can also differ between the two areas. Another important observation in the context of this paper is that average age of rural plants in ASI data is significantly smaller than the average age of urban plants. This

industry (NIC 4-digit) level, I cluster the standard errors at the level of the plant's main industry in all the regressions. In the baseline specification, I use lag length *l=1* for the changes in import value shares.[25]

According to the theory of multi-product firms, β_1 would be positive if the increase in Chinese import competition leads to an improvement in plant performance as plants reallocate resources towards core competence product 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.[26]

In the above specification (8), I do not control for import competition from other sources, which may bias the coefficient β_1. One possibility is that increase in imports from China in a particular industry drives out 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, competition from China and developed countries would be negatively correlated. 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 β_1. However, the coefficient β_1 may over-estimate 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. In order to address this issue, I modify the plant performance regression equation as follows:

$$\Delta_5 lnPr_{ijt} = \alpha + \tau_{st} + \boldsymbol{\mu} X_{\boldsymbol{i}} + \beta_1 \Delta_5 (M_{IN}^{CH})_{jt-l} + \beta_2 \Delta_5 (M_{IN}^{EJU})_{jt-l} + \xi_{ijt} \;, \qquad (9)$$

evidence suggests that more new plants have been formed in rural than in urban areas. Therefore, the inclusion of rural (or urban dummy) is expected to capture differences in patterns of plant growth dynamics.

25 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.

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

where $\Delta_5(M_{IN}^{EJU})_{jt}$ represents the change in the combined share of EU, Japan and US in India's industry-wise imports. As a robustness check, I also report results after controlling for changes in import competition from other low-wage countries, $\Delta_5(M_{IN}^{LW})_{jt}$, along with two main sources of import shocks. For notational simplicity, in the discussion that follows, I use ΔCHN for $\Delta_5(M_{IN}^{CH})_{jt}$, ΔEJU for $\Delta_5(M_{IN}^{EJU})_{jt}$ and ΔLW for $\Delta_5(M_{IN}^{LW})_{jt}$.

Table 4 shows the regression results of changes in plant revenue productivity measured by the WLP approach on changes in import competition measured at industry (NIC 4-digit) level. In order to check the sensitivity of the results to outliers in TFP, I report the regression results separately both for unwinsorized and winsorized TFP series. Since ASI data contain both census and sample plants and the impact of import competition might differ by plant size, I perform regressions by different size threshold of the plants. Block-A reports the results for the LFirst200 sample (at least 200 employees) and Block-B reports the results for the LFirst100 sample (at least 100 employees). In Table A.6, I report the regression results for the LFirst20 (at least 20 employees) sample. In Table 4, the first and fourth columns in each table show the results when only lagged changes in the Chinese import ratio are included in the regression. The second and fifth columns add the lag changes in EJU's import share; and third and sixth columns add lag changes in both EJU's and other LW's import share in addition to changes in China's share. Note that regressions include the plants that are sampled and non-missing at the starting and end point of the five-year interval. In this table, standard errors are clustered at the 4-digit industry level and reported in parentheses below the estimated coefficients.

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

	Block-A (LFirst200)			Block-B (LFirst100)		
Panel-A	**Dependent Variable:** $\Delta_5 TFP_{ijt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5(CHN)_{(t-1)}$	0.374**	0.408**	0.438**	0.400**	0.427**	0.451**
	(0.186)	(0.206)	(0.199)	(0.191)	(0.213)	(0.213)
$\Delta_5(EJU)_{(t-1)}$		0.103	0.15		0.077	0.116
		(0.138)	(0.138)		(0.136)	(0.148)
$\Delta_5(LW)_{(t-1)}$			0.134			0.108
			(0.094)			(0.109)
R-squared	0.027	0.027	0.027	0.026	0.026	0.027
Panel-B	**Dependent Variable:** $\Delta_5 TFP_{ijt}$ **(winsorized)**					
$\Delta_5(CHN)_{(t-1)}$	0.392**	0.427**	0.447**	0.420**	0.446**	0.459**
	(0.183)	(0.201)	(0.195)	(0.189)	(0.211)	(0.211)
$\Delta_5(EJU)_{(t-1)}$		0.102	0.135		0.074	0.096
		(0.132)	(0.132)		(0.133)	(0.142)
$\Delta_5(LW)_{(t-1)}$			0.092			0.06
			(0.097)			(0.110)
R-squared	0.029	0.029	0.029	0.028	0.028	0.028
Observations	22618	22618	22618	31976	31976	31976
Plant	4970	4970	4970	7906	7906	7906
NIC4	118	118	118	118	118	118
NIC4-Year	750	750	750	787	787	787
Clusters	118	118	118	118	118	118

Notes: Table reports results from OLS regression of five-year changes in TFP on lag changes in China's, EJU's and other LW's import share in India. Columns (1)-(3) in Block-A include only LFirst200 and columns (4)-(6) in Block-B include LFirst100 sample. Robust standard errors (in parentheses) are clustered at plant's main (NIC 4-digit) industry level. All the regressions include rural/urban location dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. NIC4 and NIC4-year imply number of 4-digit industry codes and number of NIC4-year combination included in each regression. * p<.1; ** p<.05; *** p<.01

Of particular interest is $\beta_{1,}$ the coefficient of changes in Chinese import value share across various regression specifications. The results are economically and statistically significant. In Panel-A, column (1), the coefficient indicates that a 10 percentage point increase in China's share of India's imports causes a 3.7 percent increase in plant TFP. In all the specifications, the coefficient β_1 is positive and statistically significant at 5 percent level. The size of the β_1 coefficient is also slightly higher for the LFirst100 sample compared to corresponding estimates of LFirst200 sample.

In columns (2) and (5), I introduce controls for other sources of import competition by including the first lag of ΔEJU (which represents European, Japanese and US imports). The size of the β_1 coefficient increases further in columns (3) and (6) after including lag of other LW's import share in addition to lag of ΔEJU. In the table, both the import shocks of high-wage countries and other LWs are positive but remain statistically insignificant. Taken together, results suggest that there is a slight downward bias in the coefficient ΔCHN, when I do not control for the import shocks from high-wage and other LW countries. As discussed above, this downward bias is plausibly arising from negative correlation between Chinese import share and high-wage (or other low-wage) import share, where the latter is positively associated with plant productivity. Panel-B shows the regression results after correcting for outliers in estimated TFP. The baseline TFP series is winsorized at 1st and 99th percentiles before taking the five-year difference. The coefficient of interest, β_1, is slightly higher in Panel-B in comparison to their corresponding estimates in Panel-A. However, the level of significance and overall pattern of β_1 remain unchanged. Thus, the presence of outliers in base TFP slightly underestimates the impact of Chinese competition on plant TFP.

Endogeneity emanating from unobserved Shocks: Our baseline estimation strategy is not free from endogeneity concerns, such as bias emanating from unobserved demand and supply shocks. One possibility is that industry-specific unobserved technology shocks are partly correlated with the changes 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. In contrast, positive demand shocks will generate an upward bias in $\beta_{1.}$ 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. Therefore, whether OLS underestimates or overestimates the import competition coefficient is an empirical issue.

In order to identify the causal effect of Chinese import exposure on India's manufacturing performance, I employed 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 would capture China's supply-side driven component of its export growth 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 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 lag changes in Chinese import value share in Indonesia, a large low-wage country, as the instrument for changes in Chinese import value share in India. In particular, I use τ-1'th lag changes in Chinese import share in Indonesia as the instrument for τ'th lag changes in Chinese import share in India. The legitimacy of this identification strategy relies on the assumption that growth of China's exports to India and exports to Indonesia share a common component, which is mainly driven by China's rising competitiveness and falling barriers to trade.

Autor, Dorn, and Hanson (2013) argue that measured import exposure can also be correlated with domestic shocks to U.S. industries (e.g. labor demand shocks) that in turn affect the U.S.'s demand for import. In order to identify the effect of the supply-side driven component of imports from China, they use concurrent growth of Chinese imports in eight other developed economies.

Table 5–Impact of Import Competition from China on Plant Productivity (2SLS)

	Block-A (LFirst200)			Block-B (LFirst100)		
Panel-A	**Dependent Variable:** $\Delta_5 TFP_{ijt}$					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\Delta_5(CHN)_{(t-1)}$	0.831*	0.882**	0.913**	0.753*	0.785*	0.808*
	(0.432)	(0.446)	(0.443)	(0.447)	(0.461)	(0.460)
$\Delta_5(EJU)_{(t-1)}$		0.211	0.277		0.161	0.216
		(0.170)	(0.175)		(0.176)	(0.193)
$\Delta_5(LW)_{(t-1)}$			0.195**			0.158
			(0.093)			(0.117)
R-squared	0.024	0.024	0.025	0.025	0.025	0.025
Panel-B	**Dependent Variable:** $\Delta_5 TFP_{ijt}$ **(winsorized)**					
$\Delta_5(CHN)_{(t-1)}$	0.906**	0.959**	0.985**	0.807*	0.840*	0.857*
	(0.421)	(0.433)	(0.431)	(0.435)	(0.447)	(0.449)
$\Delta_5(EJU)_{(t-1)}$		0.224	0.279*		0.166	0.207
		(0.162)	(0.167)		(0.171)	(0.186)
$\Delta_5(LW)_{(t-1)}$			0.162*			0.115
			(0.088)			(0.110)
R-squared	0.025	0.025	0.026	0.026	0.027	0.027
Observations	22618	22618	22618	31976	31976	31976
Plant	4970	4970	4970	7906	7906	7906
NIC4	118	118	118	118	118	118
NIC4-Year	750	750	750	787	787	787
Clusters	118	118	118	118	118	118
Panel-C First Stage Results	**Dependent Variable:** $\Delta_5(CHN)_{(t-1)}$					
Instruments	$\Delta_5(CH)IDN_{(t-1)-1}$					
R-sq.	0.39	0.44	0.45	0.38	0.43	0.45
F(2,117)	53.39	40.87	34.22	57.27	48.24	40.32
Prob > F	0	0	0	0	0	0

Notes: Table reports results from 2SLS regression of changes in TFP on lag changes in China's, EJU's as well as LW's import share in India. All regressions are based on five-year difference data. In the first stage, $\Delta_5(CHN)_{(t-1)}$ is instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia $\Delta_5(CH)IDN_{(t-1)-1}$. Columns (1)-(3) in Block-A include only LFirst200 and columns (4)-(6) in Block-B include LFirst100 sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. All the regressions include rural/urban location dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. NIC4 and NIC4-year imply number of 4-digit industry codes and number of NIC4-year combination included in each regression.

Bloom, Draca, and Van Reenen (2016) use three alternative identification strategies to identify the effect of trade on technical change. Their main identification strategy is the China's accession to WTO in 2001 and subsequent removal of most of the MFA quotas. It is implicitly assumed that the level of quotas in 2000 were exogenous to technology shocks in the future as these quotas were initiated during the 1950s and their phasing out was designed during the late 1980s prior to Uruguay Round. Secondly, they utilize pre-accession (1999) exposure to Chinese import as an initial condition in instrumenting the growth of import from China. Lastly, an industry trend is used to control for technology shocks.

In Table 5, Panel-A and Panel-B report 2SLS regression estimates for unwinsorized and winsorized samples and Panel-C reports corresponding first stages. Block-A reports the results for LFirst200 sample and Block-B for LFirst100 sample. For LFirst200 sample, results in Block-A suggest that 2SLS estimates of the impact of Chinese import competition on plant TFP are much larger than their corresponding OLS estimates both for unwinsorized and winsorized TFP and the results are statistically significant at 5 percent level in most cases. In Panel-A, for unwinsorized TFP, the estimate is statistically significant at 10 percent level in column (1), and at 5 percent level in columns (2) and (3). In Panel-B of Block-A, the coefficient of interest is significant at 5 percent level in all cases. On the other hand, in the case of LFirst100 sample (Block-B), the estimates of β_1 are still much larger than their OLS counterparts and statistically significant at 10 percent level in all the columns. Again, I find similar results for LFirst20 sample reported in appendix of this chapter (Table A.6).

Panel-C shows strong first stage regression results across all the specifications. In column (1), the adjusted r-squared from first-stage regression is 0.39 and the F-statistics is 53.39. The corresponding 2SLS estimate of the coefficient of interest β_1 is 0.831 for unwinsorized (column 1, Panel-A) and 0.906 for winsorized TFP (column 1, Panel-B). As in the case OLS, the magnitude of the impact of Chinese import competition increases after adding changes in EJU's (column 2), and both EJUs and other LW's imports (column 3).

Therefore, it appears that the OLS coefficient of Chinese competition shock is biased downward. The results are consistent with the findings of the earlier studies. For example, Bloom, Draca, and Van Reneen (2016) find that the 2SLS estimates are generally larger than the OLS counterparts. As discussed earlier, unobserved technology shocks coupled with error in measurement of import exposure variable may cause OLS to underestimate the competition effects of China.

In order to verify that our results are not driven by plant entry and exit or missing data problem, I re-estimate the model with a balanced sample of plants, which are available from 1998 to 2009 period. Table A.8 (appendix) reports the results for balanced sample. The table confirms that the main results of this chapter hold in the balanced panel. In fact, in each specification, the coefficient of Chinese import exposure is larger than the corresponding unbalanced counterpart.

Preexisting Industry Confounds and Pre-Trend: In this section, I investigate the sensitivity of the results from OLS regressions in five-year difference form to alternative specifications by incorporating 2-digit initial sector specific fixed effects. In this case, I exclude the initial technology intensity dummies and replace them with NIC 2-digit dummies.

Table 6 reports the regression results with NIC 2-digit sector fixed effects. Inclusion of these sector specific fixed effects addresses the concern that changes in import competition from China are likely to be correlated with the technological progress within sectors. Given that our regression is in difference form, incorporation of these fixed effects is equivalent to allowing for sector-specific differential trends in the levels. The specification with sector fixed effects, therefore, exploits the variation in import exposure across industries within sector to identify the plant-level impacts of import competition shocks. However, 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.

Panel-A in Table 6 reports OLS regression results for the unwinsorized TFP and Panel-B reports the results for winsorized TFP with 2-digit sector fixed effects. In the case of LFirst200 sample, in column (1) of Panel-A, the estimate of the impact of Chinese import competition on productivity is 0.287 with NIC 2-digit sector fixed effects, which is significant at 10 percent level with a standard error of 0.15. This estimate is about 9 percentage points smaller than the corresponding coefficient of 0.374 in the base model results in Table 4. In column (2), after adding the changes in EJU's share in imports the coefficient remains almost unchanged compared to column (1) and significant at 10 percent level. As in the base specification, after controlling for the changes in other LW's share in imports in column (3), the coefficient of ΔCHN is slightly larger compared to estimates in columns (1) and (2) and significant at 5 percent level. In Panel-B, for winsorized TFP the estimates of β_1 are larger than their corresponding unwinsorized counterparts in Panel-A but all the coefficients are significant at 5 percent level.

In column (4) of Panel-A, I find that for the LFirst100 sample, after controlling for NIC 2-digit fixed effects, the magnitude of the coefficient is marginally higher and the coefficient is now significant at 5 percent level rather than at 10 percent level. Though the estimates of β_1 are smaller in columns (5) and (6) compared to their corresponding estimates in the base specification, these coefficients are also significant at 5 percent level. Overall, the impact of Chinese import competition on plant productivity remains significant even when we control for sectoral trends.

Remarkably, the coefficient of changes in high-wage countries' import competition has the "opposite" sign and is statistically insignificant in Panel-A. A possibility is that the coefficient of changes in high-wage countries' imports shock appears with a positive sign in the base specification because of positive correlation between industry-level import exposure from high-wage countries and technological progress of the sector. On the other hand, the sign of the LW coefficient remains positive and insignificant in all the specifications.

Table 6–Impact of Import Competition from China on Plant Productivity (OLS with Sector Fixed Effects)

	Block-A (LFirst200)			**Block-B (LFirst100)**		
Panel-A	**Dependent Variable:** $\Delta_5 TFP_{ijt}$					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\Delta_5(CHN)_{(t-1)}$	0.287*	0.286*	0.318**	0.356**	0.347**	0.373**
	(0.152)	(0.159)	(0.150)	(0.170)	(0.168)	(0.162)
$\Delta_5(EJU)_{(t-1)}$		-0.002	0.031		-0.02	0.01
		(0.140)	(0.132)		(0.135)	(0.133)
$\Delta_5(LW)_{(t-1)}$			0.082			0.072
			(0.106)			(0.109)
NIC-2 Fixed Effects	yes	yes	yes	yes	yes	yes
R-squared	0.044	0.044	0.044	0.044	0.044	0.044
Panel-B	**Dependent Variable:** $\Delta_5 TFP_{ijt}$ **(winsorized)**					
$\Delta_5(CHN)_{(t-1)}$	0.326**	0.326**	0.345**	0.404**	0.397**	0.409**
	(0.147)	(0.153)	(0.144)	(0.166)	(0.163)	(0.158)
$\Delta_5(EJU)_{(t-1)}$		0.00	0.02		-0.015	-0.002
		(0.137)	(0.129)		(0.133)	(0.130)
$\Delta_5(LW)_{(t-1)}$			0.049			0.033
			(0.116)			(0.116)
NIC-2 Fixed Effects	yes	yes	yes	yes	yes	yes
R-squared	0.045	0.045	0.045	0.046	0.046	0.046
Observations	22618	22618	22618	31976	31976	31976
Plant	4970	4970	4970	7906	7906	7906
NIC4	118	118	118	118	118	118
NIC4-Year	750	750	750	787	787	787
Clusters	118	118	118	118	118	118

Notes: Table reports results from regression of changes in TFP on lag changes in China's, EJU's and other LW's import share in India and NIC 2-digit industry fixed effects. All regressions are based on five-year differenced data. Columns (1)-(3) in Block-A include only LFirst200 and columns (4)-(6) in Block-B include LFirst100 sample. Robust standard errors (in parentheses) are clustered at plant's main (NIC 4-digit) industry level. All the regressions include rural/urban location dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. NIC4 and NIC4-year imply number of 4-digit industry codes and number of NIC4-year combination included in each regression.
* p<.1; ** p<.05; *** p<.01

2.6.B Import Competition and Product Scope

The empirical results in the previous section provide evidence that Chinese import competition played a significant 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 theories 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 rise in import competition from China on product scope of plants. I begin by examining impact on the number of products produced by a plant, using the following specification:

$$\Delta_5 lnNp_{ijt} = \alpha + \tau_{st} + \mu R + \beta_1 \Delta_5 (M_{IN}^{CH})_{jt-l} + \beta_1 \Delta_5 (M_{IN}^{EJU})_{jt-l} + \xi_{ijt} \qquad (10)$$

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

Table 7 shows the OLS regression results based on five-year difference specification. Columns (1)-(3) in Block-A report results for the LFirst200 and columns (4)-(6) in Block-B report results for the LFirst100 sample. In Block-A, I observe that an increase in Chinese imports is associated with a statistically significant reduction in plant product scope for the LFirst200 sample. In column (1) the coefficient β_1 is -0.10, which indicates that a 10 percentage point increase in an industry's exposure to Chinese import competition leads to a 1 percent decrease in the number of products produced by the plants in that industry. This coefficient is significant at 1 percent level. Column (2) shows the results after adding changes in import share of high-wage countries and column (3) shows the results after adding both changes in high-wage and other LWs import share. Inclusion of these other source of imports shocks has minimal effect on the coefficient of interest β_1 and the coefficient remains significant at 1 percent level in column (2) and at 5 percent level in column (3). Interestingly, unlike the productivity regression, the coefficients of ΔEJU and ΔLW appear with a sign opposite to ΔCHN for the LFirst200 sample, though the results are statistically insignificant in all cases for these two sources.

In Block-B, I find that the impact of Chinese import competition on plant product scope is negative but the magnitude of the coefficients is much smaller than the corresponding estimates for the LFirst200 sample reported in Block-A. The coefficients are also statistically insignificant for the LFirst100 sample. Again, the coefficient of high-wage countries import shocks appears with a positive sign in Block-B, but the coefficient of other LWs appears with a negative sign. Both remain statistically insignificant.

Table 7–Impact of Import Competition from China on Plant Product (CPC) Scope (OLS)

	Block-A (LFirst200)			**Block-B (LFirst100)**		
	Dependent Variable: $\Delta_5$lnNPijt					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\Delta_5(CHN)_{(t-1)}$	-0.104***	-0.099***	-0.095**	-0.047	-0.039	-0.041
	(0.035)	(0.035)	(0.038)	(0.032)	(0.032)	(0.032)
$\Delta_5(EJU)_{(t-1)}$		0.015	0.021		0.025	0.022
		(0.045)	(0.048)		(0.040)	(0.042)
$\Delta_5(LW)_{(t-1)}$			0.019			-0.009
			(0.028)			(0.028)
R-squared	0.005	0.005	0.005	0.006	0.006	0.006
Observations	18226	18226	18226	26993	26993	26993
Plant	4815	4815	4815	7669	7669	7669
NIC4	117	117	117	117	117	117
NIC4-Year	537	537	537	564	564	564
Cluster	117	117	117	117	117	117

Notes: Table reports results from regression of changes in log number of CPC products on lag changes in China's as well as EJU's and other LW's import share in India. All regressions are based on five-year difference data. Years 1998 and 1999 are excluded from regression as number of products is not available at CPC level in these years. Columns (1)-(3) in Block-A include only LFirst200 and columns (4)-(6) in Block-B include LFirst100 sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. All the regressions include rural/urban location dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. NIC4 and NIC4-year imply number of 4-digit industry codes and number of NIC4-year combination included in each regression.

Table 8–Impact of Import Competition from China on Plant Product (CPC) Scope (2SLS)

	Block-A (LFirst200)			Block-B (LFirst100)		
Panel-A	**Dependent Variable: $\Delta_5 lnNP_{ijt}$**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\Delta_5(CHN)_{(t-1)}$	-0.129**	-0.128**	-0.125*	-0.016	-0.013	-0.014
	(0.063)	(0.065)	(0.067)	(0.076)	(0.078)	(0.080)
$\Delta_5(EJU)_{(t-1)}$		0.009	0.013		0.031	0.03
		(0.045)	(0.049)		(0.044)	(0.047)
$\Delta_5(LW)_{(t-1)}$			0.015			-0.005
			(0.030)			(0.030)
R-squared	0.005	0.005	0.005	0.006	0.006	0.006
Observations	18226	18226	18226	26993	26993	26993
Plant	4815	4815	4815	7669	7669	7669
NIC4	117	117	117	117	117	117
NIC4-Year	537	537	537	564	564	564
Cluster	117	117	117	117	117	117
Panel-B						
First Stage Results	**Dependent Variable:** $\Delta_5(CHN)_{(t-1)}$					
Instruments	$\Delta_5(CH)IDN_{(t-1)-1}$					
R-sq.	0.36	0.43	0.44	0.35	0.42	0.43
F(2,117)	27.21	27.21	22.13	30.46	31.11	25.65
Prob > F	0	0	0	0	0	0

Notes: Table reports results from 2SLS regression of changes in log number of CPC products on lag changes in China's as well as EJU's and other LW's import share in India. All regressions are based on five-year difference data. In the first stage, $\Delta_5(CHN)_{(t-1)}$ is instrumented by (t-1)-1 lag of five-year changes in Chinese Import Share in Indonesia $\Delta_5(CH)IDN_{(t-1)-1}$. Years 1998 and 1999 are excluded from regression as number of products is not available at CPC level in these years. Columns (1)-(3) in Block-A include only LFirst200 and columns (4)-(6) in Block-B include LFirst100 sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. All the regressions include rural/urban location dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. NIC4 and NIC4-year imply number of 4-digit industry codes and number of NIC4-year combination included in each regression.

Overall, the OLS regression results suggest that Chinese import competition induces plants to rationalize their product scope. But the impact is statistically significant only for plants with at least 200 employees in the initial period. One plausible explanation for this finding is that Chinese competition was high in labor-intensive sectors or sectors in which significant proportion of plants are large. Another issue is that a significant proportion of large plants in ASI data were producing multiple products in the initial year. For instance, in 2000, approximately 68 percent of large plants were producing more than one product (averaging

2.44 products per plant), whereas 48 percent of 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 large plants. As in the case of the revenue productivity regression, there is no statistically significant evidence of the impact of high-wage countries and other LW countries on plant product scope.

Endogeneity and Negative Supply Shocks: Plants may drop products for reasons unrelated to import competition but the decision may coincide with the rise in Chinese import share in India in that particular industry. One such source of endogeneity is negative supply shock. For example, a negative supply shock may raise the marginal cost of producing a particular product 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 shocks is then replaced by increasing supply of similar products from China.

Panel-A of Table 8 presents the 2SLS estimates of coefficient of interest, β_1 for the one period lag specification and panel-B reports corresponding first stage results. Again the coefficients 2SLS regressions are larger than their OLS counterparts (Table 7). Columns (1)-(3) report results for the LFirst200 sample and columns (4)-(6) for the LFirst100 sample. The estimated coefficient of β_1 in column (1) is -0.129, significant at 5 percent level. In column (2), β_1 is significant at 5 percent level and in column (3) at 10 percent level. On the other hand, β_1 tends to zero for the LFirst100 sample. Therefore, the IV results confirm the strong impact of Chinese competition on the LFirst200 plants only.

Controlling for Sector Specific Trends: Table 9 reports results of OLS regressions with sector specific trends for plant product scope. In this table, I include NIC 2-digit sector specific fixed effects in addition to import competition variables.

Table 9–Impact of Import Competition from China on Plant Product (CPC) Scope with Sector (NIC 2-digit) Specific Trend

	Block-A (LFirst200)			Block-B (LFirst100)		
	Dependent Variable: $\Delta_5 lnNP_{ijt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5(CHN)_{(t-1)}$	-0.102**	-0.094*	-0.091	-0.023	-0.012	-0.019
	(0.051)	(0.053)	(0.057)	(0.043)	(0.046)	(0.048)
$\Delta_5(EJU)_{(t-1)}$		0.02	0.023		0.027	0.020
		(0.056)	(0.062)		(0.046)	(0.049)
$\Delta_5(LW)_{(t-1)}$			0.009			-0.018
			(0.029)			(0.025)
NIC-2 Fixed Effects	yes	yes	yes	yes	yes	yes
R-squared	0.007	0.007	0.007	0.009	0.009	0.009
Observations	18226	18226	18226	26993	26993	26993
Plant	4815	4815	4815	7669	7669	7669
NIC	117	117	117	117	117	117
NICYear	537	537	537	564	564	564
No.Cluster	117	117	117	117	117	117

Notes: Table reports results from regression of changes in log number of CPC products on lag changes in China's as well as EJU's import share in India and NIC 2-digit industry fixed effects. All regressions are based on five-year difference data. Years 1998 and 1999 are excluded from regression as number of products is not available at CPC level in these years. Columns (1)-(3) in Block-A include only LFirst200 and columns (4)-(6) in Block-B include LFirst20 sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. All the regressions include rural/urban location dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. NIC4 and NIC4-year imply number of 4-digit industry codes and number of NIC4-year combination included in each regression.

In Block-A, for the LFirst200 sample, the estimates of the impact of Chinese import competition are very close to the corresponding OLS coefficients reported in Table 7. In column (1) the coefficient is -0.102, which is only slightly smaller than its OLS counterpart -0.104 in absolute terms. However, the coefficient is now significant at 5 percent level instead of 1 percent level. In column (2), I add the changes in import competition from high-wage countries, which leads to a slightly smaller coefficient of -0.094 and the estimate is now significant only at 10 percent level. Though the coefficient in column (3) is quite close to its corresponding OLS coefficient, it is now statistically insignificant. Therefore, the magnitude of β_1 coefficient remains close to its OLS counterpart even after including initial sector (NIC 2-digit) fixed effects for LFirst200 sample, though its statistical significance moves downward.

However, inclusion of sector fixed effects causes a significant decline in the size of the β_1 coefficient for LFirst100 sample.

The negative impact of import competition on product scope in conjunction with the positive impact on plant productivity supports the theoretical implication of multi-product firms: plants rationalize their product portfolio to increase productivity in response to heightened competition. In order to explore this channel of within-plant growth of productivity further, I next investigate the impact of import competition at product level on the selection of the products at the plant-level.

2.7 Import Competition and Plant-product Level Adjustment

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

2.7.A Decision to Drop a Product

In this section, I examine the impact of Chinese import competition on plants' decision to drop products. I present an empirical framework of within-plant product selection mechanism guided by the theoretical models of multi-product firms. I relate a firm'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 categories 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.[27] The specification below jointly tests whether the probability of decision to drop a product increases due to increased 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. For the purpose of analysis, the share of a product in total revenue from all products is used as a measure of 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).

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

$$+\delta_1 (S_{ikt-5} \times (M_{IN}^{CH})_{ikt-5}) + \delta_2 \left(S_{ikt-5} \times \left(M_{IN}^{EJU}\right)_{ikt-5}\right) + \xi_{ikt} \qquad (11)$$

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. 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.

[27] This is because the industry-level measure of competition represents the average of the mix of products in that industry. Therefore, industry-level measure of competition may be subject to measurement error bias in the plan-product selection model.

I hypothesize that the sign of the coefficient of product-specific Chinese import shock, β_1, is positive: the higher a product's (k's) exposure to import competition from China, the greater is the likelihood that a product is dropped in the subsequent period.

Table 10–Impact of Import Competition on Decision to Drop a product (OLS)

	Block-A (LFirst200)			**Block-B (LFirst100)**			**Block-C (LFirst20)**		
	Dependent Variable: Dropped (1 if dropped or 0 otherwise)								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
$Share_{(t-5)}$	-0.215***	-0.129*	-0.105	-0.239***	-0.158**	-0.120*	-0.226***	-0.143***	-0.110**
	(0.050)	(0.070)	(0.067)	(0.045)	(0.066)	(0.065)	(0.039)	(0.055)	(0.055)
$CHN_{(t-5)}$	0.220**	0.225**	0.215**	0.195**	0.212***	0.204**	0.188**	0.204**	0.205**
	(0.092)	(0.088)	(0.090)	(0.087)	(0.081)	(0.084)	(0.088)	(0.081)	(0.083)
$Share_{(t-5)}\times CHN_{(t-5)}$	-0.244	-0.300*	-0.327**	-0.218*	-0.268*	-0.313***	-0.276**	-0.315***	-0.357***
	(0.151)	(0.159)	(0.134)	(0.130)	(0.139)	(0.120)	(0.124)	(0.122)	(0.115)
$EJU_{(t-5)}$		0.150**	0.149**		0.173***	0.172**		0.181***	0.184***
		(0.067)	(0.072)		(0.062)	(0.068)		(0.051)	(0.056)
$Share_{(t-5)}\times EJU_{(t-5)}$		-0.261***	-0.300***		-0.249***	-0.301***		-0.260***	-0.302***
		(0.088)	(0.094)		(0.088)	(0.093)		(0.074)	(0.076)
$LW_{(t-5)}$			-0.112			-0.113			-0.046
			(0.109)			(0.098)			(0.078)
$Share_{(t-5)}\times LW_{(t-5)}$			0.022			-0.002			-0.037
			(0.135)			(0.123)			(0.100)
Plant FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.216	0.22	0.222	0.236	0.241	0.242	0.28	0.284	0.285
Observations	36106	36106	36106	50014	50014	50014	65823	65823	65823
Plant	4455	4455	4455	7033	7033	7033	11143	11143	11143
Plant-Product	14553	14553	14553	21624	21624	21624	32072	32072	32072
Product (Cluster)	680	680	680	706	706	706	738	738	738

Notes: Table reports results from regression of a dummy variable indicating whether a plant drops a product in year t on the level of China's, EJU's and LW's import share in India in t-5. Years 1998 and 1999 are excluded from the regressions as detail product level data are not available in these years. Columns (1)-(3) in Block-A include LFirst200 and columns (4)-(6) in Block-B include LFirst100 and columns (7)-(9) in Block-C include results for LFirst20 sample. Standard errors (in parentheses) are clustered at product level (5-digit CPC) level. All the regressions include plant and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. Plant-product and product imply number of plant product combination and unique product (CPC 5-digit) included in each regression.

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, the plant is less likely to drop the product if it is close to its core competence.

Table 10 reports the OLS regression results of decision to drop a product at plant *i* in year *t* on the level of import competition at period *t*-5 and its interaction with the share of that product in total revenue from all products. All the regressions include plant fixed effects. Columns (1)-(3) in Block-A present results for LFirst200 sample. Columns (4)-(6) in Block-B and columns (7)-(9) in Block-C show results for LFirst100 and LFirst20 sample respectively. Columns (2), (5) and (8) present results for the base specification given in equation (11).

The first row shows the coefficient on the share of a product in period *t*-5, γ. In all the columns, the estimates of γ are negative and remain statistically significant in most of the specifications except in column (3), in the case of LFirst200 sample, where the import shock from other low-wage countries is added. The result implies that everything else constant the higher the share of a product or the closer the product 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 10 shows that the main coefficient of interest β_1 is positive and statistically significant at 5 percent level in all the specifications. The third row reports the coefficient of the interaction term (δ_1) between the five-year lag level of Chinese import competition and the share of the product in that period, which is negative and statistically significant at least at 10 percent level in most of the specifications except in column (1), where only import shocks from China is considered for LFirst200 sample.

In column (2) of Block-A, the baseline specification for LFirst200 sample, the coefficient on five-year lag of Chinese import exposure (β_1) is 0.225 and the coefficient of interaction between the Chinese import exposure and initial share of a product, δ_1, is -0.300. Together these two coefficients imply that the impact of Chinese import exposure on selection of a product depends on the position of the product within the portfolio of the plants. For example, a 10 percentage point increase in Chinese import exposure in a particular product increases the probability that the plant drop the product by 1.95 percentage points if the product holds only 10 percent share of plant revenue from all products in the initial period. However, the same amount of increase reduces the probability to drop a product by 0.4 percentage point for a product that holds 90 percent share of revenue from all products. The results suggest that the impact of Chinese import competition is asymmetric across products. The remarkable feature of the results is that the asymmetry in plant-product level margin of adjustment to Chinese import exposure remains robust for alternative threshold level of plant employment in Block-B and Block-C.

Another interesting observation is that the import competition from EJU also has similar asymmetric impact on selection of products within-plant as in the case of Chinese competition. The coefficient of EJU and its interaction with the initial period share of a product remains statistically significant at least at 5 percent level in all the specifications. In contrast, the sign of the coefficient of other low-wage country import shocks is negative and statistically insignificant in all the cases.

Table 11 reports the 2SLS regression results for decision to drop a product at the plant-level. In this case, the (t-5)-1 lag of Chinese import exposure in Indonesia for a particular product k is used as an instrument for the t-5 lag of Chinese import exposure in product k in India. Panel-A reports 2SLS estimates and Panel-B reports their corresponding instruments. In Panel-A, I observed that the sign of the estimates of the product level measure of Chinese import competition (β_1) and the associated coefficient of interaction, δ_1, remain unchanged but the magnitudes are much larger than their corresponding OLS coefficients in Table 10. Therefore, the IV estimates magnify the asymmetric impact of import competition shocks.

Table 11–Impact of Import Competition on Decision to Drop a product (2SLS)

	Block-A (LFirst200)			Block-B (LFirst100)			Block-C (LFirst20)		
	Dependent Variable: Dropped								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
$Share_{(t-5)}$	-0.125**	0.005	0.061	-0.161***	-0.043	0.022	-0.164***	-0.06	0.005
	(0.062)	(0.094)	(0.106)	(0.055)	(0.085)	(0.092)	(0.044)	(0.063)	(0.072)
$CHN_{(t-5)}$	0.789**	0.684**	0.791***	0.740**	0.662***	0.759***	0.712***	0.632***	0.676***
	(0.334)	(0.297)	(0.297)	(0.294)	(0.256)	(0.254)	(0.231)	(0.196)	(0.195)
$Share_{(t-5)} \times CHN_{(t-5)}$	-1.455***	-1.640***	-1.640***	-1.267***	-1.411***	-1.449***	-1.182***	-1.253***	-1.304***
	(0.422)	(0.495)	(0.463)	(0.345)	(0.403)	(0.391)	(0.268)	(0.288)	(0.295)
$EJU_{(t-5)}$		0.159**	0.165**		0.182***	0.190***		0.185***	0.197***
		(0.066)	(0.069)		(0.062)	(0.064)		(0.049)	(0.051)
$Share_{(t-5)} \times EJU_{(t-5)}$		-0.337***	-0.412***		-0.314***	-0.398***		-0.298***	-0.379***
		(0.104)	(0.122)		(0.097)	(0.108)		(0.075)	(0.086)
$LW_{(t-5)}$			-0.074			-0.083			-0.024
			(0.100)			(0.090)			(0.071)
$Share_{(t-5)} \times LW_{(t-5)}$			-0.121			-0.123			-0.139
			(0.149)			(0.126)			(0.104)
Plant FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.202	0.203	0.207	0.226	0.229	0.231	0.272	0.277	0.278
Observations	36106	36106	36106	50014	50014	50014	65823	65823	65823
Plant	4455	4455	4455	7033	7033	7033	11143	11143	11143
Plant-Product	14553	14553	14553	21624	21624	21624	32072	32072	32072
Product (Cluster)	680	680	680	706	706	706	738	738	738

	Panel-B
First Stage	**Dependent Variable:** CHN_{t-5} and $Share_{(t-5)} \times CHN_{(t-5)}$
Instruments	$(CH)IDN_{(t-1)-5}$ and $Share_{(t-5)} \times (CH)IDN_{(t-1)-5}$

Notes: Table reports 2SLS results from regression of a dummy variable, indicating whether a plant drops a product in year t on the level of China's, EJU's and LW's import share in India in t-5. Years 1998 and 1999 are excluded from the regressions, as detailed product level data are not available in these years. Columns (1)-(3) in Block-A include LFirst200 and columns (4)-(6) in Block-B include LFirst100 and columns (7)-(9) in Block-C include results for LFirst20 sample. Standard errors (in parentheses) are clustered at product level (5-digit CPC) level. All the regressions include plant and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. Plant-product and product imply number of plant product combination and unique product (CPC 5-digit) included in each regression.

For example, in column (2) for the sample of plants with at least 200 employees, the 2SLS estimate of β_1 is 0.684 and δ_1 is -1.640, 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 points if it holds only 10 percent share of revenue in the initial period. In contrast, the same amount of change causes a 7.9 percentage point decline in the probability to drop a product that contributes 90 percent share of total revenue from all products.

The sign of the coefficient of import exposure from high-wage countries and the corresponding interaction term remain similar in the 2SLS regression and statistically significant at least at 5 percent level. On the other hand, import shock from low-wage countries remains statistically insignificant as in the case of OLS.

2.7.B Decision to Add a Product

In this section, I examine whether Chinese import exposure has any effect on plant's product choice.

$$A_{ikt} = \alpha + \tau_{st} + \rho_i + \beta_1 (M_{IN}^{CH})_{ikt-5} + \beta_2 \left(M_{IN}^{EJU}\right)_{ikt-5} + \xi_{ikt} \qquad (12)$$

A_{ikt} indicates whether a plant add a product in period *t* which was not produced in period *t*-5. Rest of the variables are as defined in specification (11). The expected sign of the coefficient β_1 is negative implying that a plant would be less likely to add a product in which import competition from China is high. The difference between add and drop regression is that in the case of the latter, the share of the product is used to represent the distance from core competence.

Table 12 reports the results from regression of plants' product adding decision on the level of import competition from China in the initial period based on specification (12). All the regressions include plant fixed effects to control for plant characteristics that are common across products within-plant and state by year fixed effects to control for macroeconomic shocks.

Panel-A of Table 12 reports the estimates from OLS and Panel-B reports, the estimates from IV regressions. In the case of OLS regression, Chinese import exposure coefficient remains statistically insignificant in all the specifications. In Block-A, I find that the magnitude of the coefficient is close to zero for LFirst200 sample. In columns. (1) and (2), β_1 appears with a positive sign, but it becomes negative in column (3). In Block-B and Block-C of Panel-A, for LFirst100 and LFirst20 sample respectively, the sign of the β_1 coefficient becomes negative and its magnitude is larger than the corresponding columns in Block-A. Similarly, import competition from high-wage countries also has no statistically significant effect on plants' decision to add a product. Interestingly, the coefficient of import competition shocks from other low-wage countries is negative, statistically significant and much larger than the estimates of β_1 and β_2.

Table 12–Product Add Regression (OLS and IV)

Panel-A OLS Regression									
	Block-A (LFirst200)			**Block-B (LFirst100)**			**Block-C (LFirst20)**		
	Dependent Variable: Added (1 if added or 0 otherwise)								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
$CHN_{(t-5)}$	0.008	0.006	-0.005	-0.023	-0.026	-0.038	-0.016	-0.021	-0.031
	(0.049)	(0.05)	(0.057)	(0.044)	(0.046)	(0.053)	(0.034)	(0.035)	(0.039)
$EJU_{(t-5)}$		-0.009	-0.022		-0.012	-0.027		-0.017	-0.029
		(0.021	(0.023)		(0.019)	(0.021)		(0.016)	(0.018)
$LW_{(t-5)}$			-0.089**			-0.096***			-0.085**
			(0.036)			(0.035)			(0.035)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.061	0.061	0.063	0.06	0.06	0.062	0.069	0.069	0.071
Panel-B 2SLS Regression									
	Block-A (LFirst200)			**Block-B (LFirst100)**			**Block-C (LFirst20)**		
	Dependent Variable: Added (1 if added or 0 otherwise)								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
$CHN_{(t-5)}$	-0.291	-0.296	-0.183	-0.338**	-0.347*	-0.249*	-0.275**	-0.279**	-0.214**
	(0.214)	(0.219)	(0.165)	(0.172)	(0.178)	(0.133)	(0.118)	(0.12)	(0.096)
$EJU_{(t-5)}$		-0.024	-0.032		-0.031	-0.040*		-0.034*	-0.041**
		(0.024)	(0.026)		(0.022)	(0.024)		(0.017)	(0.02)
$LW_{(t-5)}$			-0.096**			-0.105**			-0.092**
			(0.042)			(0.042)			(0.039)
R-squared	0.055	0.055	0.061	0.054	0.054	0.059	0.066	0.066	0.069
N	50295	50295	50295	70895	70895	70895	96829	96829	96829
Plant	4701	4701	4701	7616	7616	7616	13230	13230	13230
Plant-Product	21215	21215	21215	32036	32036	32036	50234	50234	50234
Product (Cluster)	726	726	726	759	759	759	783	783	783

Notes: Table reports 2SLS results from regression of a dummy variable indicating whether a plant add a product in year t on the level of China's, EJU's and LW's import share in India in t-5. Panel-A reports OLS regression and Panel-B reports 2SLS regression results. Years 1998 and 1999 are excluded from the regressions as detailed product level data are not available in these years. Columns (1)-(3) in Block-A include LFirst200 and columns (4)-(6) in Block-B include LFirst100 and columns (7)-(9) in Block-C include results for LFirst20 sample. Standard errors (in parentheses) are clustered at product level (5-digit CPC) level. All the regressions include plant and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. Plant-product and product imply number of plant product combination and unique product (CPC 5-digit) included in each regression.

In Panel-B of Table 12, I observe that the magnitude of the 2SLS coefficient of Chinese import competition (β_1) dramatically increases across all specifications and the sign of the coefficient also appears to be negative as expected. However, the coefficient β_1 remains statistically insignificant for LFirst200 sample. In column (5), the estimate of β_1 is -0.347 for LFirst100 sample, which implies that a 10 percentage point increase in China's share of India's imports of a particular product leads to a decline in the probability that a plant adds the product by 3.4 percentage points.

2.8 Concluding Remarks

In this paper, I examine the impact of import competition from China on the performance of India's manufacturing plants. The empirical analysis of the paper is guided by the mechanism highlighted by the multi-product firm models of trade. For this purpose, I use the ASI data on India's formal manufacturing sector plants over the period 1998 to 2009, 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. This finding stands in stark contrast to the GKPT's (2010) finding that the firms in India rarely churns products. However, the behavior of product churning in ASI data during the 2000s is consistent with the behavior of the firms in the United States during 1987-1997. At the aggregate level, I find that the proportion of plants producing multiple products as well as average number of products produced by the plants marginally declined in the second half of the 2000s (2005-09). The fact that India's manufacturing sector experienced a sharp rise in import competition from China in the 2000s provides a primary motivation to examine the role of this trade shock in the creative destruction process.

Using the 1998-2009 ASI data, I find that the increase in Chinese imports exposure leads to an increase in plant revenue productivity measured by WLP approach. I address the endogeneity concern pertaining to changes in Chinese import competition by employing the 2SLS regression analysis and allowing for sector specific trends in the baseline regression. The relationship between plant performance and Chinese import exposure remains robust to alternative identification strategies. In the next step, I explore the relationship between Chinese import competition and plant product scope using product-level data from 2000 to 2009. The results suggest the plants reduce their product range in response to import competition from China. Again, this finding remains robust to alternative identification strategies mentioned above. On the other hand, I find that import competition from both high-wage countries and other low-wage countries have no significant effect on plant product scope. Together these two margins of adjustment at the plant-level suggest that plants may be improving their performance by eliminating products that are away from their core competence as predicted by the theoretical models of multi-product firms. 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 exposure from China but the closer the product to the core competence of the plants, the less likely it is to drop the product. In contrast to plant-level finding, in the plant-product level analysis, I find that import competition from high-wage countries also contributes towards reallocation products within-plant and the impact is quantitatively similar to that of China. However, again I find that import competition from other low-wage countries has no effect on plant product level adjustment.

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. One interesting extension of the study is to investigate the role of import competition on quality upgrading of the products within-plant. Another possible area of investigation is to explore the role of intermediate input imports from China on the performance of plants.

2.9 Appendix

Figure A.1–Share of Import from China in Each Group of Products Imported in India

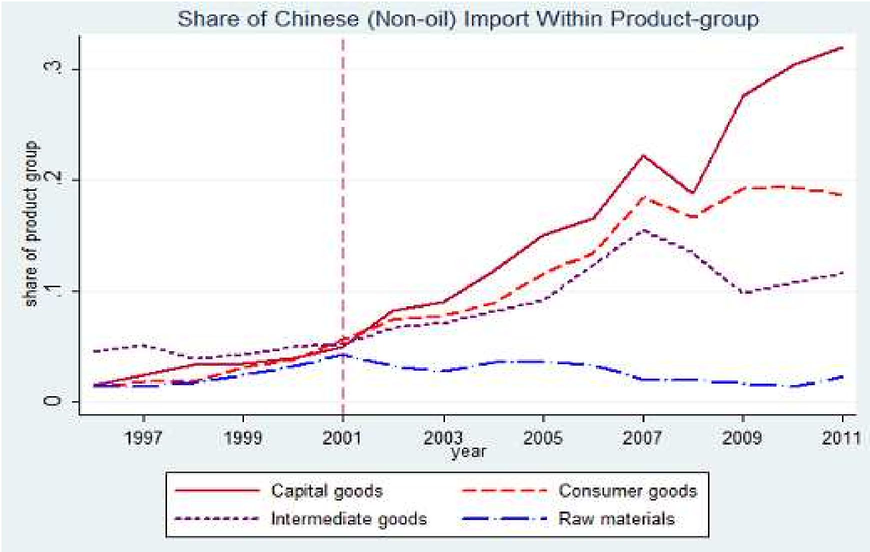
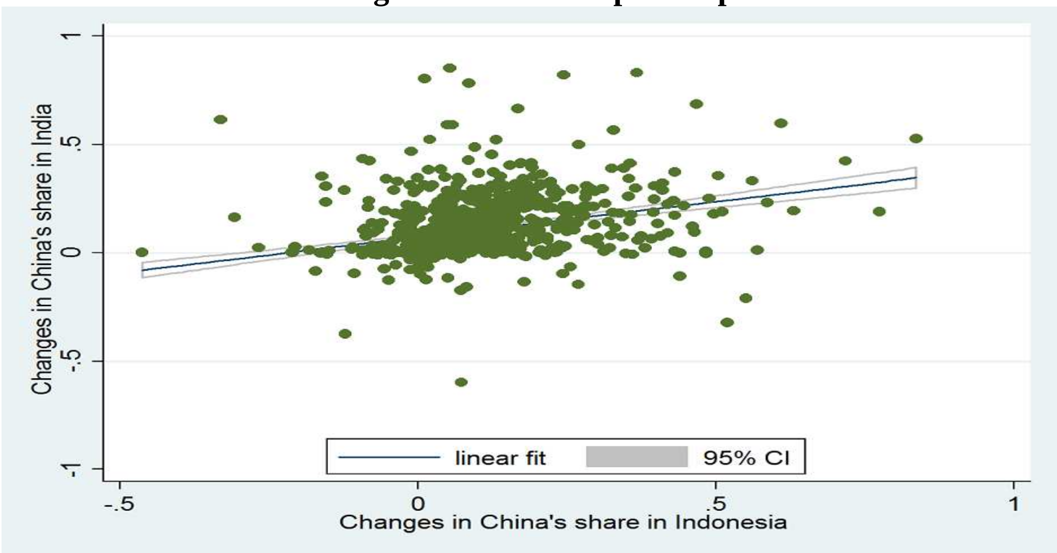


Figure A.2–Scatter Plot of Changes in Chinese Import Exposure in India and Indonesia



The graph is a scatter plot of five-year changes in China's share of India's imports and one year lag of 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 OLS regression.

Table A.1–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.2–Frequency Distribution of Non-missing ASI-all plants

Frequency	Observations	Plants	Percent
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

Table A.3–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. & computing 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 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.4–Proportion of Multi-product Plants in the Sample

	Percentage of Plants			Average CPC Products			Average ASICC Product
Year	MpC	MpI	MpS	5-digit	4-digit	2-digit	
	(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 denote 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 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 pattern of unweighted figures are similar.

Table A.5–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 product 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.

Table A.6–Impact of Import Competition from China on Plant Productivity (LFirst20)

	Block-A (OLS)			Block-B (IV)		
Panel-A	**Dependent Variable:** $\Delta_5 TFP_{ijt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5(CHN)_{(t-1)}$	0.354*	0.349	0.367*	0.763*	0.779*	0.798*
	(0.183)	(0.212)	(0.217)	(0.447)	(0.463)	(0.465)
$\Delta_5(EJU)_{(t-1)}$		-0.013	0.015		0.088	0.134
		(0.127)	(0.142)		(0.164)	(0.185)
$\Delta_5(LW)_{(t-1)}$			0.082			0.147
			(0.110)			(0.122)
R-squared	0.025	0.025	0.025	0.023	0.023	0.023
Panel-B	**Dependent Variable:** $\Delta_5 TFP_{ijt}$ **(winsorized)**					
$\Delta_5(CHN)_{(t-1)}$	0.371**	0.365*	0.374*	0.804*	0.821*	0.836*
	(0.181)	(0.209)	(0.215)	(0.435)	(0.450)	(0.454)
$\Delta_5(EJU)_{(t-1)}$		-0.016	-0.002		0.091	0.125
		(0.123)	(0.137)		(0.159)	(0.178)
$\Delta_5(LW)_{(t-1)}$			0.042			0.11
			(0.110)			(0.117)
R-squared	0.026	0.026	0.026	0.024	0.024	0.024
Observations	41116	41116	41116	41116	41116	41116
Plant	11793	11793	11793	11793	11793	11793
NIC4	119	119	119	119	119	119
NIC4-Year	807	807	807	807	807	807
Clusters	119	119	119	119	119	119
Panel-C First Stage Results Dependent Variable: $\Delta_5(CHN)_{(t-1)}$						
Instruments				$\Delta_5(CH)IDN_{(t-1)-1}$		
R-sq.				0.37	0.43	0.45
F(2,117)				62.36	53.53	44.91
Prob > F				0	0	0

Notes: Table reports results from regression of five-year changes in TFP on lag changes in China's, EJU's and other LW's import share in India. Columns (1)-(3) in Block-A report OLS regression results and columns (4)-(6) in Block-B report 2SLS regression results for LFirst20 sample. Robust standard errors (in parentheses) are clustered at plant's main (NIC 4-digit) industry level. All the regressions include rural/urban location dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. NIC4 and NIC4-year imply number of 4-digit industry codes and number of NIC4-year combination included in each regression. * p<.1; ** p<.05; *** p<.01

Table A.7–Import Competition and Changes in Plant Product (CPC) Scope (LFirst20)

	Block-A (OLS)			Block-B (IV)		
	Dependent Variable: $\Delta_5 lnNP_{ijt}$					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\Delta_5(CHN)_{(t-1)}$	-0.068*	-0.064	-0.071*	-0.08	-0.08	-0.086
	(0.035)	(0.04)	(0.04)	(0.095)'	(0.096)'	(0.099)'
$\Delta_5(EJU)_{(t-1)}$		0.012	0.003		0.008	-0.001
		(0.037)	(0.041)		(0.045)'	(0.050)'
$\Delta_5(LW)_{(t-1)}$			-0.032			-0.035
			(0.03)			(0.035)'
R-squared	0.009	0.009	0.009	0.009	0.009	0.009
Observations	34484	34484	34484	34484	34484	34484
Plant	10926	10926	10926	10926	10926	10926
NIC4	118	118	118	118	118	118
NIC4-Year	578	578	578	578	578	578
Cluster	118	118	118	118	118	118

Notes: Table reports results from OLS and 2SLS regression of changes in log number of CPC products on lag changes in China's as well as EJU's import share in India based on LFirst20 sample. All regressions are based on five-year differenced data. In the first stage of 2SLS regression, $\Delta_5(CHN)_{(t-1)}$ is instrumented by (t-1)-1 lag of five-year changes in Chinese Import Share in Indonesia, $\Delta_5(CH)IDN_{(t-1)-1}$. Years 1998 and 1999 are excluded from regression as number of products is not available at CPC level in these years. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. All the regressions include rural/urban location dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. NIC4 and NIC4-year imply number of 4-digit industry codes and number of NIC4-year combination included in each regression.

Table A.8–Impact of Import Competition from China on Plant Productivity (Balanced)

	Block-A (OLS)			Block-B (IV)		
Panel-A	**Dependent Variable:** $\Delta_5 TFP_{ijt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5(CHN)_{(t-1)}$	0.420***	0.403**	0.444***	0.879**	0.898**	0.929**
	(0.148)	(0.177)	(0.167)	(0.376)	(0.402)	(0.387)
$\Delta_5(EJU)_{(t-1)}$		-0.044	0.024		0.089	0.171
		(0.132)	(0.133)		(0.176)	(0.178)
$\Delta_5(LW)_{(t-1)}$			0.207***			0.266***
			(0.073)			(0.081)
R-squared	0.021	0.021	0.022	0.017	0.017	0.018
Panel-B	**Dependent Variable:** $\Delta_5 TFP_{ijt}$ **(winsorized)**					
$\Delta_5(CHN)_{(t-1)}$	0.442***	0.422**	0.457***	0.974***	0.998**	1.026***
	(0.145)	(0.174)	(0.166)	(0.364)	(0.389)	(0.378)
$\Delta_5(EJU)_{(t-1)}$		-0.051	0.007		0.103	0.179
		(0.128)	(0.130)		(0.171)	(0.173)
$\Delta_5(LW)_{(t-1)}$			0.176**			0.246***
			(0.076)			(0.072)
R-squared	0.021	0.021	0.022	0.017	0.016	0.017
Observations	12418	12418	12418	12418	12418	12418
Plant	1774	1774	1774	1774	1774	1774
NIC4	112	112	112	112	112	112
NIC4-Year	756	756	756	756	756	756
Clusters	112	112	112	112	112	112

Notes: Table reports results from OLS and IV regression of five-year changes in TFP on lag changes in China's, EJU's and other LW's import share in India using a balanced sample of plants. The balanced sample contains non-missing ASI plants with at least 20 employees and that appear in all the years from 1998 to 2009. However, as in the case of LFirst20 sample, only plants with positive value added, for which productivity measure is available are included in the regressions. Columns (1)-(3) in Block-A report OLS and columns (4)-(6) in Block-B report IV results. Robust standard errors (in parentheses) are clustered at plant's main (NIC 4-digit) industry level. All the regressions include rural/urban location dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. NIC4 and NIC4-year imply number of 4-digit industry codes and number of NIC4-year combination included in each regression. * p<.1; ** p<.05; *** p<.01

Table A.9–Impact of Import Competition from China on Plant Productivity (LFirst5)

	Block-A (OLS)			Block-B (IV)		
Panel-A	**Dependent Variable:** Δ_5TFP_{ijt}					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_5(CHN)_{(t-1)}$	0.317*	0.32	0.338	0.696	0.718	0.739
	(0.178)	(0.207)	(0.217)	(0.469)	(0.490)	(0.497)
$\Delta_5(EJU)_{(t-1)}$		0.007	0.034		0.106	0.152
		(0.127)	(0.147)		(0.176)	(0.205)
$\Delta_5(LW)_{(t-1)}$			0.082			0.148
			(0.118)			(0.139)
R-squared	0.022	0.022	0.022	0.02	0.02	0.02
Panel-B	**Dependent Variable:** Δ_5TFP_{ijt} **(winsorized)**					
$\Delta_5(CHN)_{(t-1)}$	0.312*	0.308	0.322	0.691	0.71	0.728
	(0.175)	(0.205)	(0.214)	(0.460)	(0.481)	(0.488)
$\Delta_5(EJU)_{(t-1)}$		-0.008	0.012		0.091	0.132
		(0.121)	(0.140)		(0.169)	(0.197)
$\Delta_5(LW)_{(t-1)}$			0.062			0.13
			(0.118)			(0.137)
R-squared	0.022	0.022	0.022	0.021	0.021	0.021
Observations	46791	46791	46791	46791	46791	46791
Plant	14259	14259	14259	14259	14259	14259
NIC4	119	119	119	119	119	119
NIC4-Year	812	812	812	812	812	812
Clusters	119	119	119	119	119	119

Notes: Table reports results from OLS and IV regression of five-year changes in TFP on lag changes in China's, EJU's and other LW's import share in India using plants with at least 5 employees in the initial period. However, as in the case of LFirst20 sample only plants with positive value added, for which productivity measure is available are included in the regressions. Columns (1)-(3) in Block-A report OLS and columns (4)-(6) in Block-B report IV results. Robust standard errors (in parentheses) are clustered at plant's main (NIC 4-digit) industry level. All the regressions include rural/urban location dummy, technology intensity dummies and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In the lower panel, "Plant" indicates number of unique ASI plants included in the regression. NIC4 and NIC4-year imply number of 4-digit industry codes and number of NIC4-year combination included in each regression. * p<.1; ** p<.05; *** p<.01

Concordance between Industry and Trade data:

In 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 ISIC-3.1 concordance provided by the United Nations Statistics Division.[28] Therefore, all the plants are identified by a unique NIC 4-digit (2004) industry code.

UN Comtrade Data:

I use country level bi-lateral imports and exports 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 at 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 regions: 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 US 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

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

products are classified into raw materials, intermediate goods, consumer goods and capital goods using the HS-standard product group classification provided by WITS.[29]

Data for Product Level Analysis:

In the ASI survey, products are identified by ASI Commodity Classification (ASICC) system. Plants report value of products and by-products produced in a given financial year against specific ASICC product codes. There are two main versions of ASICC classification: ASICC-1998 and ASICC-2008-09. In the ASI data all product-specific information are coded under ASICC-1998 from 1998 to 2007 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 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. 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 collapsed all the ASICC products to CPC products by using the concordance from ASICC-2009 to NPCMS-2011 published by CSO.

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

Moreover, in some cases a plant uses same ASICC code to report multiple rows of data. 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.

Chapter 3

Import Competition, Employment and Wage Inequality in India's Formal Manufacturing Sector: Does Labor Market Regulation Matter?

3.1. Introduction

The impact of trade on wage inequality and on unemployment are the two core issues of the globalization debate that has been reignited with the economic rise of China and the concurrent increase in South-South trade. In 2011, world merchandise exports reached a level of USD (US Dollar) 18 trillion from a level of USD 6 trillion in 2001 (at current prices and current exchange rates). Remarkably, South-South trade alone has contributed 30 percent (or USD 3.6 trillion) of this USD 12 trillion increase in world exports.[30] Such a spectacular expansion of South-South trade in a very short period has been driven largely by an extraordinary expansion of China's exports following its integration into WTO together with rapid export growth from other major developing countries.

This paper investigates how import competition shocks from China affect the pattern of wage inequality and employment in another large developing country, India. In particular, this paper shows that import competition from China after its accession to WTO in 2001 increases wage inequality between skilled and unskilled labor in large manufacturing plants and that the institutional flexibility of the labor market influences the distributional consequences of trade

[30] As of 2011, the share of South-South trade accounts for a quarter (or USD 4.4 trillion) of world merchandise exports, almost twice as much compared to 2001. During 2002-2011, South-South export increased by 19 percent on average annually, whereas manufacturing sector export alone grew by 17 percent. Developing Asia accounts for 73 percent (or 3.2 trillion USD) of total South-South trade in 2011. Source: UNCTAD Handbook of Statistics 2013.

shocks. This paper finds that the rise in import competition from China leads to a general increase in within-plant wage inequality between skilled and unskilled workers in large plants. But when plants located in flexible labor markets are separated from those located in inflexible markets, it appears that the overall pattern is driven by much larger adjustment of within-plant skill premium in the flexible markets. But there is no evidence of skill premium adjustment in response to intensified Chinese import competition in the inflexible markets. Another key finding is that in the flexible labor markets, only the average wage of white-collar workers rises in the face of rising Chinese import competition. Finally, for the sample comprising large plants, it is observed that rising import competition from China causes a downsizing of low-productivity plants through employment destruction, and an expansion of high-productivity plants via employment creation, particularly in the flexible labor market.

Recent studies (Acemoglu et al. 2016; Autor, Dorn, and Hanson 2013; and Bloom, Draca, and Van Reneen 2016) find that the rise in import competition from China after its WTO accession has a strong destructive impact on the labor markets of developed economies. A few recent studies (Mion and Zhu 2013; Utar 2014) document that Chinese import competition also led to skill upgrading in the manufacturing sector of developed countries. In a recent study, Lu and Ng (2013) show that though import competition affects skill content in the U.S. manufacturing industries, this result is not driven by low-wage sources or China. However, their paper is based on data that predate China's accession to WTO in 2001. As mentioned above, the pattern of international competition has dramatically changed after China's integration into WTO in December 2001. Against this backdrop, there are reasons to believe that the integration of China into the world economy also has an impact on wage inequality in labor-abundant countries. However, the impact of this huge trade shock on the evolution of low-wage developing economies remains unexplored. The paper aims to fill this gap in the literature by investigating the impact of this extraordinarily large trade shock on employment and wage inequality in low-wage developing country context. For instance, in the 2000s, India's formal manufacturing sector experienced a sharp rise in inequality between skilled and unskilled workers – the ratio of the average wages of non-production and production employees increased from 2.27 in 2001 to 3.03 in 2009. At the same time, China's share of India's imports (non-oil) increased from 5 percent in 2001 to 16 percent in 2010. Is there a causal link between the rise in India's imports from China and rising wage inequality in India?

While I focus on the impact of import competition from China on labor market outcomes, rigidity of the labor market can influence the consequences of such trade shock. Firstly, labor market inflexibility can influence labor market effects of import competition by creating higher cost of adjustment and impeding the reallocation of resources across firms. One key component of labor market regulation in India is that a plant with more than 100 workers must obtain permission from the government to retrench any worker or close its operation even while incurring losses. This kind of labor market regulation imposes significant restrictions on plants' ability to adjust to shocks. Secondly, labor regime is not uniform across Indian states (Besley and Burgess 2004). As a result, labor market consequences of trade shock in the flexible states may be different from those in the inflexible states. The variation in India's labor market environment presents an ideal setup to test whether plants located in inflexible labor markets face any additional cost while adjusting to intensified import competition from China.

To investigate the impact of the rise in Chinese import exposure on plant-level outcomes, I use plant-level micro data from India's formal manufacturing sector and HS 6-digit product level bilateral trade data from UN Comtrade database. I primarily rely on differential changes in China's import share across industries and over time to identify the impact of Chinese import competition on wage inequality and employment. The rapidly growing trade between China and India, particularly in the aftermath of China's accession to WTO, coupled with intrinsic diversity of the large Indian economy presents an appropriate setup for this analysis. It appears that China's accession to WTO in 2001 occurred during a period when Indian economy was relatively stable, which allows us to uniquely identify the effects of China's emergence on Indian economy.[31]

I separate my empirical analysis into two core labor market issues –wage inequality and employment. In order to control for plant-specific unobserved heterogeneity, I use five-year difference form of plant-level outcomes and associate them with a similarly differenced measure of Chinese import competition. However, how such a trade shock affects plant-level margin of adjustment depends on the labor market regulations of the state where the plant resides. In order to address this potential heterogeneity in exposure to shocks across states, I estimate the impact of Chinese import competition separately for different labor market regimes using the classification of India's labor market developed by Besley and Burgess (2004). The authors developed a labor market classification of Indian states based on their direction of amendment (pro-employer or neutral or pro-worker) to Industrial Disputes Act (IDA) of 1947. In the baseline specification, I classify the states into two broad groups –flexible (or pro-employer) and inflexible (either neutral or pro-worker). In order to control for state-level macroeconomic shocks that are common to all the plants within a state, I include state-year fixed effects. Another interesting feature of India's labor market regulation is that the extent of regulatory burden increases with size of the plants. In order to test whether import competition has a disproportionate effect on plants within a particular labor market regime, I perform regressions separately for different plant size thresholds.

Though the above framework addresses a number of important issues for the identification of the impact of exposure to Chinese import competition, there are still potential sources of

[31] Indian economy went through substantial changes in the first half of the 1990s following liberalization shock in the early 1990s. The trade reforms in the late 1990s were rather slow and more selective, allowing the economy to become settled in a new liberalized environment.

endogeneity that may bias our coefficients of interest. First, there may be unobserved technology shocks that can have a simultaneous effect on an industry's relative demand for skilled workers and imports in that industry. Second, there may be causality running from skill premium or employment to changes in import demand in an industry. Third, industry-specific policy shocks may affect firms in a particular industry and imports from China. Finally, the import competition variable may be subject to measurement error that can lead to attenuation bias in the coefficient of interest. I address these endogeneity concerns by applying an instrumental variable (IV) estimation approach. I use one period lag changes in share of Chinese imports at the industry-level in Indonesia as an instrument for changes in Chinese import exposure in India.

This paper contributes to the literature on international trade by investigating the causal effects of import competition from China on wage inequality and employment at the plant-level in low-wage country context. There are a few recent studies that investigate the impact of globalization on adjustment of wages and employment within-plant. Amiti and Cameron (2012) and Amiti and Devis (2012) explore the impact of tariff liberalization on changes in wage inequality, and wages within-firm, respectively, using firm-level data from Indonesia. A few studies exploit the Indian liberalization episodes in the 1990s, particularly in the early 1990s, to identify the impact of trade reform on wage inequality in India. On the poverty impact of trade reform, Topalova (2007, 2010) observes that the benefits of trade liberalization differ across Indian districts corresponding to their exposure to international trade. Chamarbagwala and Sharma (2011) using ASI data from 1980-81 to 1994-95 find that in pre trade liberalization era industrial de-licensing played a role in increasing the demand for skilled labor via output-skill or capital-skill complementarities, which is reflected in the rise of wage bill share and relative employment of skilled workers in the de-licensed industries. However, there is weaker evidence of capital-skill and output-skill complementarities in post liberalization era, which they argued as an indication of less significant role of trade on demand for skilled workers.[32]

The rest of the paper is organized as follows. Section two discusses the theoretical link between import competition, wage inequality and employment. Section three describes the data. Sections four and five define the measures of import competition and labor market flexibility, respectively. Section six presents the empirical strategy and section seven discusses the regression results. Section eight concludes the paper.

3.2 The Link between Import Competition, Wage Inequality and Employment

The link between trade and wage inequality is one of the principal predictions of Heckscher-Ohlin (H-O) model of international trade. The Stolper-Samuelson theorem of H-O model predicts that trade between skilled-labor-abundant North and unskilled-labor-abundant South increases wage-inequality in the North and reduces it in the South. However, the overwhelming finding is that trade liberalization increases wage inequality in both developed and developing countries alike (for a survey Goldberg and Pavcnik 2007).[33] There could be numerous underlying factors including globalization, skill-biased technical change and urbanization that may have contributed towards rising wage inequality in low-wage developing countries. This paper emphasizes on the role of globalization in general and South-South globalization in particular as the source of rising wage inequality in low-wage developing countries. Understanding the patterns and causes of wage-inequality within firm can enrich our understanding of overall wage inequality. In the discussion that follows, I delineate a few

[32] They use repeated cross section of plant-level ASI data from 1980-81 to 1994-95.

[33] This finding is supported by theoretical trade models developed by Feenstra and Hanson (1996) and Zhu and Trefler (2005). Helpman, Itskhoki, and Redding (2010) show that trade liberalization can increase wage inequality across firms within-industry in both developed and developing countries but unemployment can rise or fall.

channels through which import competition can affect wage inequality and employment changes within firm.

Quality upgrading: A new line of research proposes product quality upgrading as one of the sources of rising wage inequality in developing countries. Trade can lead to quality upgrading of products both through export incentive channel and import competition channel. Verhoogen (2008) highlights the former channel of rising wage inequality by extending heterogeneous firm model of trade developed by Melitz (2003). In this quality upgrading model, within industry most productive plants export and as the income of consumers differ across countries, exporters in developing countries produce higher quality goods for foreign than for the home market and pay higher wages for high quality workers. The model predicts that a fall in exporting cost incentivizes plants to improve product quality –as product quality improvement requires higher productivity plants to demand more of high quality workers and pay higher wages within the same industry, ultimately wage inequality rises within-industry.

Amiti and Khandelwal (2013) highlight the link between import competition and product quality upgrading. The authors find that tariff liberalization encourages quality upgrading of products that are close to world quality frontier but discourages for the products that are far away from the frontier. Martin and Mejean (2014) explore the impact of low-wage competition on product quality of French exports. They find that product quality upgrading is more pronounced in sectors and destinations where firms face more intense competition from low-wage countries. The observed relationship between import competition and quality upgrading suggests that import competition can also affect relative demand for skilled and unskilled workers and hence wage inequality within industry through the mechanism highlighted by Verhoogen (2008). By the same token, if competition leads to an improvement of product quality of the plants, then the wages of skilled workers may also rise relative to unskilled workers within-plant.

Product Mix: Recent developments in the theory of multi-product heterogeneous firms suggest that firms reduce their product scope in response to trade liberalization and drop the products away from their core competence. If skill-intensity of products differs from each other within firm, then the relative demand for skilled workers will also be affected by trade shocks. Bernard, Redding, and Schott (2011) show that trade liberalization induces the surviving firms to drop their low quality products in the domestic market due to rise in product market competition, and derive more revenue from higher quality products in the foreign market. Eckel and Neary (2010) develop a multi-product model of firms where marginal cost differs across varieties. A rise in competition induces firms to drop their higher marginal cost varieties and focus on the core competence, which the firm can produce most efficiently. These multi-product models of firms suggest that competition can affect firms' relative demand for skilled workers through its effect on firms' product portfolio.

Cotemporary empirical evidence also supports the theoretical predictions of these models. Bernard, Jensen, and Schott (2006) find that the U.S. firms alter their product mix in response to low-wage import growth and these switches are biased toward skill- and capital-intensive industries. Iacovone, Rauch, and Winters (2013) and Liu (2010) also find that in the face of import competition plants are more likely to drop the products away from their core competence and refocus on core competence products. The former study investigates the impact of Chinese import exposure in Mexico during 1994-2004 and the latter explores the effect of import competition in the United States over the period 1984-1996.

Innovation: Recent developments in endogenous growth literature (Aghion et al. 1997, 2001, and Aghion et al. 2005) highlight the relationship between product market competition and innovation. This literature suggests that heightened product market competition encourages firms to innovate to help escape competition. Thoenig and Verdier (2003) suggest that international competition may lead to wage inequality by encouraging firms to invest in skilled-biased technology. Bloom, Draca, and Van Reenen (2016) find significant within-firm effect of Chinese trade on various measures of technical change: patents, IT intensity, R&D, management practices and TFP in European firms. Utar (2014) documents that competition from China has affected the skill composition within firm in Danish Textile and Clothing industry by having a significant negative impact on the employment of low-educated workers. Mion and Zhu (2013) using Belgian manufacturing firm data find that import competition leads to skill-upgrading in low-tech industries.

3.3 Data

In this paper, I use the Annual Survey of Industries (ASI) plant-level data from 1998 to 2009 period. The survey is conducted by Central Statistical Office (CSO), Government of India and it collects detailed information about registered manufacturing establishments in India. Each establishment in the survey is identified by a unique factory identifier from 1998 survey onwards.[34] The ASI data include all establishments registered under the Factories Act, 1948: (i) factories that use power and employ more than 10 employees and (ii) factories that do not use power and employ more than 20 workers. The Chief Inspector of Factories in each state maintains a list of registered factories, which serves as a sampling frame. The frame is regularly updated on periodic basis to take into account of entry and exit of plants. The ASI data are recorded by financial year (e.g. April 1998 to March 1999). The ASI data reports the name of the state where it is located and whether it is a rural or urban area.

Based on employment level, the ASI sampling frame divides the plants into census and sample sectors. The census sector includes plants with at least 200 workers in the 1998 and

[34] Factory identifiers are made available only recently and not available for surveys before 1998. As a result, previous studies have been unable to use the panel information (Nataraj, 2011) or relied on a form of matching algorithm (Harrison et al. 2011; Bollard, Klenow, and Sharma 2013) to construct a panel.

1999 survey and with at least 100 workers from 2000 onwards. The census plants are surveyed every year. The sample sector plants are randomly selected from the list of sample sector plants. ASI sampling weight (inverse of the sampling frequency) is available against each of the plant identifiers. The ASI data use National Industrial Classification (NIC) for the industrial classification of the plants. From 1998 to 2007 survey plants are classified by NIC-2004 and from 2008 to 2009 survey by NIC-2008. The first one follows Industrial Standard of Industrial Classification (ISIC) Rev 3.1 and the second one ISIC Rev 4. I use NIC-2004 as the main classification system by using a concordance from ISIC Rev 4 to ISIC 3.1. For the purpose of this paper, I use only manufacturing sector plants for analysis,- sector 15 to 36 of NIC-2004 industry codes.

The ASI records information on employment and labor cost (wage bill) by occupational categories – regular workers, contract workers, supervisors and managers, other employees and unpaid workers. These categories are then broadly defined into two main groups –production (or blue-collar) workers and non-production (or white-collar) workers. The set of production workers comprises regular and contract workers, and that of non-production workers comprises supervisors and managers, other employees and unpaid workers. The ASI reports total number of employees (L) of a plant as the sum of the average number of production (Lbl) and non-production workers (Lwh). The share of white-collar workers is defined as the ratio of number of white-collar workers and total employees. Total wage bill is calculated as the sum of the wages and salaries including bonuses, provident fund and welfare expenses. The average wage of white-collar (blue-collar) workers is calculated as the total white-collar (blue-collar) wage bill divided by the total number of paid white-collar (blue collar) workers –comprising supervisors and managers and other employees. The skill premium at the plant-level is calculated as the ratio of the average wage bill to paid white-collar workers to the average wage bill to blue-collar workers. For the purpose of the analysis, I include the plants that report all the information required to construct employment, wages and skill premium. All the key inputs and output variables are winsorized at 1st and 99th percentiles.

I restrict the sample size for the analysis to 16 major states in India which are included in the study of Besley and Burgess (2004) for the construction of labor market flexibility variable. Since the extent of labor market regulations depends on a certain predefined threshold number of employees, I classify each ASI plant by its level of employment in the year when it is first observed in the ASI data. As the sample of the ASI data only span from 1998 to 2009, I calculate the initial size of the plants using the average number of total employees reported by the plants in the year when it is first observed in ASI data. I refer to plant size in the initial year as "LFirst". For instance, a sample comprising only plants with at least 200 workers in the initial period is denoted as "LFirst200" sample.

Table A.1.b (appendix) shows how wage inequality evolved over time in India's formal manufacturing sector across different labor markets. The table highlights few important points. First, wage inequality increased steadily over the entire period, 1998-2009, in the manufacturing sector overall. Second, the rising pattern of wage-inequality is a common phenomenon in all the three different types of labor market. Third, average wage inequality in the pro-employer states has always been higher than that of pro-worker states. Fourth, there is no substantial difference between pro-employer and neutral states in terms of average wage inequality during 1998-2009, though the latter frequently exceeds the former in most years from 2000 to 2004. Therefore, the concern that high-skill-intensive firms may self select themselves to establish plants only in pro-employer states and experience a faster increase in skill premium is unlikely to undermine our identification strategy.

3.4 Measure of Import Competition

In this paper, I use a variant of the "value share" approach proposed by Schott (2002) and Bernard and Jensen (2002) as the measure of import competition. The authors define

$$I_{IN,jt}^{S} = \frac{\sum_k V_{kjt,S}}{\sum_k V_{kjt,W}} \quad (1)$$

where $V_{kjt,s}$ ($V_{kjt,w}$) is the import value of product *k* in industry *j* at time *t* from source *S* (W). Here *k* represents a particular HS 6-digit product category that corresponds to industry *j* (ISIC 4-digit industry). $I_{IN,jt}^{S}$ is the source S's share of the value of India's imports in Industry *j*.

However, this measure includes four different types of products - consumer goods, capital goods, intermediate goods and raw materials.[35] Industry-level aggregation of all the types of (HS 6-digit) products may therefore hide the competitive effects that particular types of imports may exert in some industries, leading to attenuation bias in the estimated impact of import competition. In order to obtain a more precise measure of competition at the industry-level, I modify the above measure of import competition by excluding all raw materials (RM) imports from the numerator. That is, the degree of import competition in industry *j* is the ratio of the sum of the value of all products imported from source S (China or high-wage countries) except raw materials and the sum of the value of all products including raw materials imported from the world.

$$M_{IN,jt}^{S} = \frac{\sum_{k,k \neq RM} V_{kjt,S}}{\sum_k V_{kjt,W}} \quad (2)$$

[35] The catagorization is based on UNCTAD standard product group classification.

3.5 Labor Market Rigidity and its Implications for India's Manufacturing Sector Performance

India's labor market regulation has been considered as one of the major obstacles to efficiency in the organized manufacturing sector (Besley and Burgess 2004) in general and growth of labor-intensive manufacturing sector in particular (Panagariya 2008). Even during this spectacular era of liberalization, there were no major changes in India's labor regulations.

India's manufacturing firms are divided into formal (or organized) and informal (or unorganized) sector. The organized sector includes factories that use power for manufacturing activities and employ more than 10 employees (20 if operate without power) and are registered under the Factories Act, 1948.[36] All organized sector firms are subject to inspection on a range of issues under the act: health and safety provisions, working hours, employment of women and young persons, annual leave and facilities within the premise. The number of regulatory issues increases as firms grow larger (in terms of employment). Once firms reach 20 or more workers, a firm is required to set up retirement funds, while at 50 or more workers it has to offer mandatory health insurance services.[37] In addition, firms with more than 50 employees are also subject to Industrial Disputes Act (IDA) of 1947 for settlement of disputes between workers and management. IDA contains especially stringent set of rules and regulation for firms with 100 or more workers. The most conspicuous part of the act is that any establishment with more than 100 workers must get prior permission from the appropriate government agency in order to layoff a worker or stop production.[38] Because the state governments are generally responsible for approving such authorizations, retrenchment of workers has become an extremely difficult task for the large employers (Panagariya 2008). However, firms partially

[36] Only around 10 percent of the manufacturing workers are employed in organized sector, while the rest belong to informal sector.
[37] The former is under Employees Provident Fund and Miscellaneous Provisions Act of 1952 and the latter is under the Employee State Insurance Act of 1948.
[38] The amendment was originally introduced in 1976 with applicability for the plant having three hundred or more workers and the threshold brought down to 100 or more with a further amendment in 1982.

circumvent the stringency of IDA by employing contract workers who are not protected by IDA.

Rigidity in the labor market limits the ability of the firms to adjust to shocks by increasing cost of hiring and dismissal of labor. For example, Aghion, Burgess, Redding and Zilibotti (hereafter, ABRZ, 2008) show that the impact of industrial de-licensing on performance of manufacturing sector differs across states with different labor market regulations.[39] Lafontaine and Sivadasan (2009) using outlet level data of a fast-food chain find that the responsiveness of labor cost with respect to previous period labor cost (hysteresis) is higher in highly regulated countries. Their study also find some evidence that labor cost responds less to sales revenue in inflexible labor market. Another important implication of labor market rigidity is that it hinders reallocation of resources from less to more productive firms. Kambourov (2009) highlights that labor market rigidity in the form of high firing cost slows down reallocation of labor across sectors in response to trade reforms.

The Measure of Labor Market Rigidity: In this paper, I exploit the variation in labor regulations across states to identify the differential impact of labor market outcomes in response to intensified import competition. State level differences in India's labor regulations arise from the fact that both central and state governments have concurrent jurisdiction over industrial relation laws in India. State governments have the authority to amend labor regulation legislation that was set at the federal level. For the purpose of this paper, I primarily use IDA based labor market classification of Besley and Burgess (2004) to categorize the states by labor market regime. Many studies (Panagariya 2008; ABRZ 2008; Dougherty 2008) consider IDA as the key legislation for determining labor market stringency in India. According to Panagariya (2008) the amendments to IDA, in 1976 and 1982, that impose

[39] Industrial licensing was the key tool of the Central government in India to regulate the manufacturing activities towards a desired direction: the characteristics of entrants, how much a plant can produce, the amount of input firms are allowed to use among others.

restriction on large plants ability to retrench workers, have severely impacted the efficiency of the workers and thereby effective costs of labor. Besley and Burgess (2004) document a strong positive relation between IDA based labor regulation measure and working time lost due to strikes. In order to develop a measure of labor market stringency, Besley and Burgess (BB) evaluate state level amendments to the IDA 1947, and assign a particular numeric code (1, -1, 0) to each amendment to indicate whether adjustments are made in favor of workers (1) or employers (-1) or whether no considerable impact in either direction (0). For instance, an amendment that prohibits strikes and lockouts is considered as a move towards pro-employer direction, whereas an amendment that imposes a requirement to include union representative in worker retrenchment negotiations is considered a move towards pro-worker direction. They aggregate the index over time to obtain a summary measure of regulatory environment at state level. Finally, they classify 16 major states of India into pro-employer, neutral and pro-worker category: Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu are classified as pro-employer states; Orissa, Gujarat, Maharashtra and West Bengal as pro-worker states; and Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh as neutral states.

The analysis of the paper is based on the ASI sample of these sixteen states covered by Besley and Burgess (2004). Over the period 1998 to 2009, these sixteen major states account for 91 percent of employment and 89 percent of total output of the formal manufacturing sector, on average. For the baseline analysis, I reclassify them into two groups –flexible or pro-employer and inflexible comprising neutral and pro-worker states. In the appendix, I also report results based on original BB classifications. ABRZ (2008) update the BB index until 1997, where they noted that overall regulatory stance of the states remains unchanged over the 1980-1997 period with one exception: Madhya Pradesh moved towards pro-employer direction in 1982 but reversed to neutral status by a pro-worker change in 1983. OECD (2007) updates the BB study through 2005 and documents that after 1990 only three states brought some changes to IDA by eight amendments in total and only change that has some labor market implication is that of 2004 amendment in Gujarat. Therefore, the original BB classification is still applicable for the purpose of this study.

3.6 Empirical Strategy

3.6.A Import Competition and Wage Inequality

In order to estimate the effect of Chinese competition on plant-level skill premium and wages of different categories of employees, I use the following specification,

$$\Delta_5 ln(y)_{ijt} = \alpha + \tau_{st} + \boldsymbol{\mu} X_i + \beta_1 \Delta_5 (M_{IN}^{CH})_{j,t-l} + \beta_2 \Delta_5 (M_{IN}^{EJU})_{j,t-l} + \xi_{ijt} \quad (3)$$

where y is a particular outcome variable of interest: skill premium (w_w/w_b), average wages of production or blue-collar workers (w_b) or average wages of non-production or white-collar workers (w_w). If y is (w_w/w_b), then $\Delta_5 ln(w_w/w_b)_{ijt}$ is the five-year change in log of the ratio of average wages of non-production (or white-collar) employees to average wages of production (or blue-collar) employees at plant *i* in industry *j* at time *t.* If y is w_b (or w_w), then $\Delta_5 \ln(w_b)_{ijt}$ (or $\Delta_5 \ln(w_w)_{ijt}$) is the five-year change in employment of production (or non-production) workers at plant *i*. The matrix X_i includes a set of control variables –a set of initial technology intensity dummies and a rural/urban location dummy. The term ξ_{ijt} is an idiosyncratic error term assumed to be uncorrelated with the measures of trade shocks and other right hand side variables. The key coefficient of interest in equation (3) is β_1 corresponding to $\Delta_5 (M_{IN}^{CH})_{jt-l}$ that measures changes in China's share of India's imports in industry *j* in period *t-l*. In this specification, I also control for changes in import competition from high-wage countries ($\Delta_5 (M_{IN}^{EJU})_{jt-l}$) in order to address the issue that import competition from high-wage sources is also skill-intensive and can have an effect on plant-level outcomes. The set of high-wage countries includes EU, Japan and USA (EJU). In the appendix, I also report results after controlling for import competition from other low-wage (LW) countries.

Differencing eliminates the plant fixed effects that account for sources of time-invariant unobserved heterogeneity, such as differences in production efficiency, managerial ability or organizational characteristics that could be correlated with the plant-level skill premium and the firms' general capacity to face import competition.

The state-year fixed effects, τ_{st}, control for macroeconomic shocks over time at the state level that are common to all plants within state. The inclusion of the state-year fixed effects also addresses the concern that labor market regulations in India can change over time across states. τ_{st} also control for the potential changes in speed of adjustment to workforce due to change in political regime at the state level. For example, if political power of a state switches towards a pro-employer government then it may be easier for the plants to adjust their workforce by retrenching workers.

3.6.B Import Competition and Employment

The empirical specification for plant employment analysis is similar to Bloom, Draca, and Van Reenen (2016). I take five-year difference form of the employment and measures of import competition to remove the influence of unobserved plant characteristics that may bias the coefficient of interest. In a heterogeneous firm model of trade, Melitz and Ottavanio (2008) predict that import competition intensifies competition in the domestic product market causing the least productivity firms to exit and relatively higher productivity firms to survive. In line with this prediction, I hypothesize that import competition causes reallocation of resources (labor) from less to more productive plants. In order to capture this asymmetric impact of import competition, I include five-year lagged plant Total Factory Productivity (TFP) along with its interaction with the measure of import competition. In order to examine the overall impact of import competition on employment dynamics, I perform pooled regressions on the sixteen state sample. To test whether labor market rigidity creates any additional adjustment cost for plants, I perform regressions separately for flexible and inflexible labor market.

$$\Delta_5 lnL_{ijt}^{C} = \alpha + \tau_{st} + \boldsymbol{\mu} X_i + \beta_1 \Delta_5 (M_{IN}^{CH})_{jt-l} + \beta_2 \Delta_5 (M_{IN}^{EJU})_{jt-l} + \delta lnPr_{ijt-5} + \gamma_1 \Delta_5 (M_{IN}^{CH})_{jt-l} * lnPr_{ijt-5} + \gamma_2 \Delta_5 \left(M_{IN}^{EJU}\right)_{jt-l} * lnPr_{ijt-5} + \xi_{ijt} \quad (4)$$

In equation (4), the dependent variable, $\Delta_5 lnL_{ijt}^{C}$, is the change in log employment of a particular category of workers over a five-year period in plant *i* in industry *j* at time *t*. The superscript *c*, refers to the type of workers: all, blue-collar or white-collar. The first coefficient of interest is β_1 that shows the effect of Chinese import competition on plant employment. The second coefficient of interest is γ_1, which shows whether import competition from China disproportionately affects plants with different productivity levels.

The expected signs of both β_1 and β_2 are negative. The reallocation coefficients γ_1 and γ_2 would be positive if there is a reallocation of resources from less to more productive plants in response to import competition. When the lag operator *l* equal to 1, the trade variable becomes $\Delta_5 (M_{IN}^{CH})_{jt-1}$ or the first lag of the five-year difference in China's value share. The state-year fixed effects, τ_{st}, control for any state specific macro shocks over time that affect all the plants within the same state. For notational simplicity, in the discussion that follows, I use ΔCHN for $\Delta_5 (M_{IN}^{CH})_{jt}$ and ΔEJU for $\Delta_5 (M_{IN}^{EJU})_{jt}$.

3.6.C Endogeneity

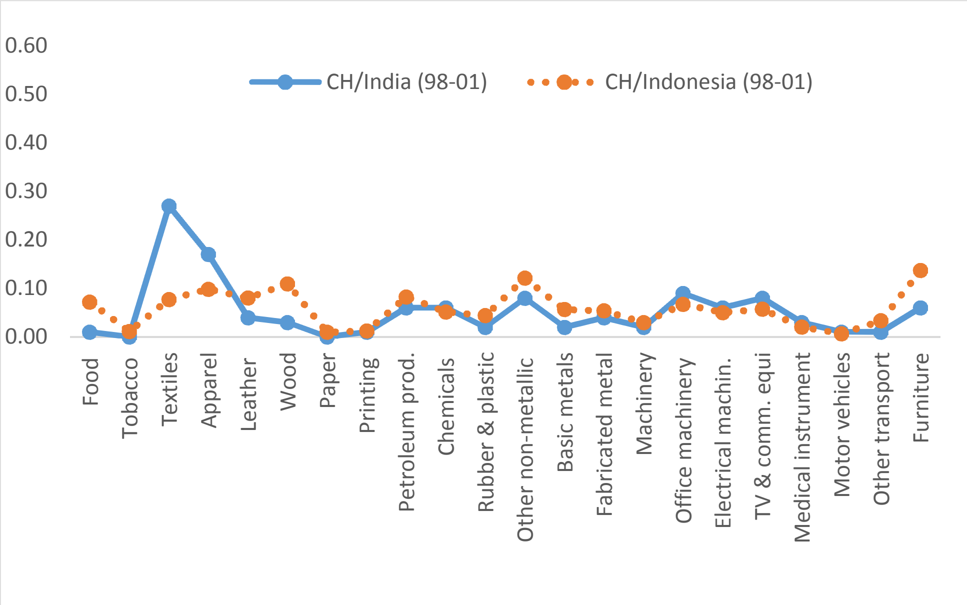
The empirical frameworks mentioned above exploit the differential changes in Chinese import exposure across industries and over time in the aftermath of China's accession to WTO to identify the impact of intensified Chinese import competition on plant-level outcomes. The structure also controls for time invariant unobserved heterogeneity by taking the five-year difference of variable of interest, which can also help reduce measurement error bias. The approach also controls for omitted variable bias emanating from changes in macroeconomic policies and labor market regulations over time and across states. Nonetheless, there are still potential sources of endogeneity that may bias our coefficients of interest.

First, there may be skill-biased technology shocks that may simultaneously affect the relative demand for skilled workers in plants of a particular industry and imports from China in that industry. A related concern is that an industry's skill intensity in the home country may affect the level and growth of imports in that industry. If India employs comparatively more skilled workers vis-à-vis China in a particular industry, there could be observed or unobserved import barriers in place to protect its domestic industry. This type of reverse causality may bias the coefficient of Chinese import competition. Another source of concern is that India has been experiencing gradual liberalization changes over the last two decades. Though, as a WTO member, India cannot restrain Chinese imports differentially by tariff barriers, it can apply a few non-tariff barriers, such as antidumping, to deter imports from China. This type of measures can also bias the estimates of interest. Finally, though the five-year differencing helps to reduce the error in the measure of import competition, there could still be some error leading to attenuation bias in the coefficient of interest. In order to address the concerns mentioned above, I utilize instrumental variable estimation approach to identify the impact of Chinese import competition.

I use one period lag changes in China's share of Indonesia's imports by industry (ISIC Rev 3.1) as the instrument for corresponding changes in China's share of India's imports. The instrument is similar to spirit of Acemoglu et al. (2016) and Autor, Dorn, and Hanson (2013), where they use growth of Chinese imports in eight other developed economies as instrument for growth of U.S. imports from China. The aim here is to identify the impact of supply-driven component of India's imports from China, which has been contributed by several factors including economic liberalization within China and its WTO accession in 2001. For example, Khandelwal et al. (2013) show that removal of export quotas paved the way for more efficient Chinese exporters to flourish in the global market. The dismantling of quotas induced entry of more productive firms and thereby lowered the prices of exported products. The validity of the instrument relies on the assumption that Chinese import growth is not driven by the shocks to import demand in Indonesia. Since Indonesia is a much smaller economy relative to China, this assumption seems innocuous.

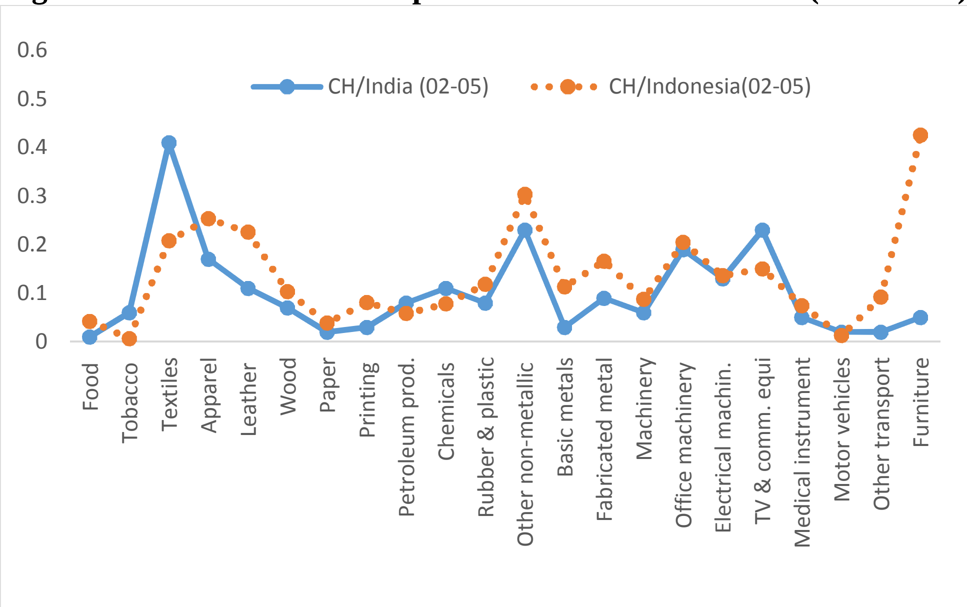
Indonesia is the third largest low-wage economy after China and India, and it has experienced a significant rise in imports from China in the 2000s. Importantly, Indonesia accounts for only a fraction of India's total trade –between 1998 and 2009, Indonesia contributed, on average, only 2.2 percent of India's total imports and 1.4 percent of total exports. More specifically, the share of Indonesia's imports increased from 2.0 percent in 1998 to only 2.9 percent in 2009, while the share of exports increased from only 0.56 percent in 1998 to 1.70 percent in 2009, though both series show some fluctuations over the period. In Figure 1, I find that both India and Indonesia had roughly similar exposure to Chinese competition at the sector-level (NIC 2-digit) during 1998-2001 period. In Figure 2, I observe that they have experienced approximately similar pattern of changes in exposure to Chinese imports after China's WTO accession. A comparison between Figure 1 and 2 clearly suggests that both the countries experienced increase in exposure to imports from China in most of the sectors.

Figure 1–Share of Chinese Imports in India and Indonesia (1998-2001)



Source: UN Comtrade Database

Figure 2–Share of Chinese Imports in India and Indonesia (2002-2005)



Source: UN Comtrade Database

3.7 Results

This section presents the relationship between labor market outcomes and industry-level import exposure from China. The analysis shows how plant-level skill premium, wages and employment change in response to import competition and whether import competition effects skilled and unskilled workers differentially. Further, in order to investigate the implications of labor market rigidities for the impact of import exposure on skill premium and wages, I present regression results separately by different labor market regimes along with the full sample results. To address the fact that regulatory burden in India increases with the size threshold of the plants, the regression results are shown according to different threshold levels of initial firm employment.

3.7.A Effect of Import Competition on Wage Inequality

Table 1 shows the impact of Chinese import exposure on changes in skill premium, blue-collar wages and white-collar wages. Panel-A reports the results for LFirst200 sample and Panel-B reports the results for LFirst100 sample and Panel-C reports the results for LFirst20 Sample. Columns (1)-(3) report results for the full sample, columns (4)-(6) include only the flexible and (7)-(9) include only the inflexible market sample. All the regressions include state by year fixed effects, rural/urban dummy and technology intensity dummies. Plant specific sampling weights are applied in all regressions. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level.

Columns (1), (4), and (7) show the results for OLS regression for changes in skill premium. Column (1) in Panel (A) shows that the coefficient of changes in Chinese import exposure (ΔCHN), β_1 is positive and statistically significant at 5 percent level. The estimate implies that a 10 percentage point increase in share of Chinese imports leads to a 1.35 percent increase in skill premium within-plant in the full sample. In column (4), I find that the same amount of increase in Chinese import intensity leads to a 2.65 percent increase in skill premium in the flexible market, which is statistically significant at 5 percent level. In contrast, in the inflexible labor market, in column (7), the estimate of β_1 is just 0.013 with a much higher standard error of 0.05. The result suggests that the observed increase in skill premium, in the full sample, is mostly driven by the rise in skill premium in the flexible labor market. In Table A.7 (appendix) separate regression results for neutral and pro-worker states show that skill premium is negatively associated with Chinese import competition in the neutral regime and but not in the pro-employer states.

Columns (2), (5) and (8) show the results of OLS regression for changes in blue-collar wages. In columns (2) and (5) of Panel-A, the coefficient of ΔCHN is -0.02 and -0.105, respectively, though both the coefficients are statistically insignificant. In contrast, the sign of the same coefficient of ΔCHN is actually positive (0.058) and statistically significant at 10 percent level in column (8). Table A.7 (section 3.9 appendix) reveals that Chinese competition positively affects blue-collar wages only in the neutral labor market. One plausible explanation for this finding is that there is some selection effect within the set of blue-collar workers. In the neutral market, although it is difficult to retrench regular workers who are covered by IDA, plants can retrench their contractual workers who are not protected by IDA and whose wages are relatively lower than the regular workers. As a result, average wage of blue-collar workers increases in the wake of rising import competition.

Columns (3), (6) and (9) show the results for changes in white-collar wages. In column (3) of Panel-A, for the full sample, the estimate of β_1 is 0.103 with a standard error of 0.045. In the flexible market, in column (6), the estimate of β_1 is 0.183 with a standard error of 0.082. The latter result suggests that a 10 percentage point increase in Chinese import exposure leads to a 1.8 percent increase in wages of white-collar workers in the flexible market. In column (9), the β_1 coefficient for the inflexible labor market is statistically insignificant and much smaller than the flexible market. Again, the reading remains the same in Table A.7 (appendix), where the regressions are shown separately for neutral and pro-worker market.

Table 1–Effect of Import Competition on Wage Inequality (OLS)

	Full Sample			Flexible			Inflexible		
Panel A OLS Regression Results LFirst200 Sample									
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5CHN_{(t-1)}$	0.135**	-0.022	0.103**	0.265**	-0.105	0.183**	0.013	0.058*	0.038
	(0.059)	(0.04)	(0.045)	(0.113)	(0.074)	(0.082)	(0.052)	(0.034)	(0.048)
$\Delta_5EJU_{(t-1)}$	-0.028	-0.022	-0.034	0.125	-0.126**	0.015	-0.138***	0.054	-0.071
	(0.049)	(0.037)	(0.054)	(0.084)	(0.054)	(0.079)	(0.039)	(0.035)	(0.048)
R-squared	0.007	0.016	0.018	0.007	0.014	0.017	0.008	0.019	0.02
N	22596	22596	22596	9415	9415	9415	13181	13181	13181
Panel B OLS Regression Results LFirst100 Sample									
	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5CHN_{(t-1)}$	0.104	0.024	0.118**	0.261**	-0.046	0.231**	-0.034	0.087**	0.025
	(0.076)	(0.046)	(0.051)	(0.13)	(0.073)	(0.096)	(0.043)	(0.035)	(0.04)
$\Delta_5EJU_{(t-1)}$	-0.014	-0.036	-0.043	0.079	-0.123**	-0.031	-0.085**	0.026	-0.056
	(0.05)	(0.037)	(0.049)	(0.086)	(0.052)	(0.078)	(0.041)	(0.036)	(0.043)
R-squared	0.007	0.02	0.019	0.007	0.017	0.019	0.007	0.021	0.02
N	31452	31452	31452	13106	13106	13106	18346	18346	18346
Panel C OLS Regression Results LFirst20 Sample									
	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5CHN_{(t-1)}$	0.099	-0.001	0.091	0.226**	-0.079	0.165	-0.002	0.059	0.03
	(0.064)	(0.041)	(0.056)	(0.110)	(0.071)	(0.103)	(0.051)	(0.036)	(0.047)
$\Delta_5EJU_{(t-1)}$	0.005	-0.059	-0.045	0.069	-0.140**	-0.06	-0.043	-0.002	-0.038
	(0.042)	(0.036)	(0.046)	(0.074)	(0.059)	(0.086)	(0.041)	(0.029)	(0.039)
R-squared	0.009	0.024	0.022	0.007	0.021	0.018	0.01	0.025	0.025
N	38062	38062	38062	15915	15915	15915	22147	22147	22147

Notes: Table reports results from OLS regression of five-year changes in log skill premium/average blue-collar wages/average white-collar wages on lag changes in China's and EJU's import share in India. Here skill premium is measured as ratio of average wages paid to non-production workers to average wages paid to production workers. Columns (1)-(3) include full sample and columns (4)-(6) include flexible and (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log of wage skill premium (SK), columns (2), (5) and (8) use changes in log of average wages of blue-collar workers and columns (3), (6) and (9) use changes in log of average wages of white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant-specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly: Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

The changes in import competition from high-wage countries (ΔEJU) has no statistically significant impact on skill premium, blue-collar wages and white-collar wages in the full sample results reported in Panel-A and Panel-B of Table 1. In the flexible market, average wage of blue-collar workers (column 5) is negatively correlated with import competition from EJU, though there is no statistically significant impact on skill premium or white-collar wages. In the inflexible states, skill premium is negatively associated with EJU import exposure (column 7) for LFirst200 sample. The results suggest that a 10 percentage point increase in EJU import exposure leads to a 1.38 percent fall in skill premium in the inflexible market.The results for LFirst100 sample in Panel-B and LFirst20 sample in Panel-C show that the coefficient of ΔCHN becomes statistically insignificant in skill premium regression for the full sample (column 1), but remains statistically significant in the flexible sample in column (4). The coefficient of ΔCHN for average wages of blue-collar workers remains positive and statistically significant for LFirst100 sample in the inflexible market, but becomes statistically insignificant for LFirst20 sample.

Table 2 reports the 2SLS regression where (*t*-1) lag of five-year changes in Chinese import competition in India is instrumented by ((*t*-1)-1) lag of five-year changes in Chinese import share in Indonesia. The dependent variable in each columns of Table 2 remains the same to corresponding columns in Table 1. Panel-A of Table 2 reports the IV regression results for LFirst200 sample. In column (1), the IV estimate of ΔCHN coefficient is 0.236 with a standard error of 0.107. This is almost twice as much relative to the corresponding OLS estimates in column (1) of Table 2. The result implies that a 10 percentage point increase in Chinese import competition causes a 2.3 percent increase in skill premium in India’s formal manufacturing sector. Again, in the case of flexible labor market in column (4), the IV estimate of Chinese import exposure is much stronger than the corresponding OLS estimate in Table 1. Though the coefficient of ΔCHN also increases in the case of inflexible labor market, it becomes statistically insignificant as in the case of OLS.

Table 2–Effect of Import Competition on Wage Inequality (2SLS)

Panel A IV Regression Results LFirst200 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	0.236**	0.013	0.222**	0.362**	-0.071	0.262**	0.09	0.115	0.186*
	(0.107)	(0.098)	(0.091)	(0.157)	(0.152)	(0.12)	(0.106)	(0.078)	(0.101)
Δ_5EJU$_{(t-1)}$	-0.012	-0.014	-0.009	0.136	-0.120*	0.029	-0.125**	0.067*	-0.036
	(0.06)	(0.039)	(0.057)	(0.092)	(0.062)	(0.081)	(0.051)	(0.035)	(0.055)
R-squared	0.007	0.016	0.018	0.007	0.014	0.017	0.01	0.019	0.019
N	22596	22596	22596	9415	9415	9415	13181	13181	13181

Panel B IV Regression Results LFirst100 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	0.098	0.072	0.145	0.259	-0.036	0.19	-0.069	0.175**	0.089
	(0.137)	(0.099)	(0.108)	(0.208)	(0.14)	(0.167)	(0.096)	(0.082)	(0.095)
Δ_5EJU$_{(t-1)}$	-0.014	-0.026	-0.038	0.079	-0.121**	-0.038	-0.091*	0.047	-0.041
	(0.063)	(0.041)	(0.055)	(0.1)	(0.058)	(0.084)	(0.048)	(0.039)	(0.05)
R-squared	0.007	0.02	0.019	0.007	0.017	0.019	0.008	0.02	0.02
N	31452	31452	31452	13106	13106	13106	18346	18346	18346

Panel C IV Regression Results LFirst20 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-0.034	0.133	0.099	0.079	0.069	0.15	-0.139	0.185**	0.048
	(0.182)	(0.106)	(0.158)	(0.244)	(0.177)	(0.225)	(0.159)	(0.084)	(0.146)
Δ_5EJU$_{(t-1)}$	-0.02	-0.031	-0.043	0.033	-0.112	-0.063	-0.064	0.027	-0.034
	(0.068)	(0.046)	(0.053)	(0.098)	(0.070)	(0.095)	(0.061)	(0.038)	(0.048)
R-squared	0.009	0.023	0.022	0.006	0.019	0.018	0.011	0.023	0.025
N	38062	38062	38062	15915	15915	15915	22147	22147	22147

Notes: Table reports results from IV regression of five-year changes in log skill premium/average blue-collar wages/average white-collar wages on lag changes in China's and EJU's import share in India. In the first stage, Δ_5CHN$_{(t-1)}$ is instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia Δ_5(CH)IDN$_{(t-1)-1}$. Here skill premium is measured as ratio of average wages paid to non-production workers to average wages paid to production workers. Columns (1)-(3) include full sample and columns (4)-(6) include flexible and columns (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log of wage skill premium (SK), columns (2), (5) and (8) use changes in log of average wages of blue-collar workers and (3), (6) and (9) use changes in log of average wages of white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly: Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

In columns (2), (5) and (8) of Panel-A, I find that there is no statistically significant impact of Chinese import exposure on the wages of blue-collar workers for LFirst200 sample. In column (8), the estimate is significantly greater than the OLS counterpart in Table 1, but it has become statistically insignificant.

In columns (3), (6) and (9), I find that the coefficient of ΔCHN is much larger than the corresponding OLS estimates. In column (3), the IV estimate is 0.222 with a standard error of 0.09. In column (9), the IV estimate for ΔCHN coefficient is 0.186 with a standard error of 0.10, which is quite close to full sample estimate in column (3). This IV estimate is statistically significant at 10 percent level. Notice that, the corresponding OLS estimate was much smaller and statistically insignificant.

Therefore, it appears that in general OLS underestimates the impact of import competition shocks from China on skill premium for the sample of large plants. One potential explanation for this finding is that unobserved skill-biased technology shocks in India may be negatively correlated with India's imports from China. This kind of reverse causality can bias the OLS coefficient downwards. In addition, measurement error problem may also cause OLS to underestimate the impact of Chinese import competition.

The 2SLS regressions for LFirst100 sample in Panel-B and LFirst20 sample in Panel-C find no statistically significant impact of import competition from China on skill premium and average wages of white-collar workers. However, in the inflexible labor market average wage of blue-collar workers increases with the rise in import competition from China. In fact, Table A.9 (section 3.9 appendix) reveals that this changes happen only in the neutral states.

The preceding analysis suggests that, overall, an increase in import exposure from China has a statistically significant impact on skill premiums in the large plants (with at least 200 employees in the initial period). However, when plants are separated by the flexibility of labor market, it appears that the skill premium increases in the face of rising Chinese import competition only in the flexible or pro-employer labor market, whereas the coefficient is much smaller and statistically insignificant in the inflexible labor market. In the flexible market, the rise in skill premium is mainly driven by rise in the plant-level wages of white-collar workers. In the neutral labor market, the Chinese competition has some positive impact on average wages of blue-collar workers.

The result suggests that even in the neutral labor market there may be some adjustment taking place within the group of blue-collar workers. The findings in this section is consistent with the quality upgrading or product mix channel that predicts an increase in wages of white-collar workers in response to import competition. In Chapter 2, I find that import competition from China induces plants to rationalize their product scope and the selection across products within-plant plays an important role in the rationalization process. The finding that Chinese import exposure has positive effect on skill premium is consistent with the findings of Bloom, Draca, and Van Reneen (2016), Mion and Zhu (2013), and Utar (2014), who document similar results in European context.

3.7.B Effect of Import Competition on Employment

Table 3.a and Table 3.b report results from OLS regression of five-year changes in employment on five-year changes in measures of import competition based on equation (4), the base specification for employment regression. In Table 3.a, Panel-A reports results for plants with at least 200 employees (LFirst200) and Panel-B reports results for plants with at least 100 employees (LFirst100) in the initial period. Table 3.b reports results for plants with at least 20 employees (LFirst20) in the initial year. Columns (1)-(3) report results for the full sample by pooling plants in both flexible and inflexible states and columns (4)-(6) include only plants in flexible states, and columns (7)-(9) include plants in the inflexible states. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. All the regressions include

state by year fixed effects, OECD technology intensity dummies and a rural/urban dummy. Plant specific sampling weights are applied in all regressions.

Table 3.a–Effect of Import Competition on Employment (OLS)

Panel A OLS Regression Results LFirst200 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-0.847**	-0.849**	-0.51	-1.297**	-1.451**	-0.78	-0.38	-0.27	-0.37
	(0.383)	(0.421)	(0.469)	(0.524)	(0.585)	(0.661)	(0.465)	(0.564)	(0.452)
TFP$_{(t-5)}$	0.011	0.008	0.034***	0.008	0.005	0.040***	0.014	0.01	0.030**
	(0.012)	(0.012)	(0.010)	(0.018)	(0.019)	(0.012)	(0.009)	(0.009)	(0.012)
Δ_5CHN$_{(t-1)}$	0.106**	0.104**	0.057	0.173***	0.190***	0.09	0.032	0.017	0.037
×TFP$_{(t-5)}$	(0.042)	(0.046)	(0.052)	(0.062)	(0.070)	(0.071)	(0.052)	(0.065)	(0.054)
Δ_5EJU$_{(t-1)}$	-0.745***	-0.816**	-0.17	-1.264***	-1.289**	-0.36	-0.16	-0.23	-0.11
	(0.265)	(0.318)	(0.394)	(0.421)	(0.503)	(0.587)	(0.323)	(0.402)	(0.345)
Δ_5EJU$_{(t-1)}$	0.082***	0.091**	-0.0	0.148***	0.153***	0.009	0.003	0.01	-0
×TFP$_{(t-5)}$	(0.030)	(0.036)	(0.048)	(0.045)	(0.054)	(0.069)	(0.039)	(0.051)	(0.042)
R-squared	0.033	0.028	0.029	0.038	0.034	0.031	0.032	0.026	0.029
N	22596	22596	22596	9415	9415	9415	13181	13181	13181

Panel B OLS Regression Results Lfirst100 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-0.56	-0.5	-0.48	-0.53	-0.43	-0.7	-0.52	-0.52	-0.36
	(0.374)	(0.396)	(0.434)	(0.516)	(0.553)	(0.548)	(0.457)	(0.529)	(0.452)
TFP$_{(t-5)}$	0.01	0.007	0.034***	0.007	0.006	0.037***	0.013	0.009	0.032***
	(0.011)	(0.011)	(0.010)	(0.017)	(0.018)	(0.011)	(0.008)	(0.008)	(0.011)
Δ_5CHN$_{(t-1)}$	0.078*	0.07	0.06	0.084	0.071	0.084	0.062	0.06	0.046
×TFP$_{(t-5)}$	(0.043)	(0.045)	(0.047)	(0.065)	(0.069)	(0.059)	(0.050)	(0.060)	(0.052)
Δ_5EJU$_{(t-1)}$	-0.853***	-0.886***	-0.54	-1.372***	-1.351***	-0.76	-0.4	-0.47	-0.44
	(0.223)	(0.258)	(0.368)	(0.346)	(0.400)	(0.512)	(0.299)	(0.361)	(0.331)
Δ_5EJU$_{(t-1)}$	0.098***	0.103***	0.048	0.157***	0.158***	0.06	0.041	0.048	0.044
×TFP$_{(t-5)}$	(0.025)	(0.029)	(0.045)	(0.039)	(0.045)	(0.061)	(0.038)	(0.047)	(0.040)
R-squared	0.026	0.021	0.029	0.028	0.022	0.028	0.027	0.021	0.032
N	31452	31452	31452	13106	13106	13106	18346	18346	18346

Notes: Table reports results from OLS regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. Panel-A reports results for LFirst200 and panel-B reports LFirst100 sample. Columns (1)-(3) include full sample, and columns (4)-(6) include flexible, and (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly: Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

Table 3.b–Effect of Import Competition on Employment (LFirst20, OLS)

OLS Regression Results LFirst20 Sample									
	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5CHN_{(t-1)}$	-0.59	-0.565	-0.446	-0.924	-0.933	-0.699	-0.347	-0.305	-0.302
	(0.425)	(0.464)	(0.412)	(0.668)	(0.729)	(0.566)	(0.412)	(0.469)	(0.435)
$TFP_{(t-5)}$	0.011	0.008	0.030***	0.006	0.003	0.030***	0.014**	0.011	0.030***
	(0.009)	(0.009)	(0.009)	(0.014)	(0.015)	(0.010)	(0.007)	(0.007)	(0.009)
$\Delta_5CHN_{(t-1)}$	0.085	0.081	0.062	0.122	0.122	0.086	0.054	0.049	0.046
$\times TFP_{(t-5)}$	(0.052)	(0.056)	(0.047)	(0.082)	(0.089)	(0.065)	(0.047)	(0.055)	(0.050)
$\Delta_5EJU_{(t-1)}$	-0.719***	-0.795***	-0.351	-1.130***	-1.267***	-0.325	-0.376	-0.428	-0.334
	(0.252)	(0.297)	(0.338)	(0.395)	(0.473)	(0.502)	(0.274)	(0.317)	(0.292)
$\Delta_5EJU_{(t-1)}$	0.092***	0.103***	0.033	0.136***	0.151***	0.031	0.051	0.061	0.03
$\times TFP_{(t-5)}$	(0.027)	(0.032)	(0.042)	(0.044)	(0.053)	(0.060)	(0.032)	(0.037)	(0.036)
R-squared	0.023	0.019	0.023	0.023	0.018	0.019	0.025	0.021	0.028
N	38062	38062	38062	15915	15915	15915	22147	22147	22147

Notes: Table reports results from OLS regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. Table reports results for LFirst20 sample only. Columns (1)-(3) include full sample, and columns (4)-(6) include flexible, and (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly: Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

Columns (1), (4) and (7) show the results for total employment in full sample, flexible and inflexible labor market, respectively, by regressing changes in log of total employment on one year lag changes in industry import exposure from China (ΔCHN) and high-wage countries (ΔEJU) and five-year lag of plant TFP (TFP_{t-5}) and its interaction with import exposure variables. The key estimates of interest are the coefficient of ΔCHN, β_1 and the coefficient of interaction, between TFP and ΔCHN, γ_1.

In column (1) of Panel-A in Table 3.a, for LFirst200 sample, the coefficient β_1 is -0.847 with a standard error of 0.383 and γ_1 is 0.106 with a standard error of 0.042. These results suggest that Chinese import competition has a negative effect on the demand for labor in low productivity plants, while a positive effect on the demand for labor in high productivity plants. In order to estimate the impact of import competition for plants at different points of initial TFP distribution, summary statistics of five-year lag TFP is calculated separately for the full sample, flexible market and inflexible market at each threshold level of employment (200, 100 and 20) and reported in Table A.6 (appendix). In the sample of all states, a 10 percentage point increase in China's share of India's imports leads to a 1.2 percent decline in total employment of a plant at the 25th percentile of initial TFP (6.86), in the set of plants with at least 200 employees. On the other hand, the same 10 percentage point increase in Chinese import exposure leads to a 0.5 percent increase in total employment of a plant at the 75th percentiles of initial TFP (8.57).

Column (2) of Panel A in Table 3.a uses five-year difference of only blue-collar workers (ΔlnLbl) as the dependent variable for LFirst200 sample. The results are almost unchanged: β_1 is -0.849 and γ_1 is 0.104, with standard error 0.421 and 0.046 respectively. A 10 percentage point increase in Chinese import exposure induces a 1.36 percent decline in blue-collar employment of a plant at the 25^{th} percentile, but leads to a 0.3 percent increase in employment of a plant at the 75th percentiles of initial TFP. Column (3) in Panel A shows the results for changes in non-production or white-collar workers (ΔlnLwh) only. In this case, the size of the estimates of both β_1 and γ_1 has fallen, though the sign of the coefficients remain unchanged. The estimates together imply that employment of non-production workers declines by 1.2 percent in plants at the 25^{th} percentile and by 0.28 percent in plants at the 75th percentiles of initial TFP. However, both the estimates are statistically insignificant for non-production workers.

Columns (4)-(6) in Panel-A show the results for LFirst200 plants located in flexible labor market only. The sign and statistical significance of the estimates of β_1 and γ_1 remain similar to the full sample results, but the size of both the coefficients increases considerably – magnifying the asymmetric response to plant employment toward high productivity plants in the face of rising import exposure. The estimates in column (5) imply that in the flexible market a 10 percentage point increase in Chinese import exposure leads to a decline in blue-collar employment by 0.9 percent for plants at the 25th percentiles, but leads to a 2 percent increase for plants at the 75th percentiles. For the white-collar workers, the sign of the coefficients β_1 and γ_1 is negative and positive respectively, as in the case of full sample, but the magnitude of the coefficients is higher in the case of flexible states. Again, the impact on the demand for white-collar workers is statistically insignificant even in the flexible labor market.

Columns (7)-(9) in Panel-A present results for LFirst200 sample in the inflexible labor market only. Though the estimates of Chinese import competition and its interaction with lag TFP are statistically insignificant, there are some interesting observations. First, both β_1 and γ_1 for white-collar workers (9) are slightly larger than blue-collar workers (8). Second, the interaction coefficient γ_1 is not large enough to command any reallocation of employment toward high productivity plants. For example, in the case of plants at 75th percentiles of TFP a 10 percent increase in Chinese import competition leads to a 1.1 percent fall in blue-collar employment (column 8) and 0.6 percent fall in white-collar employment (column 9). A clearer picture emerges from Table A.11 (appendix), which shows separate regression results for neutral and pro-employer states. As in the case of inflexible sample regression, the impact of Chinese competition remains statistically insignificant in both types of states. Though both β_1 and γ_1 appear with theoretically expected sign in neutral states, the sign of these coefficients is not reasonably consistent in the pro-worker states.

OLS results for LFirst100 sample (Panel-B of Table 3.a) and LFirst20 sample (Table 3.b) show that the sign of β_1 and γ_1 remains similar to their LFirst200 sample counterparts. However, the coefficient of Chinese import competition and its interaction with initial plant TFP become statistically insignificant for LFirst100 and LFirst20 sample.

The coefficient of initial TFP, δ, is positive in all the columns in Panel-A and Panel-B. A noticeable point is that the coefficient is larger for non-production employment compared to the production or total employment in all the cases –full sample, flexible and inflexible labor market. Moreover, the coefficient is statistically significant only in the case of non-production (white-collar) workers, column (3), (6) and (9). In column (1) of Panel-A, for LFirst200 sample, the coefficient is 0.011 with a standard error of 0.012 for total employment, whereas the coefficient is 0.034 with a standard error of 0.01 in the case of the non-production workers. The latter is statistically significant at 1 percent level. The result suggests that holding the level of import exposure fixed, higher the initial productivity of the plants, the greater the increase in employment of white-collar workers. The relationship between initial productivity and employment of white-collar workers holds in all cases irrespective of labor market rigidity and size threshold of the plants.

Import competition from high-wage countries also causes reallocation of labor from less productive plants to ones that are more productive. In Table 3.a, for LFirst200 sample, impact of import competition from EJU on total employment is statistically significant in the full sample (column 1) and flexible market sample only (column 4). Separate regressions for blue-collar (columns 2 and 5) and white-collar employment (columns 3 and 6) suggest that in both full sample and flexible market, the effect is statistically significant for blue-collar employment only. Columns (1) and (2) of Table 3.a show that the coefficient of changes in high-wage countries import share (ΔEJU) and the coefficient of interaction term between TFP and ΔEJU, are similar in magnitude and statistical significance to the corresponding coefficient for China. Therefore, the results suggest that import competition from China and from high-wage countries have similar effects on reallocation of employment across large plants in India. But interestingly, the impact of import competition shocks from high-wage countries remains statistically significant for the sample of plants with initial employment of at least 100 workers and 20 workers, respectively. In Panel-B of Table 3.a, both size and statistical significance of the coefficients β_2, and γ_2 for LFirst100 sample remain close to that of Panel-A.

IV regression Results:

Table 4.a and Table 4.b show the relationship between plant employment and Chinese import penetration based on 2SLS regression. In Table 4.a, Panel-A and Panel-B report regression results for LFirst200 and LFirst100 sample, respectively. Table 4.b shows 2SLS regression results for LFirst20 sample. In general, I find that the size of the IV estimates for Chinese import competition are much larger in comparison to corresponding OLS estimates and the impacts are statistically significant for LFirst200 plants. In Panel-B, for LFirst100 sample, IV estimates are again larger than their OLS counterparts, but statistically insignificant.

In this section, I discuss the key finding from LFirst200 sample reported in Panel-A. In column (1), the coefficient of changes in Chinese import share, β_1 is -2.442 and the coefficient of TFP interaction, γ_1, is 0.315, where both are significant at 10 percent and 5 percent level, respectively, for LFirst200 sample. Together the result implies that a 10 percentage point rise in Chinese import competition leads to a 2.8 percent fall in total employment of a plant at the 25th percentiles of the TFP, whereas the same amount of increase causes a 2.2 percent increase of employment of a plant at the 75th percentiles of TFP. In column (2), the IV estimates of β_1 and γ_1 for blue-collar workers are very close to total employment regression in column (1) as in the case of OLS. Both the coefficients are statistically significant at 5 percent level. In column (3), IV estimates for white-collar workers are again larger than the corresponding OLS estimates, but remain statistically insignificant.

In the flexible labor market, for LFirst200 sample, both β_1 and γ_1 are larger for total employment in column (4) and blue-collar employment in column (5) compared to full sample regression. As already seen in the case of OLS regression, the growth of total employment in the high-productivity plants is higher in the flexible market, which is driven by changes in employment of blue-collar workers. The IV estimates suggest that a 10 percentage point increase in Chinese import exposure leads to 5 percent increase in employment of blue-collar workers of plants at the 75th percentiles of TFP distribution, which is more than twice as much of what we observe for the full sample.

Table 4.a–Effect of Import Competition on Employment (2SLS)

Panel A IV Regression Results LFirst200 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5CHN_{(t-1)}$	-2.442*	-2.509**	-1.517	-3.607**	-3.883**	-1.329	-1.583	-1.493	-1.773*
	(1.246)	(1.264)	(1.138)	(1.833)	(1.839)	(1.519)	(1.024)	(1.101)	(1.071)
$TFP_{(t-5)}$	-0.003	-0.006	0.025**	-0.011	-0.015	0.035**	0.004	0	0.018
	(0.016)	(0.016)	(0.013)	(0.024)	(0.025)	(0.016)	(0.012)	(0.012)	(0.014)
$\Delta_5CHN_{(t-1)}$ $\times TFP_{(t-5)}$	0.315**	0.325**	0.197	0.471*	0.507**	0.169	0.188	0.176	0.230*
	(0.161)	(0.163)	(0.135)	(0.244)	(0.246)	(0.176)	(0.123)	(0.132)	(0.129)
$\Delta_5EJU_{(t-1)}$	-1.025***	-1.106***	-0.34	-1.563***	-1.601***	-0.42	-0.43	-0.507	-0.43
	(0.318)	(0.375)	(0.444)	(0.474)	(0.548)	(0.638)	(0.358)	(0.438)	(0.381)
$\Delta_5EJU_{(t-1)}$ $\times TFP_{(t-5)}$	0.119***	0.129***	0.022	0.185***	0.193***	0.019	0.038	0.046	0.044
	(0.037)	(0.044)	(0.054)	(0.054)	(0.062)	(0.075)	(0.043)	(0.054)	(0.047)
R-squared	0.029	0.025	0.027	0.03	0.027	0.03	0.03	0.025	0.026
N	22596	22596	22596	9415	9415	9415	13181	13181	13181

Panel B IV Regression Results LFirst100 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
$\Delta_5CHN_{(t-1)}$	-1.22	-1.233	-0.921	-1.727	-1.707	-0.89	-0.955	-1.005	-1.141
	(1.300)	(1.334)	(1.076)	(1.750)	(1.767)	(1.294)	(1.023)	(1.121)	(1.048)
$TFP_{(t-5)}$	0.004	0.001	0.029**	-0.003	-0.005	0.035**	0.009	0.005	0.024
	(0.016)	(0.016)	(0.014)	(0.022)	(0.023)	(0.015)	(0.012)	(0.011)	(0.015)
$\Delta_5CHN_{(t-1)}$ $\times TFP_{(t-5)}$	0.165	0.167	0.132	0.228	0.228	0.123	0.124	0.13	0.162
	(0.179)	(0.183)	(0.128)	(0.242)	(0.245)	(0.152)	(0.128)	(0.141)	(0.121)
$\Delta_5EJU_{(t-1)}$	-0.974***	-1.020***	-0.618	-1.544***	-1.535***	-0.78	-0.5	-0.575	-0.612*
	(0.301)	(0.340)	(0.396)	(0.401)	(0.452)	(0.540)	(0.342)	(0.412)	(0.350)
$\Delta 5EJU_{(t-1)}$ $\times TFP_{(t-5)}$	0.114***	0.120***	0.061	0.177***	0.179***	0.066	0.055	0.064	0.070*
	(0.038)	(0.043)	(0.047)	(0.050)	(0.056)	(0.063)	(0.042)	(0.052)	(0.041)
R-squared	0.025	0.02	0.028	0.026	0.021	0.028	0.026	0.021	0.03
N	31452	31452	31452	13106	13106	13106	18346	18346	18346

Notes: Table reports results from IV regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. In the first stage, $\Delta_5CHN_{(t-1)}$ and $\Delta_5CHN_{(t-1)} \times TFP_{(t-5)}$ are instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia $\Delta_5(CH)IDN_{(t-1)-1}$ and its interaction with lag TFP, $\Delta_5(CH)IDN_{(t-1)-1} \times TFP_{(t-5)}$. Panel-A reports results for LFirst200 and panel-B reports LFirst100 sample. Columns (1)-(3) include full sample, and columns (4)-(6) include flexible, and (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

Table 4.b–Effect of Import Competition on Employment (2SLS)

Panel A IV Regression Results LFirst20 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-0.744	-0.785	-0.288	-1.558	-1.739	-0.195	-0.296	-0.239	-0.513
	(1.303)	(1.352)	(1.055)	(1.759)	(1.827)	(1.325)	(1.045)	(1.150)	(1.005)
TFP$_{(t-5)}$	0.009	0.005	0.030**	0	-0.004	0.034**	0.014	0.01	0.027**
	(0.015)	(0.014)	(0.013)	(0.021)	(0.021)	(0.015)	(0.010)	(0.011)	(0.013)
Δ_5CHN$_{(t-1)}$	0.118	0.125	0.061	0.212	0.236	0.047	0.061	0.056	0.089
×TFP$_{(t-5)}$	(0.179)	(0.185)	(0.128)	(0.246)	(0.255)	(0.162)	(0.130)	(0.143)	(0.118)
Δ_5EJU$_{(t-1)}$	-0.752**	-0.841**	-0.328	-1.233***	-1.397***	-0.242	-0.379	-0.43	-0.395
	(0.337)	(0.383)	(0.367)	(0.441)	(0.515)	(0.529)	(0.343)	(0.397)	(0.310)
Δ_5EJU$_{(t-1)}$	0.099**	0.112**	0.035	0.151***	0.169***	0.025	0.054	0.065	0.042
×TFP$_{(t-5)}$	(0.040)	(0.045)	(0.043)	(0.054)	(0.062)	(0.062)	(0.040)	(0.046)	(0.037)
R-squared	0.023	0.019	0.023	0.022	0.017	0.018	0.025	0.02	0.027
N	38062	38062	38062	15915	15915	15915	22147	22147	22147

Notes: Table reports results from IV regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. In the first stage, Δ_5CHN$_{(t-1)}$ and Δ_5CHN$_{(t-1)}$ ×TFP$_{(t-5)}$ are instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia Δ_5(CH)IDN$_{(t-1)-1}$ and its interaction with lag TFP, Δ_5(CH)IDN$_{(t-1)-1}$×TFP$_{(t-5)}$. Table reports results for LFirst20 sample only. Columns (1)-(3) include full sample, and columns (4)-(6) include flexible, and (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

In the inflexible labor market, though the impact of import competition appears to be statistically insignificant for total (7) and blue collar employment (8), both the coefficients, β_1 and γ_1 are now statistically significant at 10 percent level for white-collar employment (9). For plants at the 75 percentiles of TFP, a 10 percent point increase in the Chinese import exposure leads to a 1.4 percent increase in employment of white-collar workers, but causes a 0.27 percent decline in employment of blue-collar workers in the inflexible market.

Table 4.a shows that the impact of import competition from high-wage countries is now even higher in the IV regression and statistically significant for total and blue-collar employment in the full sample and flexible market, both in Panel-A and Panel-B.

In IV regression, the coefficient of lag TFP becomes negative for total employment and blue-collar employment but remains positive for white-collar workers. Though the TFP coefficient for white-collar workers is also slightly smaller than the corresponding OLS estimates, it is statistically significant at 5 percent level in the full sample and flexible market.

Overall, both OLS and IV estimates suggest that Chinese import exposure has a significant impact on total employment and blue-collar employment for plants with at least 200 employees in the initial period but has no statistically significant impact on white-collar employment in the full sample and flexible labor market. However, in the inflexible labor market, the impact of competition seems to have slightly stronger effect on white-collar employment. However, plants located in the inflexible labor market show no statistically significant adjustment to employment of blue-collar workers in response to import competition shocks.[40]

3.8 Concluding Remarks

Competition from imports can significantly affect labor market outcomes in destination countries through both destruction and reallocation of employment and redistribution of income across skill-categories. Based on plant-level data from 16 major Indian states this paper documents that intensified import competition from China leads to an increase in within-plant wage inequality between skilled and unskilled workers in large plants. One key finding of the paper is that the impact of trade shocks on within-plant wage-inequality differs by flexibility of labor market. I find that in flexible labor markets, in large plants, only the average wage of white-collar workers rises due to increase in Chinese import competition, while no significant

[40] I have verified the robustness of the main results using a modified version of BB classification proposed by Gupta, Hasan and Kumar (2009). The authors suggest that Gujrat should be considered as a neutral state rather than a pro-worker state. Similarly, Madhya Pradesh should be treated as a neutral state rather than a pro-employer state. Our main findings remain robust to this modified classification of labor market flexibility. Results are not reported in the paper.

adjustment of blue-collar wages occurs, which leads to rise in wage-inequality within-plant. In the inflexible (neutral and pro-worker) labor markets skill premium does not respond to import exposure from China.

However, import competition from high-wage countries is not associated with wage inequality in the sample of 16 major states. Similar results appear in the flexible labor market as well. But the picture changes dramatically for the inflexible labor market, where import competition from high-wage countries has a negative on impact wage inequality. This finding is consistent with Bloom, Draca, and Van Reneen (2016) and Mion and Zhu (2013), who also find that competition from China is different from that of high-wage countries.

I observe that reallocation of labor across plants occurs in response to import competition, in the sample of large plants. In the face of rising import competition from China, the low-productivity plants shrink by reducing the number of employees, whereas the high-productivity plants expand by hiring more employees. However, mainly blue-collar workers bear the brunt of the shocks, while there is no significant impact on the employment of white-collar workers. Therefore, the impact of Chinese import exposure on plant employment is not symmetric across different skill categories of workers.

The results suggest that the impact of Chinese import exposure on plant labor adjustment differs across labor market regime. This result is consistent with ABRZ (2008), who show that the impact of reform differs by labor market flexibility in India, and with the cross country evidence that speed of adjustment to shocks is slower in more rigid labor markets (Lafontaine and Sivadasan 2009; Caballero et al. 2013). The findings also support the prediction of Kambourov (2009), who shows that labor market rigidity hinders reallocation of labor across sectors.

3.9 Appendix

Table A.1.a–India's and Indonesia's Exposure to Chinese Imports by sector (NIC 2-digit)

	India's Imports from China			Indonesia's Imports from China		
	1998-01	2002-05	2006-09	1998-01	2002-05	2006-09
Food	0.01	0.01	0.01	0.07	0.04	0.04
Tobacco	0.00	0.06	0.04	0.01	0.01	0.04
Textiles	0.27	0.41	0.52	0.08	0.21	0.33
Apparel	0.17	0.17	0.28	0.10	0.25	0.46
Leather	0.04	0.11	0.25	0.08	0.23	0.35
Wood	0.03	0.07	0.18	0.11	0.10	0.18
Paper	0.00	0.02	0.11	0.01	0.04	0.06
Printing	0.01	0.03	0.07	0.01	0.08	0.09
Petroleum prod.	0.06	0.08	0.07	0.08	0.06	0.03
Chemicals	0.06	0.11	0.17	0.05	0.08	0.12
Rubber & plastic	0.02	0.08	0.23	0.04	0.12	0.16
Other non-metallic	0.08	0.23	0.39	0.12	0.30	0.33
Basic metals	0.02	0.03	0.07	0.06	0.11	0.17
Fabricated metal	0.04	0.09	0.27	0.05	0.17	0.30
Machinery	0.02	0.06	0.16	0.03	0.09	0.16
Office machinery	0.09	0.19	0.39	0.07	0.20	0.33
Electrical machin.	0.06	0.13	0.28	0.05	0.14	0.23
TV & comm. Equi	0.08	0.23	0.43	0.06	0.15	0.25
Medical instrument	0.03	0.05	0.09	0.02	0.07	0.12
Motor vehicles	0.01	0.02	0.06	0.01	0.01	0.03
Other transport	0.01	0.02	0.05	0.03	0.09	0.08
Furniture	0.06	0.05	0.09	0.14	0.43	0.45
Minimum	0.00	0.01	0.01	0.01	0.01	0.03
Maximum	0.27	0.41	0.52	0.14	0.43	0.46
Standard Deviation	0.06	0.10	0.14	0.04	0.10	0.14

Table A.1.b–Wage Inequality 1998-2009 and Labor Market Rigidity

Year	Overall	Pro-employer	Neutral	Pro-worker
1998	2.14	2.21	2.13	2.04
1999	2.20	2.38	2.16	2.01
2000	2.22	2.30	2.32	2.04
2001	2.27	2.31	2.34	2.15
2002	2.33	2.40	2.41	2.18
2003	2.38	2.45	2.43	2.24
2004	2.46	2.52	2.53	2.31
2005	2.52	2.56	2.66	2.35
2006	2.65	2.69	2.75	2.51
2007	2.77	2.81	2.85	2.64
2008	2.98	3.01	3.15	2.81
2009	3.03	3.10	3.24	2.78
1998-01	2.21	2.30	2.24	2.06
2002-05	2.42	2.48	2.51	2.27
2006-09	2.86	2.90	3.00	2.69

Note: The Table shows the ratio of the wage of white-collar to the wage of blue-collar employees based on balanced sample of ASI plants from 1998 to 2009 period. Labor Market Classification is based on Besley and Burgess (2004).

Table A.2–Effect of Import Competition on Wage Inequality with other LWs (OLS)

Panel A OLS Regression Results LFirst200 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	0.150***	-0.019	0.121***	0.310***	-0.118	0.215***	0.011	0.070**	0.048
	(0.056)	(0.041)	(0.046)	(0.101)	(0.072)	(0.073)	(0.051)	(0.032)	(0.052)
Δ_5EJU$_{(t-1)}$	-0.004	-0.017	-0.006	0.196**	-0.147**	0.065	-0.140***	0.072**	-0.055
	(0.049)	(0.041)	(0.057)	(0.078)	(0.059)	(0.078)	(0.041)	(0.036)	(0.054)
Δ_5LW$_{(t-1)}$	0.065	0.014	0.078***	0.183**	-0.053	0.130***	-0.007	0.054	0.046
	(0.044	(0.029)	(0.029)	(0.075)	(0.042)	(0.046)	(0.028)	(0.035)	(0.036)
R-squared	0.007	0.016	0.019	0.008	0.014	0.018	0.008	0.019	0.02
N	22596	22596	22596	9415	9415	9415	13181	13181	13181

Panel B OLS Regression Results LFirst100 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
Δ_5CHN$_{(t-1)}$	0.119	0.025	0.134**	0.302**	-0.057	0.260***	-0.035	0.096***	0.031
	(0.074)	(0.048)	(0.052)	(0.123)	(0.073)	(0.093)	(0.043)	(0.037)	(0.044)
Δ_5EJU$_{(t-1)}$	0.011	-0.034	-0.018	0.149*	-0.142**	0.019	-0.087**	0.04	-0.047
	(0.052)	(0.042)	(0.054)	(0.087)	(0.058)	(0.083)	(0.041)	(0.038)	(0.048)
Δ_5LW$_{(t-1)}$	0.069	0.005	0.070*	0.185**	-0.051	0.133**	-0.005	0.039	0.028
	(0.046)	(0.031)	(0.036)	(0.08)	(0.037)	(0.055)	(0.028)	(0.032)	(0.036)
R-squared	0.007	0.02	0.019	0.008	0.017	0.02	0.007	0.021	0.02
N	31452	31452	31452	13106	13106	13106	18346	18346	18346

Panel C OLS Regression Results LFirst20 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
Δ_5CHN$_{(t-1)}$	0.104	-0.001	0.095	0.251**	-0.091	0.179*	-0.011	0.066*	0.028
	(0.065)	(0.042)	(0.058)	(0.108)	(0.070)	(0.105)	(0.051)	(0.037)	(0.048)
Δ_5EJU$_{(t-1)}$	0.012	-0.059	-0.039	0.11	-0.159**	-0.038	-0.055	0.007	-0.042
	(0.046)	(0.040)	(0.052)	(0.077)	(0.066)	(0.095)	(0.043)	(0.030)	(0.043)
Δ_5LW$_{(t-1)}$	0.02	0	0.018	0.117	-0.052*	0.062	-0.039	0.029	-0.012
	(0.041)	(0.023)	(0.041)	(0.076)	(0.031)	(0.065)	(0.030)	(0.029)	(0.038)
R-squared	0.009	0.024	0.022	0.007	0.021	0.018	0.01	0.025	0.025
N	38062	38062	38062	15915	15915	15915	22147	22147	22147

Notes: Table reports results from OLS regression of five-year changes in log skill premium/average blue-collar wages/average white-collar wages on lag changes in China's, EJU's and LW's import share in India. Here skill premium is measured as ratio of average wages paid to non-production workers to average wages paid to production workers. Columns (1)-(3) include full sample, columns (4)-(6) include flexible and (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log of wage skill premium (SK), column (2), (5) and (8) use changes in log of average wages of blue-collar workers and (3), (6) and (9) use changes in log of average wages of white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

Table A.3–Effect of Import Competition on Wage Inequality with other LWs (2SLS)

Panel A IV Regression Results LFirst200 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
$\Delta_5CHN_{(t-1)}$	0.250**	0.016	0.236**	0.396***	-0.079	0.285**	0.094	0.125	0.196*
	(0.099)	(0.100)	(0.093)	(0.131)	(0.150)	(0.121)	(0.108)	(0.082)	(0.105)
$\Delta_5EJU_{(t-1)}$	0.021	-0.008	0.024	0.212***	-0.138**	0.081	-0.117**	0.087**	-0.015
	(0.057)	(0.044)	(0.061)	(0.082)	(0.069)	(0.083)	(0.053)	(0.037)	(0.060)
$\Delta_5LW_{(t-1)}$	0.095*	0.018	0.094***	0.205**	-0.047	0.141**	0.024	0.061*	0.064*
	(0.050)	(0.028)	(0.031)	(0.085)	(0.045)	(0.056)	(0.033)	(0.033)	(0.033)
Adj_R2	0.008	0.016	0.018	0.009	0.014	0.017	0.01	0.019	0.019
N	22596	22596	22596	9415	9415	9415	13181	13181	13181

Panel B IV Regression Results LFirst100 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
$\Delta_5CHN_{(t-1)}$	0.111	0.074	0.156	0.288	-0.043	0.209	-0.068	0.183**	0.095
	(0.13)	(0.102)	(0.108)	(0.19)	(0.139)	(0.164)	(0.096)	(0.088)	(0.097)
$\Delta_5EJU_{(t-1)}$	0.015	-0.022	-0.012	0.15	-0.139**	0.007	-0.088*	0.064	-0.029
	(0.065	(0.046	(0.061	(0.101	-0.065	(0.092	(0.049	(0.043	(0.054)
$\Delta_5LW_{(t-1)}$	0.082*	0.012	0.073*	0.194**	-0.048	0.124**	0.007	0.051*	0.036
	(0.048)	(0.031)	(0.037)	(0.084)	(0.039)	(0.06)	(0.029)	(0.031)	(0.035)
Adj_R2	0.008	0.02	0.019	0.009	0.017	0.02	0.008	0.02	0.02
N	31452	31452	31452	13106	13106	13106	18346	18346	18346

Panel C IV Regression Results LFirst20 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
$\Delta_5CHN_{(t-1)}$	-0.033	0.135	0.102	0.092	0.065	0.159	-0.145	0.192**	0.046
	(0.185)	(0.110)	(0.160)	(0.240)	(0.180)	(0.228)	(0.163)	(0.087)	(0.149)
$\Delta_5EJU_{(t-1)}$	-0.017	-0.025	-0.037	0.064	-0.122	-0.043	-0.077	0.041	-0.037
	(0.076)	(0.052)	(0.060)	(0.107)	(0.082)	(0.108)	(0.068)	(0.042)	(0.054)
$\Delta_5LW_{(t-1)}$	0.009	0.02	0.019	0.089	-0.027	0.058	-0.042	0.046	-0.009
	(0.047)	(0.027)	(0.044)	(0.082)	(0.043)	(0.073)	(0.038)	(0.029)	(0.041)
Adj_R2	0.009	0.023	0.022	0.006	0.02	0.018	0.011	0.023	0.025
N	38062	38062	38062	15915	15915	15915	22147	22147	22147

Notes: Table reports results from IV regression of five-year changes in log skill premium/average blue-collar wages/average white-collar wages on lag changes in China's, EJU's and LW's import share in India. In the first stage, $\Delta_5CHN_{(t-1)}$ is instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia $\Delta_5(CH)IDN_{(t-1)-1}$. Here skill premium is measured as ratio of average wages paid to non-production workers to average wages paid to production workers. Columns (1)-(3) include full sample and columns (4)-(6) include flexible and columns (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log of wage skill premium (SK), columns (2), (5) and (8) use changes in log of average wages of blue-collar workers and (3), (6) and (9) use changes in log of average wages of white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly: Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

Table A.4.a–Effect of Import Competition on Employment with other LWs (OLS)

Panel A OLS Regression Results LFirst200 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-0.802**	-0.801*	-0.363	-1.372**	-1.542***	-0.556	-0.244	-0.116	-0.284
	(0.389)	(0.433)	(0.471)	(0.524)	(0.584)	(0.672)	(0.483)	(0.597)	(0.462)
TFP$_{(t-5)}$	0.011	0.008	0.035***	0.007	0.004	0.042***	0.015*	0.012	0.031***
	(0.012)	(0.012)	(0.010)	(0.018)	(0.019)	(0.012)	(0.009)	(0.009)	(0.012)
Δ_5CHN$_{(t-1)}$ ×TFP$_{(t-5)}$	0.101**	0.099**	0.035	0.184***	0.204***	0.059	0.015	-0.003	0.025
	(0.043)	(0.047)	(0.051)	(0.061)	(0.068)	(0.071)	(0.055)	(0.070)	(0.055)
Δ_5EJU$_{(t-1)}$	-0.690**	-0.751**	-0.027	-1.327***	-1.357**	-0.127	-0.043	-0.095	-0.037
	(0.282)	(0.342)	(0.381)	(0.439)	(0.527)	(0.566)	(0.330)	(0.413)	(0.350)
Δ5EJU$_{(t-1)}$ ×TFP$_{(t-5)}$	0.077**	0.085**	-0.022	0.158***	0.166***	-0.021	-0.011	-0.007	-0.011
	(0.031)	(0.039)	(0.046)	(0.045)	(0.055)	(0.065)	(0.040)	(0.052)	(0.043)
Δ_5LW$_{(t-1)}$	0.223	0.268	0.502***	-0.175	-0.179	0.688**	0.562*	0.666**	0.318
	(0.169)	(0.203)	(0.186)	(0.247)	(0.308)	(0.337)	(0.285)	(0.309)	(0.210)
Δ_5LW$_{(t-1)}$ ×TFP$_{(t-5)}$	-0.023	-0.026	-0.067***	0.028	0.033	-0.089**	-0.070**	-0.082**	-0.043
	(0.020)	(0.024)	(0.022)	(0.028)	(0.035)	(0.036)	(0.035)	(0.038)	(0.027)
R-squared	0.033	0.029	0.029	0.038	0.034	0.032	0.033	0.027	0.029
N	22596	22596	22596	9415	9415	9415	13181	13181	13181

Panel B OLS Regression Results Lfirst100 Sample

	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-0.531	-0.492	-0.287	-0.583	-0.503	-0.472	-0.434	-0.439	-0.194
	(0.374)	(0.399)	(0.441)	(0.511)	(0.548)	(0.563)	(0.469)	(0.552)	(0.461)
TFP$_{(t-5)}$	0.01	0.007	0.036***	0.007	0.005	0.039***	0.014*	0.01	0.033***
	(0.011)	(0.011)	(0.010)	(0.017)	(0.018)	(0.011)	(0.008)	(0.008)	(0.011)
Δ_5CHN$_{(t-1)}$ ×TFP$_{(t-5)}$	0.075*	0.071	0.032	0.093	0.085	0.053	0.05	0.05	0.021
	(0.043)	(0.045)	(0.048)	(0.064)	(0.068)	(0.060)	(0.052)	(0.064)	(0.053)
Δ_5EJU$_{(t-1)}$	-0.814***	-0.861***	-0.348	-1.393***	-1.392***	-0.474	-0.323	-0.394	-0.294
	(0.236)	(0.276)	(0.355)	(0.340)	(0.394)	(0.497)	(0.308)	(0.379)	(0.335)
Δ_5EJU$_{(t-1)}$ ×TFP$_{(t-5)}$	0.095***	0.103***	0.021	0.164***	0.169***	0.024	0.031	0.039	0.022
	(0.027)	(0.032)	(0.042)	(0.038)	(0.043)	(0.058)	(0.039)	(0.049)	(0.040)
Δ_5LW$_{(t-1)}$	0.152	0.116	0.649***	-0.032	-0.08	0.828**	0.331	0.307	0.555**
	(0.201)	(0.221)	(0.224)	(0.287)	(0.315)	(0.346)	(0.272)	(0.288)	(0.232)
Δ_5LW$_{(t-1)}$ ×TFP$_{(t-5)}$	-0.014	-0.007	-0.087***	0.016	0.026	-0.102***	-0.043	-0.038	-0.079***
	(0.022)	(0.025)	(0.026)	(0.029)	(0.033)	(0.037)	(0.035)	(0.037)	(0.029)
R-squared	0.026	0.021	0.029	0.028	0.023	0.029	0.027	0.021	0.032
N	31452	31452	31452	13106	13106	13106	18346	18346	18346

Notes: Table reports results from OLS regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. Panel-A reports results for LFirst200 and panel-B reports LFirst100 sample. Columns (1)-(3) include full sample, and columns (4)-(6) include flexible, and (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly: Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

Table A.4.b–Effect of Import Competition on Employment with LWs (LFirst 20, OLS)

Panel C OLS Regression Results LFirst20 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-0.592	-0.592	-0.256	-0.987	-1.034	-0.449	-0.299	-0.275	-0.155
	(0.430)	(0.473)	(0.424)	(0.677)	(0.740)	(0.593)	(0.417)	(0.482)	(0.441)
TFP$_{(t-5)}$	0.011	0.007	0.032***	0.005	0.002	0.032***	0.015**	0.011	0.031***
	(0.009)	(0.009)	(0.008)	(0.014)	(0.015)	(0.010)	(0.007)	(0.008)	(0.009)
Δ_5CHN$_{(t-1)}$	0.087*	0.087	0.035	0.134	0.139	0.052	0.048	0.047	0.025
×TFP$_{(t-5)}$	(0.052)	(0.056)	(0.048)	(0.083)	(0.089)	(0.068)	(0.048)	(0.057)	(0.050)
Δ_5EJU$_{(t-1)}$	-0.710***	-0.808**	-0.153	-1.174***	-1.350***	-0.015	-0.328	-0.395	-0.202
	(0.267)	(0.317)	(0.330)	(0.403)	(0.483)	(0.497)	(0.286)	(0.336)	(0.297)
Δ5EJU$_{(t-1)}$	0.093***	0.108***	0.006	0.147***	0.167***	-0.008	0.045	0.059	0.01
×TFP$_{(t-5)}$	(0.029)	(0.035)	(0.040)	(0.046)	(0.054)	(0.059)	(0.034)	(0.041)	(0.036)
Δ_5LW$_{(t-1)}$	0.082	0.024	0.688***	-0.074	-0.183	0.964***	0.228	0.197	0.518**
	(0.183)	(0.198)	(0.232)	(0.268)	(0.305)	(0.367)	(0.235)	(0.254)	(0.220)
Δ_5LW$_{(t-1)}$	-0.003	0.008	-0.090***	0.022	0.038	-0.117***	-0.026	-0.018	-0.073**
×TFP$_{(t-5)}$	(0.022)	(0.024)	(0.029)	(0.027)	(0.031)	(0.042)	(0.031)	(0.034)	(0.029)
R-squared	0.023	0.019	0.024	0.023	0.019	0.02	0.025	0.021	0.028
N	38062	38062	38062	15915	15915	15915	22147	22147	22147

Notes: Table reports results from OLS regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants for LFirst20 sample only. Columns (1)-(3) include full sample, and columns (4)-(6) include flexible, and (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly: Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

Table A.5.a–Effect of Import Competition on Employment with other LWs (2SLS)

Panel A IV Regression Results LFirst200 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5CHN_{(t-1)}$	-2.580*	-2.668*	-1.386	-4.075**	-4.429**	-1.012	-1.469	-1.353	-1.783
	(1.360)	(1.381)	(1.177)	(2.066)	(2.067)	(1.550)	(1.064)	(1.152)	(1.139)
$TFP_{(t-5)}$	-0.004	-0.008	0.026**	-0.015	-0.02	0.038**	0.005	0.002	0.018
	(0.017)	(0.017)	(0.013)	(0.026)	(0.026)	(0.016)	(0.012)	(0.012)	(0.015)
$\Delta_5CHN_{(t-1)}$ $\times TFP_{(t-5)}$	0.335*	0.348*	0.178	0.536*	0.583**	0.125	0.172	0.156	0.231*
	(0.178)	(0.181)	(0.141)	(0.279)	(0.280)	(0.179)	(0.128)	(0.139)	(0.140)
$\Delta_5EJU_{(t-1)}$	-1.085***	-1.167***	-0.258	-1.842***	-1.907***	-0.213	-0.354	-0.41	-0.435
	(0.366)	(0.430)	(0.461)	(0.527)	(0.598)	(0.651)	(0.375)	(0.458)	(0.406)
$\Delta_5EJU_{(t-1)}$ $\times TFP_{(t-5)}$	0.129***	0.141***	0.011	0.224***	0.237***	-0.009	0.029	0.035	0.045
	(0.044)	(0.052)	(0.056)	(0.061)	(0.069)	(0.075)	(0.046)	(0.057)	(0.051)
$\Delta_5LW_{(t-1)}$	-0.146	-0.125	0.266	-0.750*	-0.801*	0.575	0.325	0.424	-0.013
	(0.239)	(0.262)	(0.236)	(0.409)	(0.438)	(0.429)	(0.260)	(0.282)	(0.261)
$\Delta_5LW_{(t-1)}$ $\times TFP_{(t-5)}$	0.026	0.027	-0.035	0.102**	0.113**	-0.074	-0.039	-0.049	0.002
	(0.032)	(0.034)	(0.029)	(0.051)	(0.054)	(0.048)	(0.034)	(0.036)	(0.035)
R-squared	0.029	0.024	0.028	0.028	0.025	0.031	0.031	0.025	0.026
N	22596	22596	22596	9415	9415	9415	13181	13181	13181

Panel B IV Regression Results LFirst100 Sample

	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5CHN_{(t-1)}$	-1.279	-1.346	-0.665	-1.993	-2.055	-0.576	-0.86	-0.946	-0.95
	(1.444)	(1.493)	(1.113)	(1.962)	(1.989)	(1.326)	(1.097)	(1.215)	(1.099)
$TFP_{(t-5)}$	0.004	0	0.031**	-0.005	-0.008	0.038**	0.01	0.005	0.026*
	(0.017)	(0.017)	(0.013)	(0.024)	(0.024)	(0.015)	(0.012)	(0.012)	(0.015)
$\Delta_5CHN_{(t-1)}$ $\times TFP_{(t-5)}$	0.174	0.184	0.096	0.265	0.276	0.079	0.111	0.122	0.135
	(0.200)	(0.207)	(0.132)	(0.274)	(0.278)	(0.154)	(0.139)	(0.155)	(0.129)
$\Delta_5EJU_{(t-1)}$	-0.991***	-1.063**	-0.445	-1.678***	-1.707***	-0.504	-0.44	-0.531	-0.505
	(0.373)	(0.417)	(0.409)	(0.472)	(0.515)	(0.549)	(0.376)	(0.456)	(0.372)
$\Delta_5EJU_{(t-1)}$ $\times TFP_{(t-5)}$	0.118**	0.129**	0.037	0.199***	0.207***	0.031	0.048	0.059	0.054
	(0.050)	(0.055)	(0.047)	(0.062)	(0.067)	(0.063)	(0.048)	(0.059)	(0.043)
$\Delta_5LW_{(t-1)}$	-0.014	-0.073	0.522*	-0.305	-0.386	0.769*	0.221	0.18	0.343
	(0.319)	(0.334)	(0.287)	(0.423)	(0.439)	(0.415)	(0.322)	(0.345)	(0.289)
$\Delta_5LW_{(t-1)}$ $\times TFP_{(t-5)}$	0.008	0.019	-0.068**	0.05	0.064	-0.093**	-0.028	-0.02	-0.049
	(0.042)	(0.044)	(0.035)	(0.053)	(0.054)	(0.047)	(0.043)	(0.046)	(0.037)
R-squared	0.025	0.02	0.029	0.026	0.021	0.029	0.026	0.021	0.031
N	31452	31452	31452	13106	13106	13106	18346	18346	18346

Notes: Table reports results from IV regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. In the first stage, $\Delta_5CHN_{(t-1)}$ and $\Delta_5CHN_{(t-1)} \times TFP_{(t-5)}$ are instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia $\Delta_5(CH)IDN_{(t-1)-1}$ and its interaction with lag TFP, $\Delta_5(CH)IDN_{(t-1)-1} \times TFP_{(t-5)}$. Panel-A reports results for LFirst200 and panel-B reports LFirst100 sample. Columns (1)-(3) include full sample, and columns (4)-(6) include flexible, and (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

Table A.5.b–Effect of Import Competition on Employment with other LWs (2SLS)

Panel C IV Regression Results LFirst20 Sample

	Full Sample			Flexible			Inflexible		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
Δ_5CHN$_{(t-1)}$	-0.83	-0.94	0.021	-1.848	-2.134	0.21	-0.243	-0.229	-0.298
	(1.442)	(1.506)	(1.091)	(2.003)	(2.096)	(1.368)	(1.105)	(1.224)	(1.048)
TFP$_{(t-5)}$	0.008	0.004	0.033***	-0.003	-0.007	0.037***	0.014	0.01	0.029**
	(0.016)	(0.016)	(0.012)	(0.022)	(0.023)	(0.014)	(0.011)	(0.011)	(0.013)
Δ_5CHN$_{(t-1)}$	0.131	0.147	0.018	0.253	0.292	-0.011	0.054	0.056	0.059
×TFP$_{(t-5)}$	(0.200)	(0.210)	(0.131)	(0.282)	(0.296)	(0.165)	(0.141)	(0.157)	(0.123)
Δ_5EJU$_{(t-1)}$	-0.782*	-0.908**	-0.11	-1.376***	-1.609***	0.114	-0.337	-0.409	-0.265
	(0.403)	(0.451)	(0.384)	(0.525)	(0.597)	(0.544)	(0.381)	(0.442)	(0.342)
Δ_5EJU$_{(t-1)}$	0.106**	0.125**	0.006	0.174**	0.202***	-0.019	0.05	0.065	0.023
×TFP$_{(t-5)}$	(0.052)	(0.057)	(0.045)	(0.068)	(0.076)	(0.063)	(0.048)	(0.056)	(0.041)
Δ_5LW$_{(t-1)}$	-0.01	-0.097	0.690**	-0.289	-0.459	1.049**	0.2	0.16	0.438
	(0.314)	(0.332)	(0.289)	(0.448)	(0.484)	(0.418)	(0.300)	(0.326)	(0.286)
Δ_5LW$_{(t-1)}$	0.011	0.026	-0.088**	0.051	0.075	-0.125***	-0.021	-0.012	-0.06
×TFP$_{(t-5)}$	(0.042)	(0.045)	(0.036)	(0.056)	(0.061)	(0.048)	(0.042)	(0.046)	(0.038)
R-squared	0.023	0.019	0.023	0.022	0.017	0.019	0.025	0.02	0.028
N	38062	38062	38062	15915	15915	15915	22147	22147	22147

Notes: Table reports results from IV regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. In the first stage, Δ_5CHN$_{(t-1)}$ and Δ_5CHN$_{(t-1)}$ ×TFP$_{(t-5)}$ are instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia Δ_5(CH)IDN$_{(t-1)-1}$ and its interaction with lag TFP, Δ_5(CH)IDN$_{(t-1)-1}$×TFP$_{(t-5)}$. Table reports results for LFirst200 and panel-B reports LFirst100 sample. Columns (1)-(3) include full sample, and columns (4)-(6) include flexible, and (7)-(9) include inflexible labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. Flexible or employer friendly states refer to Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu; inflexible labor market includes both worker friendly Orissa, Gujarat, Maharashtra and West Bengal, and neutral states: Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh . * p<.1; ** p<.05; *** p<.01

Table A.6–Summary Statistics for Initial TFP

	Lfirst200			Lfirst100			Lfirst20		
	Full Sample	Flexible	Inflexible	Full Sample	Flexible	Inflexible	Full Sample	Flexible	Inflexible
N:	22596	9415	13181	31452	13106	18346	38062	15915	22147
Mean:	7.73	7.94	7.59	7.69	7.85	7.57	7.62	7.76	7.53
p5:	4.84	5	4.75	4.89	5.01	4.82	4.84	4.89	4.82
p25:	6.86	6.99	6.75	6.81	6.92	6.73	6.71	6.79	6.64
p75:	8.45	8.66	8.33	8.42	8.57	8.31	8.39	8.52	8.3
p95:	11.23	11.54	10.88	11.03	11.37	10.68	10.91	11.24	10.59
SD:	1.74	1.81	1.68	1.69	1.75	1.64	1.69	1.76	1.63
Skewness:	0.32	0.31	0.29	0.32	0.33	0.28	0.3	0.31	0.27
Kurtosis:	4.02	3.77	4.22	4.13	3.93	4.26	4.05	3.87	4.16

Table A.7–Effect of Import Competition on Wage Inequality (BB, OLS)

Panel A OLS Regression Results LFirst200 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	0.265**	-0.105	0.183**	-0.111*	0.156***	0.034	0.111	-0.022	0.039
	(0.113)	(0.074)	(0.082)	(0.057)	(0.051)	(0.067)	(0.094)	(0.047)	(0.077)
Δ_5EJU$_{(t-1)}$	0.125	-0.126**	0.015	-0.151**	0.02	-0.121**	-0.140**	0.099**	-0.022
	(0.084)	(0.054)	(0.079)	(0.061)	(0.049)	(0.058)	(0.066)	(0.045)	(0.077)
R-squared	0.007	0.014	0.017	0.006	0.026	0.022	0.011	0.016	0.017
N	9415	9415	9415	5310	5310	5310	7871	7871	7871

Panel B OLS Regression Results LFirst100 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
Δ_5CHN$_{(t-1)}$	0.261**	-0.046	0.231**	-0.159**	0.190***	0.026	0.088	-0.021	0.018
	(0.130)	(0.073)	(0.096)	(0.064)	(0.052)	(0.084)	(0.070)	(0.048)	(0.074)
Δ_5EJU$_{(t-1)}$	0.079	-0.123**	-0.031	-0.085	0.01	-0.074	-0.104	0.058	-0.041
	(0.086)	(0.052)	(0.078)	(0.054)	(0.050)	(0.068)	(0.064)	(0.043)	(0.071)
R-squared	0.007	0.017	0.019	0.006	0.027	0.026	0.008	0.02	0.016
N	13106	13106	13106	7888	7888	7888	10458	10458	10458

Panel C OLS Regression Results LFirst20 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
Δ_5CHN$_{(t-1)}$	0.226**	-0.079	0.165	-0.106*	0.158***	0.038	0.107	-0.05	0.018
	(0.110)	(0.071)	(0.103)	(0.061)	(0.059)	(0.083)	(0.076)	(0.052)	(0.073)
Δ_5EJU$_{(t-1)}$	0.069	-0.140**	-0.06	-0.059	-0.007	-0.063	-0.034	0.012	-0.013
	(0.074)	(0.059)	(0.086)	(0.055)	(0.038)	(0.064)	(0.063)	(0.048)	(0.067)
R-squared	0.007	0.021	0.018	0.008	0.033	0.029	0.012	0.021	0.021
N	15915	15915	15915	9917	9917	9917	12230	12230	12230

Notes: Table reports results from OLS regression of five-year changes in log skill premium/average blue-collar wages/average white-collar wages on lag changes in China's and EJU's import share in India. Here skill premium is measured as ratio of average wages paid to non-production workers to average wages paid to production workers. Columns (1)-(3) include flexible or pro-employer and columns (4)-(6) include neutral and (7)-(9) include pro-worker labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log of wage skill premium (SK), columns (2), (5) and (8) use changes in log of average wages of blue-collar workers and (3), (6) and (9) use changes in log of average wages of white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In this table Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu are pro-employer; Orissa, Gujarat, Maharashtra and West Bengal are pro-worker; and Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh are neutral states. * p<.1; ** p<.05; *** p<.01

Table A.8–Effect of Import Competition on Wage Inequality with other LWs (BB, OLS)

Panel A OLS Regression Results LFirst200 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	0.310***	-0.118	0.215***	-0.129**	0.176***	0.036	0.118	-0.014	0.054
	(0.101)	(0.072)	(0.073)	(0.055)	(0.050)	(0.069)	(0.097)	(0.045)	(0.085)
Δ_5EJU$_{(t-1)}$	0.196**	-0.147**	0.065	-0.176***	0.049	-0.118*	-0.127*	0.111**	0.002
	(0.078)	(0.059)	(0.078)	(0.059)	(0.048)	(0.064)	(0.070)	(0.052)	(0.085)
Δ_5LW$_{(t-1)}$	0.183**	-0.053	0.130***	-0.066	0.073**	0.008	0.043	0.041	0.082
	(0.075)	(0.042)	(0.046)	(0.050)	(0.033)	(0.045)	(0.037)	(0.050)	(0.067)
R-squared	0.008	0.014	0.018	0.006	0.026	0.022	0.011	0.016	0.017
N	9415	9415	9415	5310	5310	5310	7871	7871	7871

Panel B OLS Regression Results LFirst100 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
Δ_5CHN$_{(t-1)}$	0.302**	-0.057	0.260***	-0.173**	0.211***	0.031	0.094	-0.019	0.025
	(0.123)	(0.073)	(0.093)	(0.066)	(0.051)	(0.088)	(0.072)	(0.046)	(0.079)
Δ_5EJU$_{(t-1)}$	0.149*	-0.142**	0.019	-0.103*	0.038	-0.067	-0.093	0.061	-0.029
	(0.087)	(0.058)	(0.083)	(0.056)	(0.052)	(0.077)	(0.067)	(0.052)	(0.080)
Δ_5LW$_{(t-1)}$	0.185**	-0.051	0.133**	-0.048	0.075**	0.017	0.031	0.008	0.037
	(0.080)	(0.037)	(0.055)	(0.037)	(0.033)	(0.051)	(0.039)	(0.059)	(0.072)
R-squared	0.008	0.017	0.02	0.006	0.028	0.026	0.008	0.02	0.016
N	13106	13106	13106	7888	7888	7888	10458	10458	10458

Panel C OLS Regression Results LFirst20 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
Δ_5CHN$_{(t-1)}$	0.251**	-0.091	0.179*	-0.118*	0.169***	0.036	0.101	-0.047	0.014
	(0.108)	(0.070)	(0.105)	(0.064)	(0.058)	(0.084)	(0.076)	(0.051)	(0.076)
Δ_5EJU$_{(t-1)}$	0.11	-0.159**	-0.038	-0.075	0.007	-0.065	-0.045	0.017	-0.018
	(0.077)	(0.066)	(0.095)	(0.061)	(0.040)	(0.075)	(0.063)	(0.056)	(0.074)
Δ_5LW$_{(t-1)}$	0.117	-0.052*	0.062	-0.048	0.045	-0.008	-0.034	0.016	-0.017
	(0.076)	(0.031)	(0.065)	(0.043)	(0.039)	(0.061)	(0.045)	(0.056)	(0.077)
R-squared	0.007	0.021	0.018	0.008	0.033	0.029	0.012	0.021	0.021
N	15915	15915	15915	9917	9917	9917	12230	12230	12230

Notes: Table reports results from OLS regression of five-year changes in log skill premium/average blue-collar wages/average white-collar wages on lag changes in China's, EJU's and LW's import share in India. Here skill premium is measured as ratio of average wages paid to non-production workers to average wages paid to production workers. Columns (1)-(3) include flexible or pro-employer and columns (4)-(6) include neutral and (7)-(9) include pro-worker labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log of wage skill premium (SK), columns (2), (5) and (8) use changes in log of average wages of blue-collar workers and (3), (6) and (9) use changes in log of average wages of white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In this table Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu are pro-employer; Orissa, Gujarat, Maharashtra and West Bengal are pro-worker; and Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh are neutral states. * p<.1; ** p<.05; *** p<.01

Table A.9–Effect of Import Competition on Wage Inequality (BB, 2SLS)

Panel A IV Regression Results LFirst200 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5CHN_{(t-1)}$	0.362**	-0.071	0.262**	-0.091	0.361***	0.336***	0.225	-0.068	0.075
	(0.157)	(0.152)	(0.120)	(0.147)	(0.095)	(0.125)	(0.167)	(0.086)	(0.143)
$\Delta_5EJU_{(t-1)}$	0.136	-0.120*	0.029	-0.148*	0.077	-0.037	-0.127	0.090*	-0.016
	(0.092)	(0.062)	(0.081)	(0.079)	(0.060)	(0.072)	(0.079)	(0.047)	(0.085)
R-squared	0.007	0.014	0.017	0.01	0.021	0.018	0.011	0.016	0.017
N	9415	9415	9415	5310	5310	5310	7871	7871	7871

Panel B IV Regression Results LFirst100 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
$\Delta_5CHN_{(t-1)}$	0.259	-0.036	0.19	-0.17	0.373***	0.235	0.027	-0.019	-0.054
	(0.208)	(0.140)	(0.167)	(0.110)	(0.085)	(0.157)	(0.132)	(0.097)	(0.113)
$\Delta_5EJU_{(t-1)}$	0.079	-0.121**	-0.038	-0.079	0.065	-0.011	-0.118*	0.058	-0.054
	(0.100)	(0.058)	(0.084)	(0.066)	(0.061)	(0.086)	(0.065)	(0.046)	(0.075)
R-squared	0.007	0.017	0.019	0.009	0.024	0.024	0.009	0.02	0.015
N	13106	13106	13106	7888	7888	7888	10458	10458	10458

Panel C IV Regression Results LFirst20 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
$\Delta_5CHN_{(t-1)}$	0.079	0.069	0.15	-0.163	0.378***	0.221	-0.109	-0.035	-0.146
	(0.244)	(0.177)	(0.225)	(0.213)	(0.099)	(0.229)	(0.163)	(0.113)	(0.128)
$\Delta_5EJU_{(t-1)}$	0.033	-0.112	-0.063	-0.064	0.054	-0.012	-0.065	0.015	-0.042
	(0.098)	(0.070)	(0.095)	(0.085)	(0.053)	(0.085)	(0.071)	(0.053)	(0.071)
R-squared	0.006	0.019	0.018	0.01	0.028	0.028	0.012	0.021	0.02
N	15915	15915	15915	9917	9917	9917	12230	12230	12230

Notes: Table reports results from IV regression of five-year changes in log skill premium/average blue-collar wages/average white-collar wages on lag changes in China's and EJU's import share in India. In the first stage, $\Delta_5CHN_{(t-1)}$ is instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia $\Delta_5(CH)IDN_{(t-1)-1}$. Here skill premium is measured as ratio of average wages paid to non-production workers to average wages paid to production workers. Columns (1)-(3) include flexible or pro-employer and columns (4)-(6) include neutral and (7)-(9) include pro-worker labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log of wage skill premium (SK), columns (2), (5) and (8) use changes in log of average wages of blue-collar workers and (3), (6) and (9) use changes in log of average wages of white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In this table, Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu are pro-employer; Orissa, Gujarat, Maharashtra and West Bengal are pro-worker and Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh are neutral states. * p<.1; ** p<.05; *** p<.01

Table A.10–Effect of Import Competition on Wage Inequality with other LWs (BB, 2SLS)

Panel A IV Regression Results LFirst200 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5CHN_{(t-1)}$	0.396***	-0.079	0.285**	-0.1	0.383***	0.347***	0.234	-0.063	0.086
	(0.131)	(0.150)	(0.121)	(0.150)	(0.097)	(0.125)	(0.173)	(0.087)	(0.149)
$\Delta_5EJU_{(t-1)}$	0.212***	-0.138**	0.081	-0.163**	0.115*	-0.019	-0.105	0.101*	0.009
	(0.082)	(0.069)	(0.083)	(0.078)	(0.063)	(0.077)	(0.085)	(0.055)	(0.094)
$\Delta_5LW_{(t-1)}$	0.205**	-0.047	0.141**	-0.04	0.101***	0.049	0.075*	0.036	0.085
	(0.085)	(0.045)	(0.056)	(0.059)	(0.033)	(0.050)	(0.040)	(0.052)	(0.067)
R-squared	0.009	0.014	0.017	0.01	0.022	0.018	0.011	0.016	0.017
N	9415	9415	9415	5310	5310	5310	7871	7871	7871

Panel B IV Regression Results LFirst100 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
$\Delta_5CHN_{(t-1)}$	0.288	-0.043	0.209	-0.177	0.396***	0.247	0.031	-0.018	-0.05
	(0.190)	(0.139)	(0.164)	(0.114)	(0.087)	(0.159)	(0.132)	(0.097)	(0.117)
$\Delta_5EJU_{(t-1)}$	0.15	-0.139**	0.007	-0.09	0.102	0.008	-0.106	0.061	-0.045
	(0.101)	(0.065)	(0.092)	(0.069)	(0.066)	(0.096)	(0.068)	(0.054)	(0.085)
$\Delta_5LW_{(t-1)}$	0.194**	-0.048	0.124**	-0.031	0.104***	0.05	0.039	0.008	0.028
	(0.084)	(0.039)	(0.060)	(0.042)	(0.039)	(0.057)	(0.040)	(0.057)	(0.075)
R-squared	0.009	0.017	0.02	0.009	0.025	0.024	0.009	0.02	0.015
N	13106	13106	13106	7888	7888	7888	10458	10458	10458

Panel B IV Regression Results LFirst20 Sample

	Pro-Employer			Neutral			Pro-worker		
	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw	$\Delta_5$lnSK	$\Delta_5$lnWb	$\Delta_5$lnWw
$\Delta_5CHN_{(t-1)}$	0.092	0.065	0.159	-0.169	0.391***	0.224	-0.115	-0.033	-0.15
	(0.240)	(0.180)	(0.228)	(0.219)	(0.096)	(0.233)	(0.169)	(0.114)	(0.133)
$\Delta_5EJU_{(t-1)}$	0.064	-0.122	-0.043	-0.074	0.077	-0.006	-0.08	0.02	-0.053
	(0.107)	(0.082)	(0.108)	(0.095)	(0.056)	(0.097)	(0.075)	(0.061)	(0.081)
$\Delta_5LW_{(t-1)}$	0.089	-0.027	0.058	-0.034	0.077*	0.02	-0.053	0.017	-0.038
	(0.082)	(0.043)	(0.073)	(0.056)	(0.043)	(0.068)	(0.057)	(0.054)	(0.087)
R-squared	0.006	0.02	0.018	0.01	0.029	0.028	0.011	0.021	0.02
N	15915	15915	15915	9917	9917	9917	12230	12230	12230

Notes: Table reports results from IV regression of five-year changes in log skill premium/average blue-collar wages/average white-collar wages on lag changes in China's and EJU's import share in India. In the first stage, $\Delta_5CHN_{(t-1)}$ is instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia $\Delta_5(CH)IDN_{(t-1)-1}$. Here skill premium is measured as ratio of average wages paid to non-production workers to average wages paid to production workers. Columns (1)-(3) include flexible or pro-employer and columns (4)-(6) include neutral and (7)-(9) include pro-worker labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log of wage skill premium (SK), columns (2), (5) and (8) use changes in log of average wages of blue-collar workers and (3), (6) and (9) use changes in log of average wages of white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In this table, Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu are pro-employer; Orissa, Gujarat, Maharashtra and West Bengal are pro-worker and Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh are neutral states. * p<.1; ** p<.05; *** p<.01

Table A.11–Effect of Import Competition on Employment (BB, OLS)

Panel A OLS Regression Results LFirst200 Sample

	Pro-employer			Neutral			Pro-worker		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-1.297**	-1.451**	-0.776	-0.894	-0.895	-0.673	0.042	0.219	-0.169
	(0.524)	(0.585)	(0.661)	(0.887)	(1.028)	(0.852)	(0.533)	(0.631)	(0.541)
TFP$_{(t-5)}$	0.008	0.005	0.040***	0.033**	0.031**	0.049***	0.005	0.001	0.02
	(0.018)	(0.019)	(0.012)	(0.014)	(0.015)	(0.015)	(0.010)	(0.010)	(0.013)
Δ_5CHN$_{(t-1)}$ ×TFP$_{(t-5)}$	0.173***	0.190***	0.09	0.073	0.068	0.066	-0.001	-0.023	0.019
	(0.062)	(0.070)	(0.071)	(0.107)	(0.124)	(0.105)	(0.056)	(0.069)	(0.062)
Δ_5EJU$_{(t-1)}$	-1.264***	-1.289**	-0.355	-0.568	-0.737	-0.523	0.074	0.068	0.187
	(0.421)	(0.503)	(0.587)	(0.476)	(0.561)	(0.382)	(0.412)	(0.493)	(0.499)
Δ_5EJU$_{(t-1)}$ ×TFP$_{(t-5)}$	0.148***	0.153***	0.009	0.067	0.088	0.055	-0.039	-0.042	-0.041
	(0.045)	(0.054)	(0.069)	(0.058)	(0.069)	(0.047)	(0.048)	(0.061)	(0.058)
R-squared	0.038	0.034	0.031	0.026	0.02	0.03	0.043	0.036	0.031
N	9415	9415	9415	5310	5310	5310	7871	7871	7871

Panel B OLS Regression Results Lfirst100 Sample

	Pro-employer			Neutral			Pro-worker		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-0.533	-0.426	-0.699	-1.154	-1.216	-0.991	-0.09	-0.024	-0.007
	(0.516)	(0.553)	(0.548)	(0.771)	(0.872)	(0.719)	(0.493)	(0.565)	(0.540)
TFP$_{(t-5)}$	0.007	0.006	0.037***	0.024*	0.02	0.042***	0.008	0.004	0.026**
	(0.017)	(0.018)	(0.011)	(0.012)	(0.014)	(0.015)	(0.009)	(0.009)	(0.012)
Δ_5CHN$_{(t-1)}$ ×TFP$_{(t-5)}$	0.084	0.071	0.084	0.13	0.135	0.123	0.02	0.012	0.005
	(0.065)	(0.069)	(0.059)	(0.093)	(0.105)	(0.088)	(0.053)	(0.063)	(0.062)
Δ_5EJU$_{(t-1)}$	-1.372***	-1.351***	-0.757	-0.882**	-1.008**	-0.984***	-0.132	-0.142	-0.066
	(0.346)	(0.400)	(0.512)	(0.399)	(0.470)	(0.336)	(0.390)	(0.449)	(0.481)
Δ_5EJU$_{(t-1)}$ ×TFP$_{(t-5)}$	0.157***	0.158***	0.06	0.114**	0.130**	0.116***	-0.003	-0.003	-0.002
	(0.039)	(0.045)	(0.061)	(0.050)	(0.059)	(0.041)	(0.047)	(0.056)	(0.057)
R-squared	0.028	0.022	0.028	0.018	0.015	0.028	0.036	0.028	0.035
N	13106	13106	13106	7888	7888	7888	10458	10458	10458

Notes: Table reports results from OLS regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. Panel-A reports results for LFirst200 and panel-B reports LFirst100 sample. Columns (1)-(3) include flexible or pro-employer and columns (4)-(6) include neutral and (7)-(9) include pro-worker labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In this table, Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu are pro-employer; Orissa, Gujarat, Maharashtra and West Bengal are pro-worker and Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh are defined as neutral states. * p<.1; ** p<.05; *** p<.01

Table A.12–Effect of Import Competition on Employment with LWs (BB, OLS)

Panel A OLS Regression Results LFirst200 Sample

	Pro-employer			Neutral			Pro-worker		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5 CHN_{(t-1)}$	-1.372**	-1.542***	-0.556	-0.797	-0.818	-0.605	0.198	0.423	-0.079
	(0.524)	(0.584)	(0.672)	(0.915)	(1.064)	(0.871)	(0.551)	(0.666)	(0.547)
$TFP_{(t-5)}$	0.007	0.004	0.042***	0.034**	0.032**	0.049***	0.007	0.003	0.021*
	(0.018)	(0.019)	(0.012)	(0.014)	(0.015)	(0.015)	(0.010)	(0.010)	(0.013)
$\Delta_5 CHN_{(t-1)}$	0.184***	0.204***	0.059	0.058	0.056	0.055	-0.02	-0.049	0.007
$\times TFP_{(t-5)}$	(0.061)	(0.068)	(0.071)	(0.110)	(0.129)	(0.107)	(0.059)	(0.074)	(0.064)
$\Delta_5 EJU_{(t-1)}$	-1.327***	-1.357**	-0.127	-0.48	-0.672	-0.468	0.204	0.242	0.259
	(0.439)	(0.527)	(0.566)	(0.511)	(0.608)	(0.397)	(0.414)	(0.493)	(0.510)
$\Delta_5 EJU_{(t-1)}$	0.158***	0.166***	-0.021	0.054	0.076	0.045	-0.054	-0.061	-0.05
$\times TFP_{(t-5)}$	(0.045)	(0.055)	(0.065)	(0.062)	(0.074)	(0.049)	(0.048)	(0.060)	(0.060)
$\Delta_5 LW_{(t-1)}$	-0.175	-0.179	0.688**	0.358	0.26	0.213	0.740**	1.006***	0.4
	(0.247)	(0.308)	(0.337)	(0.367)	(0.398)	(0.341)	(0.304)	(0.334)	(0.262)
$\Delta_5 LW_{(t-1)}$	0.028	0.033	-0.089**	-0.052	-0.04	-0.036	-0.087**	-0.115***	-0.048
$\times TFP_{(t-5)}$	(0.028)	(0.035)	(0.036)	(0.045)	(0.048)	(0.044)	(0.037)	(0.041)	(0.034)
R-squared	0.038	0.034	0.032	0.026	0.02	0.03	0.044	0.038	0.031
N	9415	9415	9415	5310	5310	5310	7871	7871	7871

Panel B OLS Regression Results Lfirst100 Sample

	Pro-employer			Neutral			Pro-worker		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5 CHN_{(t-1)}$	-0.583	-0.503	-0.472	-1.103	-1.202	-0.832	0.014	0.08	0.156
	(0.511)	(0.548)	(0.563)	(0.801)	(0.907)	(0.745)	(0.515)	(0.601)	(0.549)
$TFP_{(t-5)}$	0.007	0.005	0.039***	0.024*	0.02	0.043***	0.009	0.005	0.028**
	(0.017)	(0.018)	(0.011)	(0.012)	(0.014)	(0.014)	(0.009)	(0.009)	(0.011)
$\Delta_5 CHN_{(t-1)}$	0.093	0.085	0.053	0.123	0.133	0.098	0.006	-0.001	-0.018
$\times TFP_{(t-5)}$	(0.064)	(0.068)	(0.060)	(0.097)	(0.110)	(0.091)	(0.056)	(0.068)	(0.063)
$\Delta_5 EJU_{(t-1)}$	-1.393***	-1.392***	-0.474	-0.837*	-0.996*	-0.847**	-0.045	-0.049	0.065
	(0.340)	(0.394)	(0.497)	(0.433)	(0.507)	(0.353)	(0.388)	(0.457)	(0.484)
$\Delta_5 EJU_{(t-1)}$	0.164***	0.169***	0.024	0.107*	0.128**	0.093**	-0.014	-0.015	-0.021
$\times TFP_{(t-5)}$	(0.038)	(0.043)	(0.058)	(0.054)	(0.064)	(0.042)	(0.046)	(0.057)	(0.057)
$\Delta_5 LW_{(t-1)}$	-0.032	-0.08	0.828**	0.146	0.041	0.395	0.431	0.468	0.630**
	(0.287)	(0.315)	(0.346)	(0.354)	(0.401)	(0.291)	(0.337)	(0.392)	(0.298)
$\Delta_5 LW_{(t-1)}$	0.016	0.026	-0.102***	-0.021	-0.005	-0.063*	-0.055	-0.057	-0.084**
$\times TFP_{(t-5)}$	(0.029)	(0.033)	(0.037)	(0.043)	(0.048)	(0.038)	(0.042)	(0.048)	(0.038)
R-squared	0.028	0.023	0.029	0.018	0.015	0.029	0.036	0.028	0.036
N	13106	13106	13106	7888	7888	7888	10458	10458	10458

Notes: Table reports results from OLS regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. Panel-A reports results for LFirst200 and panel-B reports LFirst100 sample. Columns (1)-(3) include flexible or pro-employer and columns (4)-(6) include neutral and (7)-(9) include pro-worker labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and columns (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural/urban dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In this table, Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu are pro-employer; Orissa, Gujarat, Maharashtra and West Bengal are pro-worker and Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh are defined as neutral states. * p<.1; ** p<.05; *** p<.01

Table A.13–Effect of Import Competition on Employment (IV, BB)

Panel A IV Regression Results LFirst200 Sample

	Pro-employer			Neutral			Pro-worker		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-3.607**	-3.883**	-1.329	-3.125	-3.623	-2.038	-0.628	-0.196	-1.506*
	(1.833)	(1.839)	(1.519)	(2.314)	(2.532)	(2.304)	(0.738)	(0.766)	(0.861)
TFP$_{(t-5)}$	-0.011	-0.015	0.035**	0.017	0.011	0.038**	-0.002	-0.004	0.007
	(0.024)	(0.025)	(0.016)	(0.016)	(0.018)	(0.018)	(0.012)	(0.012)	(0.015)
Δ_5CHN$_{(t-1)}$ ×TFP$_{(t-5)}$	0.471*	0.507**	0.169	0.342	0.399	0.235	0.102	0.051	0.220**
	(0.244)	(0.246)	(0.176)	(0.275)	(0.302)	(0.280)	(0.092)	(0.094)	(0.108)
Δ_5EJU$_{(t-1)}$	-1.563***	-1.601***	-0.42	-1.081	-1.367	-0.843	-0.082	-0.038	-0.122
	(0.474)	(0.548)	(0.638)	(0.744)	(0.850)	(0.670)	(0.421)	(0.493)	(0.516)
Δ_5EJU$_{(t-1)}$ ×TFP$_{(t-5)}$	0.185***	0.193***	0.019	0.129	0.164	0.095	-0.016	-0.024	0.005
	(0.054)	(0.062)	(0.075)	(0.091)	(0.104)	(0.082)	(0.049)	(0.060)	(0.061)
R-squared	0.03	0.027	0.03	0.018	0.012	0.028	0.041	0.035	0.026
N	9415	9415	9415	5310	5310	5310	7871	7871	7871

Panel B OLS Regression Results Lfirst100 Sample

	Pro-employer			Neutral			Pro-worker		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ_5CHN$_{(t-1)}$	-1.727	-1.707	-0.89	-2.473	-2.999	-1.446	-0.086	0.174	-1.014
	(1.750)	(1.767)	(1.294)	(2.110)	(2.399)	(1.931)	(0.775)	(0.822)	(0.900)
TFP$_{(t-5)}$	-0.003	-0.005	0.035**	0.012	0.005	0.035**	0.008	0.006	0.017
	(0.022)	(0.023)	(0.015)	(0.015)	(0.018)	(0.018)	(0.013)	(0.012)	(0.015)
Δ_5CHN$_{(t-1)}$ ×TFP$_{(t-5)}$	0.228	0.228	0.123	0.319	0.381	0.213	0.017	-0.013	0.14
	(0.242)	(0.245)	(0.152)	(0.255)	(0.293)	(0.223)	(0.100)	(0.104)	(0.107)
Δ_5EJU$_{(t-1)}$	-1.544***	-1.535***	-0.78	-1.210*	-1.446*	-1.108**	-0.13	-0.102	-0.277
	(0.401)	(0.452)	(0.540)	(0.658)	(0.771)	(0.541)	(0.356)	(0.401)	(0.463)
Δ_5EJU$_{(t-1)}$ ×TFP$_{(t-5)}$	0.177***	0.179***	0.066	0.162**	0.191**	0.141**	-0.003	-0.009	0.026
	(0.050)	(0.056)	(0.063)	(0.082)	(0.096)	(0.064)	(0.041)	(0.047)	(0.054)
R-squared	0.026	0.021	0.028	0.015	0.011	0.026	0.036	0.028	0.034
N	13106	13106	13106	7888	7888	7888	10458	10458	10458

Notes: Table reports results from IV regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. In the first stage, Δ_5CHN$_{(t-1)}$ and Δ_5CHN$_{(t-1)}$×TFP$_{(t-5)}$ are instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia Δ_5(CH)IDN$_{(t-1)-1}$ and Δ_5(CH)IDN$_{(t-1)-1}$×TFP$_{(t-5)}$. Panel-A reports results for LFirst200 and panel-B reports LFirst100 sample. Columns (1)-(3) include pro-employer, columns (4)-(6) include neutral, and columns (7)-(9) include pro-worker labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In this table, Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu are pro-employer; Orissa, Gujarat, Maharashtra and West Bengal are pro-worker and Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh are neutral states. * p<.1; ** p<.05; *** p<.01

Table A.14–Effect of Import Competition on Employment with LW (IV, BB)

Panel A IV Regression Results LFirst200 Sample

	Pro-employer			Neutral			Pro-worker		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta_5CHN_{(t-1)}$	-4.075**	-4.429**	-1.012	-3.078	-3.632	-1.99	-0.482	0.044	-1.603*
	(2.066)	(2.067)	(1.550)	(2.400)	(2.633)	(2.411)	(0.784)	(0.805)	(0.942)
$TFP_{(t-5)}$	-0.015	-0.02	0.038**	0.018	0.011	0.039**	0	-0.001	0.007
	(0.026)	(0.026)	(0.016)	(0.017)	(0.019)	(0.019)	(0.013)	(0.013)	(0.015)
$\Delta_5CHN_{(t-1)}$	0.536*	0.583**	0.125	0.334	0.398	0.226	0.081	0.018	0.234*
$\times TFP_{(t-5)}$	(0.279)	(0.280)	(0.179)	(0.287)	(0.316)	(0.295)	(0.100)	(0.100)	(0.123)
$\Delta_5EJU_{(t-1)}$	-1.842***	-1.907***	-0.213	-1.065	-1.395	-0.83	0.02	0.125	-0.152
	(0.527)	(0.598)	(0.651)	(0.824)	(0.944)	(0.753)	(0.426)	(0.484)	(0.542)
$\Delta_5EJU_{(t-1)}$	0.224***	0.237***	-0.009	0.124	0.164	0.09	-0.027	-0.042	0.011
$\times TFP_{(t-5)}$	(0.061)	(0.069)	(0.075)	(0.100)	(0.115)	(0.093)	(0.050)	(0.058)	(0.066)
$\Delta_5LW_{(t-1)}$	-0.750*	-0.801*	0.575	0.028	-0.15	0.004	0.544*	0.860**	-0.035
	(0.409)	(0.438)	(0.429)	(0.401)	(0.426)	(0.487)	(0.320)	(0.336)	(0.280)
$\Delta_5LW_{(t-1)}$	0.102**	0.113**	-0.074	-0.011	0.011	-0.009	-0.059	-0.094**	0.013
$\times TFP_{(t-5)}$	(0.051)	(0.054)	(0.048)	(0.051)	(0.054)	(0.062)	(0.042)	(0.043)	(0.039)
R-squared	0.028	0.025	0.031	0.018	0.011	0.028	0.042	0.037	0.025
N	9415	9415	9415	5310	5310	5310	7871	7871	7871

Panel B IV Regression Results Lfirst100 Sample

	Pro-employer			Neutral			Pro-worker		
	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh	$\Delta_5$lnL	$\Delta_5$lnLbl	$\Delta_5$lnLwh
$\Delta_5CHN_{(t-1)}$	-1.993	-2.055	-0.576	-2.582	-3.215	-1.309	0.118	0.386	-0.83
	(1.962)	(1.989)	(1.326)	(2.294)	(2.625)	(2.070)	(0.836)	(0.895)	(0.948)
$TFP_{(t-5)}$	-0.005	-0.008	0.038**	0.011	0.003	0.036**	0.01	0.008	0.019
	(0.024)	(0.024)	(0.015)	(0.017)	(0.020)	(0.018)	(0.013)	(0.013)	(0.015)
$\Delta_5CHN_{(t-1)}$	0.265	0.276	0.079	0.334	0.411	0.193	-0.011	-0.043	0.114
$\times TFP_{(t-5)}$	(0.274)	(0.278)	(0.154)	(0.281)	(0.326)	(0.242)	(0.110)	(0.115)	(0.114)
$\Delta_5EJU_{(t-1)}$	-1.678***	-1.707***	-0.504	-1.283*	-1.591*	-1.022	-0.015	0.026	-0.178
	(0.472)	(0.515)	(0.549)	(0.776)	(0.909)	(0.637)	(0.354)	(0.397)	(0.469)
$\Delta_5EJU_{(t-1)}$	0.199***	0.207***	0.031	0.172*	0.212*	0.127*	-0.019	-0.025	0.012
$\times TFP_{(t-5)}$	(0.062)	(0.067)	(0.063)	(0.098)	(0.115)	(0.076)	(0.041)	(0.047)	(0.054)
$\Delta_5LW_{(t-1)}$	-0.305	-0.386	0.769*	-0.206	-0.412	0.215	0.467	0.543	0.391
	(0.423)	(0.439)	(0.415)	(0.462)	(0.522)	(0.457)	(0.378)	(0.415)	(0.339)
$\Delta_5LW_{(t-1)}$	0.05	0.064	-0.093**	0.029	0.057	-0.034	-0.06	-0.067	-0.052
$\times TFP_{(t-5)}$	(0.053)	(0.054)	(0.047)	(0.061)	(0.069)	(0.059)	(0.049)	(0.052)	(0.045)
R-squared	0.026	0.021	0.029	0.014	0.01	0.026	0.036	0.028	0.035
N	13106	13106	13106	7888	7888	7888	10458	10458	10458

Notes: Table reports results from IV regression of five-year changes in employment on lag of five-year changes in import exposure and lag TFP of plants. In the first stage, $\Delta_5CHN_{(t-1)}$ and $\Delta_5CHN_{(t-1)}\times TFP_{(t-5)}$ are instrumented by (t-1)-1 lag of five-year changes in Chinese import share in Indonesia $\Delta_5(CH)IDN_{(t-1)-1}$ and $\Delta_5(CH)IDN_{(t-1)-1}\times TFP_{(t-5)}$. Panel-A reports results for LFirst200 and panel-B reports LFirst100 sample. Columns (1)-(3) include pro-employer, columns (4)-(6) include neutral, and columns (7)-(9) include pro-worker labor market sample. Standard errors (in parentheses) are clustered at industry (NIC 4-digit) level. Columns (1), (4) and (7) use changes in log total employment (L), columns (2), (5) and (8) use changes in log blue-collar employment and (3), (6) and (9) use changes in white-collar employment as dependent variable. All the regressions include initial technology intensity dummies, rural dummy and state by year fixed effects. Plant specific sampling weights are applied in all regressions. In this table, Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu are pro-employer; Orissa, Gujarat, Maharashtra and West Bengal are pro-worker and Assam, Bihar, Haryana, Jammu and Kashmir, Punjab and Uttar Pradesh are neutral states. * p<.1; ** p<.05; *** p<.01

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