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ABSTRACT

Import Competition, Formalization, and the Role of Contract Labor*

Does higher import competition increase formalization and aggregate productivity? Exploiting plausibly exogenous variation from Chinese imports, we provide empirical causal evidence that higher imports increases the share of formal manufacturing enterprise employment in India. This formal share increase is both due to the rise in formal-enterprise employment driven by the high productivity firms, and a fall in informal-enterprise employment. The labor reallocation is enabled by the formal firms' hiring of contract workers, who do not carry stringent string costs. Overall, Chinese import competition increased formal sector employment share by 3.7 percentage points, and aggregate labor productivity by 2.87%, between 2000-2001 and 2005-2006.

JEL Classification: F14, F16, O17, O47, F66

Keywords: import competition, formal sector employment, informality, contract workers, Chinese imports, reallocation, misallocation

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1 Introduction

Developing countries are characterized by a large informal workforce. Higher informal enterprise employment is associated with lower income and development, in part due to the inefficient allocation of resources across sectors and firms (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008).[1] Therefore, any reallocation of employment towards more productive formal sector firms can increase aggregate productivity and promote development.[2] Given that the firms in developing countries are increasingly exposed to imports, it is crucial to investigate the role of import competition in allocating labor between informal and formal enterprises. Multiple mechanisms drive this relationship. Import competition can increase formal share of employment as unproductive informal firms exit, but can also decrease formal employment if unproductive formal firms transition to the informal sector (Dix-Carneiro et al., 2021).[3] Not surprisingly, the empirical evidence is mixed, with some studies showing null or economically small positive effects on informality (Goldberg and Pavcnik, 2003; Paz, 2014), while others showing significant positive effects on informality (Dix-Carneiro and Kovak, 2019).

Exploiting the meteoric rise of Chinese manufacturing imports, we provide new evidence that higher import competition in an industry increased the share of employment in the formal sector manufacturing enterprises in India in the industry. This was driven both by a decline in informal enterprise employment and an increase in formal enterprise employment. The latter is in turn driven by the hiring of workers on fixed term contracts through third party contractors (or, contract workers). Our findings suggest that import competition, by forcing informal firms to exit, can reallocate resources toward more productive formal firms leading to aggregate productivity gains in developing countries.

Our study makes two important contributions to the literature. First, we show that trade can induce formalization by increasing competition in the domestic market, a result

[1] A large informal sector also constrains development and growth by lowering the tax base and hindering fiscal capacity (Besley and Persson, 2013; Levy, 2010).

[2] Naturally, formalization is a popular policy tool, and a variegated set of policy options have been considered towards achieving that. These include, for example, the lowering of registration costs or taxes for formal firms, providing capital grants to small firms, and the careful dismantling of size-based policies to incentivise growth (De Mel et al., 2013; McKenzie, 2017; Rocha et al., 2018).

[3] As shown by Ulyssea (2018), formal and informal firms coexist even within narrowly defined industries.

hitherto only observed in the context of export market access (Costa et al., 2016 and McCaig and Pavcnik, 2018). Second, we provide novel evidence on the role of contract workers in enabling formalization in response to increased imports in a setting with high labor adjustment costs for firms. Our study provides rigorous empirical evidence consistent with the abundant anecdotal evidence that the Indian informal manufacturing sector was negatively impacted by Chinese import competition.[4]

Studying the impact of import competition on labor reallocation between the informal and formal sector enterprises presents several challenges. First, comprehensive data on informal enterprises are usually not available. India is one of the few countries where nationally representative surveys of informal enterprises conducted at regular intervals covering both urban and rural areas, and using non-household sampling units are available.[5] We exploit the availability of these enterprise data for the years 2000-2001 and 2005-2006, and complement them with formal sector enterprise data for the same years to study the allocation of employment between these sectors in this period.

In doing so, we follow an enterprise-based definition of informality (Nataraj (2011) and McCaig and Pavcnik (2018)). The classification of firms, and hence the bifurcation of these surveys as formal or informal, are based on the size (employment) based objective criterion set by the Factories Act 1948. As per the Factories Act, 1948, any factory using power and employing 10 or more workers, and if not using power and employing 20 or more workers is deemed to be registered in the formal sector. A number of regulations become binding at these employment thresholds that considerably increases the unit labor costs for formal enterprises relative to the informal enterprises.[6] The lower regulatory costs for informal firms let them survive despite their low productivity which hampers employment allocation to more productive formal enterprises, resulting in the misallocation of labor within industries (Hsieh and Klenow (2009); Boedo and Mukoyama (2012)). Not surprisingly, a

[4]See, for example, ASSOCHAM (2013a) for the toy industry, Sathyanarayana (2014) for the fire-crackers industry, ASSOCHAM (2013b) for the ceramics industry, and Roy (2013) for the bicycles industry.

[5]India's unorganized sector surveys cover all regions (except some extremely remote areas), and use the Economic Census of India that provides a comprehensive coverage of units undertaking any economic activity, and the population census in some rural areas as the sampling frame.

[6]These regulations relate to, inter alia, workplace safety requirements, insurance and social security taxes, gratuities, and administrative burden related to labor laws. Amirapu and Gechter (2020) find that these regulations increase the firm's unit labor costs by a significant 35%.

large share of employment in India is concentrated in the informal sector. In 2005, the share of informal workers in the manufacturing sector employment was approximately 80% (Asturias et al., 2019).

The second challenge lies in identifying the effects of import competition on employment, which is riddled with simultaneity concerns arising from unobserved demand and technology shocks that affect both imports and employment. To address this, we exploit the differential exposure of industries in India to Chinese imports. The increase in Chinese imports are plausibly exogenous because they are primarily driven by the increase in manufacturing productivity in China due to its own internal reforms (Acemoglu et al., 2016; Autor et al., 2013).[7] Chinese exports grew tremendously worldwide during the last few decades. While import share to India from China rose by over 16 times between 1998-2007, imports from other countries only doubled. Chinese imports share in India stood at a remarkable 18 percent in 2007. To address any remaining concerns, we employ an instrumental variable strategy that uses Chinese imports to a set of Latin American countries as an instrument for Chinese imports into India (following Acemoglu et al., 2016).[8] We control for alternative trade channels and a rich set of fixed effects to control for unobserved common demand and technology shocks across India and Latin American countries.[9] Further, we provide evidence that our results are not driven by differential trends based on worker, industry, and state level characteristics.

The third challenge lies in quantifying aggregate productivity gains due to reallocation of labor from the informal to the formal sector. These gains depend on the existing labor productivity gap between the two sectors. Utilizing the raw labor productivity gap between the formal and the informal sectors could however be problematic. The informal and formal

[7]Among other things, these internal reforms enabled the setting up of special economic zones (Alder et al., 2013), facilitated technology transfers through foreign direct investments (Autor et al., 2016) and multinational activity (Naughton, 2006), and promoted the mass migration of workers from rural to urban areas (Chen et al., 2010). Further, China's accession to the World Trade Organization in 2001 provided an additional boost to its exports (Branstetter and Lardy, 2006).

[8]We choose a set of Latin American countries for the instrument as they are not major trade partners of India and thus, the possibility of alternative trade channels contaminating our estimates is limited.

[9]The alternative trade channels include import competition in India from low- and middle- income and high-income countries, competition posed by China in markets that India exports to (low- and middle-income and high-income countries), India's export share to countries in the instrumental variable list, and trade policy measures such as output and input tariffs.

sector may differ in various other characteristics, such as, number of hours worked, human capital, measurement errors in reporting revenues, and output elasticity with respect to labor. Further, using revenue data to calculate the gap could captures price and markup differences, in addition to underlying physical productivity differences across the two sectors (De Loecker et al., 2016; McCaig and Pavcnik, 2018).[10] Using the development accounting framework (Caselli, 2005; Gollin et al., 2014; McCaig and Pavcnik, 2018; Vollrath, 2014), we adjust the raw (observed) productivity gap for the differences across the sectors using information from firm-level and worker-level surveys, and from prior studies. Uniquely, to adjust for price differences, we exploit the availability of physical production and sales data at the firm-product level in both formal and informal sector firm-surveys in India.

The Indian manufacturing sector labor market comprises of three types of workers: (1) Regular workers, (2) Contract workers, and (3) Informal workers. The regular and contract workers are employed in the formal sector firms, and the informal workers are employed in the informal sector firms. In India, formal registered manufacturing firms employ directly hired regular workers with open-ended contracts. Formal firms also hire contract workers through third party contractors in fixed-term contracts to achieve flexibility in hiring and firing. Specifically, the firing costs imposed on regular workers through the Industrial Disputes Act, 1947, are not applicable to contract workers (Besley and Burgess, 2004). The third-party contractors are required under the Contract Labor Act 1970 to obtain a license from the government licensing officer. The license specifies conditions, including hours of work, wage payments, and amenities to be provided to the contract workers. The license is, in effect, a legal contract between the third-party contractor and the government ensuring minimum standards related to contract worker welfare. In contrast, informal workers hired by informal or unregistered establishments do not obtain any mandated benefits.[11]

Our results imply that between 2000-2001 and 2005-2006, Chinese import competition

[10]Formal sector firms, on average, charge higher prices compared to the informal sector, because they usually have more market power and offer higher quality products. Kugler and Verhoogen (2012) find that large firms charge both higher output prices and have higher input prices. To the extent that input prices reflect higher quality inputs, large firms also produce higher quality output.

[11]Further, while the Minimum Wages Act, 1948, covers workers in both informal and formal enterprises, enforcement and thus compliance is much higher in the formal sector (Gindling and Terrell, 2009; Rani et al., 2013).

led to an increase in formal share of employment by 3.7 percentage points. While we observed both an expansion in the formal sector, and a contraction of the informal sector, the latter effect dominates, resulting in net employment losses in the industry in the short run. Our preferred estimate of labor productivity gap between the formal and informal sectors is 2.18, after adjusting for differences in prices, human capital, and hours-worked. Based on this, we estimate that Chinese import competition led to an increase in aggregate labor productivity by 2.87% relative to the baseline.

This increase in formal sector employment is driven by contract labor. We find that a 1 percentage point increase in Chinese import competition increases contract labor by 10%. These results suggest that the institution of contract labor enables the smooth reallocation of workers between the informal and formal sectors. Our results are consistent with studies showing that Employment Protection Laws (EPL) limit employment adjustment and hamper worker reallocation (Boedo and Mukoyama, 2012; Hopenhayn and Rogerson, 1993; Kambourov, 2009), and that contract or temporary workers enable smoother adjustment of workforce in these settings, as documented in India (Chaurey, 2015; Saha et al., 2013) and the United States (Autor, 2003). Our results are further consistent with Bertrand et al. (2015) that demonstrate the positive role of contract labor in the growth of the large formal sector manufacturing firms in India.

We expect import competition led reallocation to be more pronounced in contexts where misallocation and informality are already high to begin with. In India, data indicate that informality is higher in states with stringent labor firing regulations and stronger unions.[12] Indeed, we find that the overall increase in formal share of employment as a result of Chinese import competition is driven by states with more stringent EPL (classified based on Besley and Burgess (2004)) and states with higher worker unionization. Also, formalization in these states is, in turn, driven by contract labor.

Our study relates to Dix-Carneiro et al. (2021) who study the role of trade liberalization in a structural general equilibrium model in Brazil. Through counterfactual simulations,

[12] In 2000, the share of formal sector employment was 14.45% in pro-worker states and 15.25% in high unionization states. In contrast, the share of formal sector employment was higher in non pro-worker states (18.6%) and states with low unionization (19.5%).

they find that a reduction in trade barriers results in the exit of informal firms and a large decline in informal employment in the import competing sector, leading to an increase in productivity. Our findings complement these results and provide reduced-form causal evidence that Chinese import competition leads to an increase in the formal share of employment and aggregate productivity gains in the import competing sector. Our study is also related to McCaig and Pavcnik (2018), who find that export market access increases aggregate productivity by increasing the formal share in employment. Complementing their findings, we provide the first empirical evidence that import competition led formalization also leads to productivity gains from trade.

Our work also relates to empirical papers studying the effect of tariff liberalization episodes on informality. Dix-Carneiro and Kovak (2019) and Paz (2014) find that tariff reductions lead to an increase in informality in Brazil. Goldberg and Pavcnik (2003) find that tariff liberalization significantly increases informality in Colombia in the period preceding labor market reforms, while they find no effects in Brazil. Further, recent studies show that some formal firms increase the hiring of informal workers (the intensive margin of informality) in response to import competition. In Peru, Cisneros-Acevedo (2019) finds that the increase in the intensive margin of informality in response to tariff declines is driven by small/medium sized formal firms, and not by large firms because the latter are more likely to be audited by tax agencies in their setting. Ponczek and Ulyssea (2021) find a relative increase in informality and an increase in the probability of survival of formal firms in response to tariff liberalization in regions with weak labor law enforcement in Brazil, consistent with the fact that formal firms in Brazil hire informal workers (Ulyssea, 2018).

Our study differs from the literature in at least four important ways. First, the increase in the formal firm employment in response to Chinese import competition in India is driven by high productivity firms rather than smaller unproductive firms. As high productivity and larger firms are more visible to the tax authorities, our results reflect that contract workers in India are legally eligible and covered under multiple labor laws, unlike informal workers who may not be legally employed by formal firms in other contexts. Second, we provide novel evidence on the crucial role of contract workers in enabling formalization in response to increased import competition in a setting with stringent labor laws for formal firms. Third, while the extant literature focuses on tariff liberalization episodes, our study documents the effect of the relatively less explored Chinese import competition. Finally, to the best of our knowledge, ours is the first study to estimate the labor productivity gains in response to an increase in import competition.

We contribute to the growing literature on the effects of Chinese import competition, which have largely documented negative employment effects (Acemoglu et al., 2016; Autor et al., 2013, 2014; Bloom et al., 2016; Mansour et al., 2020; Utar and Ruiz, 2013). Corroborating these findings, we also document employment losses in industries more exposed to import competition. Further, our results are also consistent with the counterfactual estimates in Dix-Carneiro et al. (2021), who document that a reduction in trade barriers increases both the aggregate productivity and the unemployment rate.

The rest of the paper is organized as follows. Section 2 provides a conceptual framework. Section 3 discusses the data sources and describes the measurement of informality. Section 4 presents the empirical strategy. Section 5 presents and discusses the results and the robustness checks. Section 6 computes the aggregate productivity gains due to the reallocation. Section 7 concludes.

2 Conceptual Framework

In this section, we briefly layout the potential mechanisms linking import competition to the allocation of labor across the formal and informal sector in a developing country. The presence of a large informal sector can lead to misallocation of resources within industries as informal enterprises survive despite their low productivity. This is because they do not comply with regulations covering the formal enterprises and hence have a relatively low unit labor cost (Amirapu and Gechter, 2020). Thus, in settings with high informality, import competition can potentially improve allocative efficiency within industries by increasing the formal share of employment due to exit of informal firms (extensive margin) and by increasing the employment ratio of formal to the informal sector among the surviving firms (intensive margin).

An increase in imports to an industry reduces demand for firms, and this would disproportionately reduce the profits of lower productivity firms. Informal firms, on average, have substantially lower productivity compared to formal sector firms (McCaig and Pavcnik, 2018), either due to differences in underlying productivity (Melitz, 2003) or managerial ability (Lucas Jr, 1978).[13] Import competition would induce some low productivity formal firms to transition to the informal sector, but it would also force some unproductive informal firms to exit the industry as they are unable to earn enough profits to stay in the market (Dix-Carneiro et al., 2021). Thus, the overall effect of import competition on informal employment can be positive or negative depending on the channel that dominates.

Further, in models with heterogeneous firms, monopolistic competition, and endogenous markup, as in Melitz (2018), import competition can also lead to intensive margin reallocation toward the more productive formal firms.[14] High productivity firms, who also charge higher markups, will reduce their markups and hence prices as the price elasticity of demand increases in response to increase in import competition. This leads to reallocation of output and labor towards more productive formal firms.

In addition, high productivity formal firms could also increase employment in response to import competition. This could happen, for instance, in models where increased import competition can induce high productivity firms to increase investments and employment (escape competition effect) while low productivity firms are discouraged from investing (Schumpeterian effect) (Aghion et al., 2005).[15] The increase in employment by high productivity firms in response to increased import competition is also predicted by extensions of the standard Melitz model with endogenous wages, as in Demidova and Rodriguez-Clare

[13] If there are differences in marginal costs across firms and there is a fixed cost for exporting, only the most productive firms would earn enough profits to be able to export (Melitz, 2003). Thus, informal firms and low productivity formal firms would serve only the domestic market and be relatively more exposed to import competition.

[14] There is empirical evidence that markups vary across firms within industries in India. De Loecker et al. (2016) document considerable differences in markup across firms within industries in the manufacturing sector in India.

[15] Gutiérrez and Philippon (2017), studying US firms, find that Chinese import competition leads to increased investments and employment in firms with high market share while it reduces investments and employment in laggard firms. Bloom et al. (2016) study European manufacturing firms and find that Chinese import competition leads to reallocation of workers toward technologically more advanced firms.

(2013).

Further, import competition could also induce formal firms to increase the demand for contract workers to counter the bargaining power of permanent workers (Saha et al., 2013). Firms could also employ more contract workers in an effort to reduce wage costs in response to increased competition from Chinese imports. However, in these settings, contract and regular labor are imperfect substitutes (Kapoor and Krishnapriya, 2019), which is why firms always employ a mix of regular and contract workers. This increased demand for contract workers by high productivity formal firms would further reinforce the reallocation of workers towards the more productive formal firms.

Our discussion above linking import competition to formal share of employment has abstracted from mobility frictions that may restrict the movement of workers from informal to the formal sector and would dampen the reallocation process. If these frictions are salient, it would frustrate any attempt to empirically observe the reallocation effect of import competition. Taken together, these mechanisms highlight the complex relationship between import competition and labor allocation across the formal and informal sectors. Whether import competition leads to an increase or decrease in formal share of employment is ultimately an empirical question.

3 Data Sources and Measurement of Informality

3.1 Data Sources

Our primary source of data on informal firms is the quinquennial cross-sectional unorganized sector enterprise surveys conducted by the National Sample Survey (NSS) Organization. For the formal sector, we use data for manufacturing plants from the Annual Survey of Industries (ASI) conducted by the Central Statistical Office (CSO), Government of India. The ASI covers all registered establishments in the country with 100 or more workers, and randomly samples establishments with less than 100 workers. We use the ASI data in 2000-2001 and 2005-2006 to match with the years the NSS unorganized sector survey data are available. Henceforth, we refer to this combined dataset as ASI-NSS. We observe information on the number of employees in both the NSS and ASI establishment surveys. In addition, the ASI also reports information separately on regular employment and contract employment.[16] Further, both the NSS and ASI surveys are unique in that they capture detailed information on physical production, units of measure, and sales for disaggregated product lines produced by each firm.[17] We also use the unit level panel ASI data with firm identifiers from 1998-1999 to 2007-2008 to study outcomes within the formal sector firms over time.[18]

We also use worker level data from the Employment-Unemployment survey (EUS henceforth) conducted by the NSS. This is a quinquennial cross-section survey and we utilize data for two years, namely, 1999-2000 and 2004-2005. The survey reports data on worker characteristics such as age, gender, education, martial status, residence location, religion, and social group, and employer characteristics, such as, firm size and usage of electricity. This enables us to study the effect of import competition on workers' employment in the formal sector.[19]

Our primary source of industry level trade data is the UN-COMTRADE database.[20] From this database, we compiled data on Chinese imports to India, and to a set of low- and middle-, and high-income countries. We also compiled total imports to India from low- and middle-, and high-income (other than China and the IV countries), and India's export share to countries in the instrumental variable list. We use data on input and output tariffs from Ahsan and Mitra (2014) for the years between 1998 and 2003, and from Chakraborty and Raveh (2018) for the years between 2004 and 2007.

To construct the import competition measure, we require the baseline production data

[16] Another important micro-level dataset on Indian firms is PROWESS, which is published by the Centre for Monitoring Indian Economy (CMIE). However, unlike the ASI, PROWESS does not report employment data for the majority of firms and also does not collect data on different types of workers employed by firms.

[17] The product lines are classified according to A Standard Industrial Commodity Classification (ASICC) classification. There are over 3800 distinct product lines reported in the survey.

[18] 1998-1999 is the first year for which ASI is available with an establishment identifier.

[19] Another worker level dataset in India is the India Human Development Survey (IHDS) and is available for the years 2005 and 2011. While it is a panel dataset of workers, it does not have the necessary information (employment size of factory, whether written contract exists, etc.) to identify whether workers are employed in the formal or in the informal sector. Thus, we are unable to directly observe a worker reallocating from the informal to the formal sector due to the non-availability of panel data.

[20] Industries are classified as per the National Industries Classification (NIC) in both the EUS and ASI-NSS surveys. We map the trade data, reported in the ISIC revision 3.1 classification, to the NIC.

in India. For this, we used both formal sector output from the ASI in 1994-1995, and informal sector output from the NSS's unorganized manufacturing enterprises survey in 1994-1995. We also use data on labor institutions from two separate sources. First, we use a state level measure of strength of regulations related to unions from the OECD index reported in (Dougherty, 2009).[21] Second, we use the state level measure of labour regulation by Besley and Burgess (2004), which reflects the state level differences in stringency in the firing of regular workers under Industrial Disputes Act, 1947 (IDA), the key employment protection legislation in the Indian context.

3.2 Measuring Informality

Informality in India is closely linked to firm size and the government agencies classify firms as formal/informal based on Factories Act, 1948. As per the Factories Act, 1948, any factory using power and employing 10 or more workers, and if not using power and employing 20 or more workers is deemed to be registered in the formal sector.[22] As discussed earlier, several regulations become binding at these employment thresholds that considerably increase the unit labor costs of formal firms relative to the informal firms (Amirapu and Gechter, 2020).

We use enterprise level ASI-NSS data to measure formal share of employment in each industry. The NSS and the ASI surveys are nationally representative surveys of unorganized and formal sector enterprises, respectively. This classification of formal and informal is made by the government based on firm-size and registration status, and accurately reflects the formal-informal composition in the economy.

We aggregate employment from ASI-NSS surveys at the state-industry and at the industry level by applying sampling weights reported in these surveys.[23] We define worker-share

[21] This measure captures state level differences in regulations related to different aspects of union representation, namely, labor law reforms relating to restrictions on the minimum number of workers in an union, recognition of unions as bargaining agents, provisions for union formation in an enterprise, rules related to strikes, and code of conduct between employers and unions.

[22] A potential concern is that due to limited enforceability of the law, large firms may illegally operate in the informal sector. However, consistent with the regulatory size thresholds, we find that almost all firms that fall above these size thresholds are in the ASI surveys. Only 0.2% and 1.1% of firms in the 2000 round of the unorganized survey are above the size thresholds of 20 and 10 workers, respectively.

[23] To arrive at the aggregate employment figures, we multiply the firm level employment with the corresponding sampling weight for the firm and then sum over all firms for each state-industry or industry level.

in the formal sector in each aggregated unit as the share of workers in the ASI to total number of workers in all firms in that unit. We also employ the EUS to construct the informality measure. Specifically, we utilize the data reported on workers' employer details, such as, the number of workers and the use of electricity to apply the above Factories Act definition to identify whether workers are employed in the formal or informal sector enterprises. In cases where workers report working in registered enterprises even if their firm has fewer than 10 workers, we re-classify these workers as formal workers.

Table 1 reports the summary statistics for firm characteristics from ASI-NSS in Panel A and worker characteristics from the EUS in Panel B for the year 2000-2001. Formal firms (columns 1-3) on average have much higher sales, employ more workers, and pay much higher wages compared to informal firms (columns 4-6). Formal workers (columns 1-3) are on average better educated, are more likely to work in urban areas, and are less likely to be females and from the disadvantages social groups and minorities, as compared to informal workers (columns 4-6).

4 Empirical Strategy

4.1 Key Variables and Identification Strategy

The steep rise in Chinese imports through the 1990s and 2000s were primarily driven by China's internal reforms leading to productivity gains, and China's accession to the WTO in 2001. Our main identification strategy relies on exploiting cross-industry variation in exposure to Chinese imports to study their effect on share of employment in formal firms. Towards this end, we obtain a measure of Chinese import penetration in an industry j at time t, given by:

$$IMP_{jt}^{China} = \frac{M_{jt}^{China}}{(Y_{j,94} + M_{j,94} - X_{j,94})} \tag{1}$$

where M_{jt}^{China} is the total imports of Chinese goods in industry j at time t; $Y_{j,94}$, $M_{j,94}$ and $X_{j,94}$ refer to production, total imports, and total exports for industry j in India in

1994. By normalizing Chinese imports to India over absorption (domestic production plus imports less exports) before the start of our study period, our measure captures the relative increase in Chinese imports across industries compared to the initial size of an industry in the domestic market.

There are, however, several reasons why an ordinary least squares regression of employment on import competition could produce biased estimates. For example, industry level demand shocks that drive Chinese imports could also simultaneously influence employment, or labor saving or displacing technologies that may drive imports could also be correlated with domestic employment. We use an instrumental variable to address these endogeneity concerns. Specifically, we instrument Chinese imports to India (given by equation 1) by Chinese imports to a set of countries, following Autor et al. (2013) and Acemoglu et al. (2016), as given by:

$$IV_{jt}^{China} = \frac{M_{jt}^{Others}}{(Y_{j,94} + M_{j,94} - X_{j,94})} \tag{2}$$

where M_{jt}^{Others} refers to Chinese imports to industry j in time t in a set of developing countries. For this, we choose a set of Latin American countries, namely Argentina, Brazil, Costa Rica, Chile, Colombia, Mexico, Paraguay, Peru, Uruguay, and Venezuela. The instrument isolates the variation in Chinese imports that is only due to supply side shocks from China. Chinese imports to the instrument-country list are expected to be strongly correlated with Chinese imports to India if the basket of goods exported from China to India and these countries are similar, and if these countries experienced similar rise in Chinese exports.

Figure 1 shows the evolution of Chinese import share from 1998 to 2007 for India and various country groups. The rise in the Chinese import share was very similar for India and the instrument-countries. Further, the choice of Latin American countries ensures that the exclusion criterion is likely to be satisfied, as these countries are not major trade partners with India, and thus the correlation between Chinese imports to these countries and India is solely due to the supply side component of Chinese imports arising from gains in manufacturing productivity for Chinese firms. All our empirical specifications also control for fixed effects at the state-year, industry(3-digit)-year, and state-(4-digit)industry- levels to control for unobservables.

We further take into account alternative trade channels (varying at the same level as our import competition measure) that could influence employment, and that are potentially correlated with Chinese imports. Further, concurrent changes in trade policy may be correlated with Chinese imports to India, which is addressed by controlling for industry level output and input tariffs.

Another concern is that Chinese imports to India may be correlated with imports from other countries. To address this, we control for import penetration in India from low- and middle-, and high-income countries in all specifications. Further, Chinese imports to India may also be correlated with Chinese imports into other countries, and our estimates may capture the effect of increased competition from China in destination markets for Indian exporters. To address this, we control for Chinese import share in low- and middle-, and high-income countries, excluding the set of IV countries. Finally, we control for India's exports to the IV countries to control for the direct effect of Chinese import competition for Indian exporters in these countries. We discuss the construction of these variables in Appendix A.

4.2 Decomposition of Overall Change in Formal Share in Employment

Since we examine within industry changes in the share of formal enterprise employment in response to Chinese import competition, it is important to confirm that cross-industry changes in employment is not a major contributor to overall changes in manufacturing employment in India. For this, we analyze whether the changes in the formal share in our study period is driven by industries with high/low formal share increasing their employment share in manufacturing (between), or due to changes in formal share within the industry (within). Specifically, we decompose the overall change in formal enterprise share in employment, ΔFW, between 2000-2001 and 2005-2006 into the respective within and between industry components as follows:

$$\Delta FW = \sum_j (0.5 * (s_{jt} + s_{jt-1}))\Delta fw_{jt} + \sum_j (0.5 * (fw_{jt} + fw_{jt-1}))\Delta s_{jt} \tag{3}$$

where fw_{jt} denotes formal share in employment for industry j in year t, and s_{jt} denotes employment share of industry j in total employment in manufacturing. We aggregate employment at the industry level, using the ASI-NSS data, to conduct this analysis. The first term captures the change in formal share in employment due to changes in formal sector employment across firms within an industry whereas the second term captures movement of formal workers across industries. Table 2 reports the decomposition between 2000-2001 and 2005-2006. The share of formal enterprise workers increased between 2000 and 2005 by almost 3 percentage points, driven by an increase in both contract and regular share in total industry employment (columns 1-3). We find that change in overall formal share in employment is predominantly driven by within-industry change (column 4) and that the magnitude of the between-industry effect is relatively small (column 5). We obtain similar results if we decompose the share of contract workers and the share of regular workers. Consistent with the importance of within-industry changes we observe, our empirical analysis also similarly explores within-industry employment changes in response to increased import competition from China. Next, we turn to a more rigorous examination of the link between Chinese import competition and formalization in our empirical analysis.

5 Results

To examine the relationship between Chinese import competition and formal enterprise share of employment, we use both enterprise surveys (ASI-NSS) in Section 5.1 and worker surveys (EUS) in Section 5.2. We test for heterogeneity based on labor institutions in Section 5.3. Having examined the effect of Chinese imports on formal share of employment, we focus on the formal sector, and study within-firm employment changes and heterogeneity in responses based on initial productivity (Section 5.4). Finally, we decompose aggregate labor productivity using the Olley-Pakes decomposition and analyze the effect of Chinese import competition on the underlying components of labor productivity in Section 5.5.

5.1 Evidence from Firm Level Surveys

We employ the ASI-NSS data to study the relationship between Chinese import competition and the aggregate formal share of employment at the state-industry level. We estimate the following specification:

$$Y_{jst} = \beta_1 IMP^{china}_{jt-1} + \mathbf{Z}_{jt-1}\psi + \alpha_{j(3)t} + \alpha_{st} + \alpha_{js} + \nu_{jst} \tag{4}$$

where Y is either the share of formal sector employment in total employment or (log of) total, informal, formal, formal-regular and formal-contract employment. s denotes a state, t denotes year, and j denotes an industry defined at the 4-digit level (NIC 2004). Our main explanatory variable is the industry level (at 4-digit) import penetration ratio for Chinese imports, IMP^{China}_{jt-1}.[24] $\mathbf{Z}_{jt-1}$ is a vector of variables capturing alternative trade channels (described in Section 4). We control for state $\times$ industry (α_{js}), state $\times$ year (α_{st}), and three-digit industry $\times$ year ($\alpha_{j(3)t}$) fixed effects to control for unobservables. We conservatively cluster robust standard errors at the 3-digit industry level to account for downward bias in standard errors due to serial correlation. We cluster at the 3-digit industry level, a broader level than the treatment level (4-digit industry) to allow for possible correlation between observations across closely related industries. Regressions are weighted by the state-industry employment in the initial year, 2000-2001. Weights could be: (1) initial total employment if the outcome is share of formal employment or total employment; (2) initial informal employment if the outcome is informal employment, and (3) initial formal employment if the outcome is either total formal, regular, or contract employment.

Table 3 reports the results. Panels A and B report results from OLS and IV estimation

[24] We use a lagged measure of Chinese import penetration to alleviate endogeneity concerns related to anticipatory employment responses to Chinese import competition, and to ensure that we study employment responses to past changes in import competition.

of the specification, respectively. The first stage Kleibergen-Paap (KP) F-statistics suggest a strong first stage relationship between our IV and the endogenous variable. In column (1), the coefficient on IMP_{jt-1}^{china} is positive and significant, suggesting that a one percentage point increase in Chinese import competition leads to an increase in formal share of employment by 1.39 percentage points at the state-industry level. Further, our results are also robust to running a more parsimonious specification with only state$\times$ industry and year fixed effects and a industry (3-digit) level trend, and if we cluster our standard errors two-way at the 3-digit industry and state level. These results are reported in columns 1 and 2 of Table B1, respectively.

A potential concern is that our estimates may be capturing the effect of dereservation of products in Small Scale Industries (SSI), particularly because this policy has been shown to increase employment in the formal sector (Martin et al., 2017). If de-reservation of SSI products in an industry is also systematically related to Chinese imports in that industry, this could lead to spurious correlation between Chinese imports and formal enterprise employment. To address this concern, we control for this policy variation in our model using data on product-level de-reservation from Martin et al. (2017). For this, we construct a time varying industry-level indicator variable equal to 1 if at least one product is dereserved in that industry in a particular year. Our main results in Table 3 are robust to controlling for an industry's exposure to de-reservation of SSI. These results are reported in column 3 of Table B1.

Another concern could be that our results are driven by existing state or industry level trends in employment, and that there would have been an increase in formal share of employment even in the absence of increase in Chinese import competition. To address this, we interact quartiles of formal share in total employment in 2000, and indicator variables for high unionization states and pro-worker states with a linear time trend. The results presented in column 4 of Table B1 remain robust to controlling for the effect of differential trends based on industry and state level characteristics.

Finally, a potential concern is that our results may be capturing the effect of Chinese import competition through input-output linkages of an industry with other industries. We control for these inter industry linkages by including controls for Chinese import exposure in input industries (downstream effect) as well as industries that buy goods from the industry (upstream effect). We describe the construction of these variables in Appendix A. The results presented in column 5 of Table B1 remain robust to controlling for propagation of the effects of Chinese import competition through the input-output linkages. The coefficient on IMP^{china}_{jt-1} remains positive and statistically significant at the 1% level while the coefficient on the variables capturing the upstream and downstream effects are statistically insignificant.

In columns (2)–(4) of Table 3, we document the effect of Chinese import competition on the (log of) overall employment, informal, and formal sector employment, respectively. The results indicate that a one percentage point increase in Chinese import competition leads to a decline in overall employment by 7.93%, decline in informal employment by 14.83%, and an increase in formal sector employment by 3.88%. Thus, Chinese import competition induces a large decline in informal sector employment while increasing formal sector employment, leading to an increase in formal share in employment. Taken together, these results suggest that Chinese import competition led to a reallocation of employment from the informal to the formal sector. We further disaggregate formal sector employment into regular (column 5) and contract workers (column 6) to identify the source of increase in formal sector employment observed in column (4). The rise in formal employment is largely driven by contract labor. A one percentage point increase in Chinese import competition leads to an increase in regular employment by 2.88% and contract employment by 10.03%. We obtain qualitatively similar results if we estimate variants of Equation (4) at the industry level, rather than at the state-industry level. We report these results in Table B2.

As discussed earlier in Section 2, Chinese import competition may also lead to increase in the informality in the exposed industries as formal firms and workers transition to the informal sector (Dix-Carneiro et al., 2021; Dix-Carneiro and Kovak, 2019). Further, formal firms may subcontract manufacturing activities to the informal sector to save cost (Chakraborty et al., 2022). Even though we are unable to tease out the effects of these mechanisms separately as we do not observe entry and exit of firms, our findings suggests that while these mechanisms may be present, they are dominated by the reallocation of activity from the informal to the formal sector. Table B3 reports results from estimating variants of Equation (4) at the industry level using the number of factories and sales as outcome variables. We find that there was net exit of factories from the informal sector (column 1) and no significant effect on the number of factories in the formal sector (column 2). Columns (3) and (4) suggest that there was no significant effect on the sales in the informal and formal sectors.[25]

Import competition could also lead to increase in employment in the non-manufacturing sectors of the economy if the unemployed manufacturing workers get absorbed by these sectors. Following Autor et al. (2013), we calculate the exposure of each district to Chinese import competition. We use the EUS survey to calculate district level employment in manufacturing, agriculture & mining, and services. Table B4 reports the result from estimating a district level regression of Chinese import competition on employment outcomes. The effect of Chinese import competition on overall employment is negative, but imprecisely estimated. Districts more exposed to Chinese import competition experience a large decline in manufacturing employment, consistent with our results in Table 3. We find no significant effect on employment in the agriculture & mining, and services sectors. These findings are consistent with Autor et al. (2013) who document that displaced manufacturing workers were not absorbed by other sectors of the economy in the United States.

5.2 Evidence from Worker Level Surveys

Next, using the EUS data, we estimate the effect of Chinese import competition on the probability of a worker being employed in a formal sector enterprise:

$$formal_{ijst} = \beta_1 IMP^{China}_{jt-1} + \mathbf{X}_{ijst}\delta + \mathbf{Z}_{jt-1}\psi + \alpha_{j(3)t} + \alpha_{st} + \alpha_{js} + \nu_{ijst} \quad (5)$$

[25]Using a firm-product level panel for formal firms, we confirm that the insignificant effect on sales is driven by a simultaneous decline in prices and an increase in physical production. These results are discussed in Section 5.4.

where i denotes a worker and $formal_{ijst}$, our outcome variable of interest, is an indicator variable which is equal to 1 if a worker is employed in a formal sector enterprise. $\mathbf{X}_{ijst}$ is a vector of worker characteristics that includes age, indicators for gender, education, marital status, religious minority, disadvantaged social groups, and residence in rural areas.[26] We cluster robust standard errors at the 3-digit industry level. Regressions are weighted using sample weights from the survey.

Table 4 reports the results from Equation (5) and its variants from OLS (columns 1-3) and IV (columns 4-6) estimations. We present the specification excluding (columns 1 and 4) and including controls for worker characteristics (columns 2 and 5), and their interaction with an indicator variable for the year 2004 to control for changes in worker characteristics between the two sample rounds (columns 3 and 6). The first-stage KP F-statistics for the IV estimates in columns (4)-(6) imply a strong relationship between our instrument and IMP^{China}_{jt-1}. The coefficient on IMP^{China}_{jt-1} is positive and significant in all columns suggesting that increase in Chinese import competition significantly increases the probability of being employed in a formal enterprise.[27] The coefficient in our preferred specification in column (6) implies that a one percentage point change in Chinese import competition leads to an increase in the probability of being employed in a formal enterprise by 0.46 percentage points. Thus, the increase in the aggregate level results from enterprise surveys is corroborated by the increase in the probability of formal sector employment observed in the worker level surveys. It is encouraging that our results are qualitatively consistent across two independent data sources.

Next, we report robustness checks for the main results in Table B5. In column (1), we find that our results are robust in a more parsimonious specification. In column (2), we find that our results remain robust to two-way clustering the standard errors at the 3-digit industry and state level. Column (3) controls for de-reservation exposure of each industry and the coefficient remains statistically significant with very similar magnitudes

[26] Educational categories include primary and below, below secondary, and secondary and higher education. Social group categories in India include the Scheduled Caste, Scheduled Tribes, Other Backward Castes, and Other Castes.

[27] We find positive and significant effects when we estimate specification in column (3) using a Probit model (results available on request).

compared to the baseline results. In column (4), we interact quartiles of formal share in total employment in 2000, and indicator variables for high unionization states and pro-worker states, with a linear time trend to control for differential trends in industry and state characteristics that may impact changes in formal share of employment. Our results remain robust to the inclusion of these trends. We also show robustness to an alternative definition of informality. Recall that we reclassified workers as formal if they report working for a firm that is registered even if they are deemed to be working in an informal firm based on the size threshold. A total of 516 workers get reclassified to the formal sector, which forms about 1% of the main sample. In column (5), we use a revised measure of formal enterprise employment, where we treat the 516 workers as informal, and our results remain robust.[28] Finally, in column (6), we find that our results are robust to controlling for the downstream and upstream effect of Chinese import competition through input-output linkages.

The overall effects documented above could mask considerable heterogeneity based on worker characteristics, because workers may have different adjustment costs based on demographic characteristics (Dix-Carneiro, 2014), and because firms may have differential demand for workers based on these characteristics in response to Chinese import competition. Table B6 shows that the overall results are primarily driven by experienced workers below 45 years of age (columns 1 and 2) while the effect is insignificant for older workers (column 3). These findings suggest that experience is useful in mobility, but also that there are large mobility costs for much older workers. It also suggests specific skills gained in the informal sector over time, may not necessarily be transferable to the formal sector. Next, we test for differences in the impact of import competition on the probability of a worker being employed in the formal enterprise based on their education levels. Our results suggest that the overall effect is primarily driven by workers with medium level of education (column 5) while the effect is small and insignificant for workers with below primary level of education (column 4) and those with Secondary and higher education (column 6). Lastly, we find that the overall effects are driven by workers in urban areas (column 8) with no

[28] As an additional robustness check, we drop these reclassified workers from the estimation sample and our results continue to hold. These results are available upon request.

significant effect on rural workers (column 7).[29]

5.3 Heterogeneity Based on Institutions

We expect the effect of Chinese import competition on the formal share in employment to be higher in settings where misallocation of workers across the two sectors is high to begin with. Labor market imperfections, such as EPLs, are often cited as a potential reason for the presence of informality (Besley and Burgess, 2004). However, the reallocation of workers to the formal sectors will be hindered in these same settings as high firing costs would deter formal firms to absorb new workers (Hopenhayn and Rogerson (1993); Kambourov (2009); Boedo and Mukoyama (2012)). Thus, in settings with high firing costs for formal firms, presence of alternative institutions, like contract labor, are needed to facilitate reallocation of workers to the formal sector.

In India, two sets of labor institutions, the Industrial Disputes Act, 1947 (IDA) and high unionization, lead to higher labor adjustment costs for large formal firms. During our study period, however, the institution of contract labor was already well established in India and had considerably relaxed these constraints for the large formal firms. Firms can hire contract workers under the Contract Labor Act 1970, and these workers are not under the ambit of the IDA, and are typically not a part of firm level unions. Indeed, in a period when contract workers were not prevalent, Adhvaryu et al. (2013) find that employment adjustment for firms is less sensitive to positive rainfall shocks in states with pro-labor institutions compared to firms in pro-employer states. On the other hand, Chaurey (2015) finds an increase in employment for formal firms in pro-worker states driven by contract employment in response to positive rainfall shocks between 1998-2007.

We test for heterogeneous impacts based on labor institutions in India. First, we consider the IDA, that stipulates labor firing restrictions for large firms, but not for small firms.[30] Several states have amended the IDA, leading to variation in the level of strin-

[29] A potential explanation of the null effects for rural workers may be that firms in rural areas are shielded from import competition due to relatively higher trade costs of reaching rural markets for imported Chinese goods.

[30] Two aspects of the Industrial Disputes Act , 1947, are relevant. Under section V-A, in establishments with 50 or more workers, a worker who is retrenched could claim compensation for wages for 15 days for

gency with which it is applicable. We use a simple bifurcation of states into pro-worker and non pro-worker categories based on the codification of the amendments to the IDA by Besley and Burgess (2004).[31] Second, a strong union presence could potentially limit the size of the formal sector. We use the OECD index defined at the state-level to capture strength of unionization, and classify states into high- and low- union strength states based on the median value of the index.

We estimate Equations (4) and (5) separately for pro-worker and non pro-worker states, and low and high unionization states. Results presented in Table 5 suggest that Chinese import competition differentially increases the probability of a worker being employed in a formal enterprise in high unionization (column 1) and pro-worker states (column 3), compared to low unionization (column 2) and non pro-worker states (column 4). The results from firm surveys at the state-industry level in columns (5)-(8) corroborate the findings from the worker surveys in columns (1)-(4). Finally, as hypothesized, columns (9)-(12) provide strong evidence that the increase in the share of contract employment in total employment is also driven by firms in high unionization (column 9) and pro-worker (column 11) states.

5.4 Within-Firm Employment in the Formal Sector

To further examine the mechanism behind the increase in formal sector employment, we exploit the availability of the establishment level panel dataset from the ASI between 1998-1999 and 2007-2008. This enables us to document the within-firm changes in overall employment as well as composition of employment, contract and regular, for formal firms. We estimate the following specification:

each year of service. If worker is laid-off, they must be provided half of their basic wage and a dearness allowance for each day they are laid off, for a maximum of 45 days. Establishments with 100 or more workers are covered under Section V-B, and requires firms to obtain government permission to lay-off or retrench even a single worker. Prior notification with the government is required if an establishment plans to close down (sixty days for Section V-A or ninety days for Section V-B).

[31] Besley and Burgess (2004) exploited state level amendments to the IDA to generate state level scores indicating the stringency of these laws. The larger the value, the higher the firing costs and more "pro-worker" the state is. On the other extreme, negative values indicate low firing costs and a "pro-employer" regime. Zero indicates neutrality. States with a positive score are classified as "pro-worker" states.

$$Y_{ijst} = \beta_1 IMP^{china}_{j,t-1} + \mathbf{Z}_{jt-1}\psi + \alpha_i + \alpha_{j(3)t} + \alpha_{st} + \nu_{ijst} \tag{6}$$

where i denotes a firm. Y_{ijst}, the outcome variable, could denote either (log of) total workers, regular workers, contract workers, or the contract worker ratio. In addition to the trade channels and fixed effects in Equation (4), we include firm fixed effects, α_i, to control for time invariant firm level characteristics. Columns (1)-(4) and (5)-(8) of Table 6 report results from OLS and IV estimations, respectively. We cluster standard errors at the industry level which is the level of variation in Chinese import competition.[32] Regressions are weighted using sample weights from the ASI.

From our preferred IV specification in column (5), the coefficient on IMP is positive and significant suggesting that Chinese import competition also leads to an increase in firm level employment on average among formal sector firms. The effect on regular workers is positive, but statistically insignificant in the IV specification in column (6). The positive and significant coefficient in column (7) (contract workers) and column (8) (contract worker ratio) provides strong evidence that the overall increase in within firm employment in the formal sector is driven primarily by the increase in contract employment. The IV coefficients imply that for a one percentage point increase in Chinese import competition, there was an increase in within-firm employment in the formal sector by 0.20%, contract workers by 0.35%, and contract share in employment by 0.053 percentage points. Thus, our firm level results mirror our earlier results, in Section 5.1, documenting an increase in aggregate formal enterprise employment, primarily through contract labor.[33]

To identify the formal sector firms that expand employment in response to Chinese import competition, we estimate heterogeneous impacts based on their initial productivity

[32]Our results are very similar when we cluster at the 3-digit industry level but the strength of the first-stage is weakened. The coefficient on IMP remain statistically significant for workers, contract workers, and contract worker ratio as the outcome variables.

[33]In Table B7, we report firm product-level regression with sales, physical output, and unit values as the outcome variable. We find that Chinese import competition has no significant effect on firm product level sales (column 1), a positive effect on physical output (column 2), and a negative effect on unit values (column 3). Thus, the formal firms hire more workers as they increase their physical output in response to Chinese import competition. The decline in prices for Indian manufacturing firms in response to Chinese import competition is consistent with the findings in Chakraborty et al. (2021).

using the following regression specification:

$$Y_{ijst} = \beta_1 IMP^{china}_{jt-1} + \sum_{k=2}^{4} \beta_k (IMP^{china}_{jt-1} \times Qr_k) + \mathbf{Z}_{jt-1}\psi$$
$$+ \alpha_i + \alpha_{j(3)t} + \alpha_{st} + \alpha_{sj} + \nu_{ijst} \quad (7)$$

This specification is the same as Equation (6), but with additional interaction terms between IMP^{china}_{jt-1} and indicator variables for the quartile the firm belongs to in the initial productivity distribution (Qr_k). For this, we use labor productivity as revenue per worker in the first year in which the firm appears in the data. Results are presented in Table 7. Column (1) indicates that there is a decline in employment in the lowest quartile, and a differential increase in employment among firms in higher quartiles compared to firms in the lowest quartile. We observe similar results for regular (column 2), contract (column 3), and contract worker ratio (column 4). Thus, the overall increase in formal employment, driven by contract labor, documented in Table 3 is led by the high productivity formal firms.[34]

5.5 Aggregate Labor Productivity: Olley-Pakes Decomposition

The increase in the formal share of employment in response to Chinese import competition can improve the allocative efficiency within industries by reallocating resources towards the more productive formal firms. To estimate the effect of Chinese import competition on the allocative efficiency within industries, we decompose the aggregate industry level labor productivity, closely following the approach in Olley and Pakes (1996).[35] The decomposition

[34]In Table B8, we estimate Equation 7 with Total Factor Productivity (TFP) as a measure of firm level productivity closely following the methodology proposed by Ackerberg et al. (2015) and find that the employment increased for the initially high TFP firms. Further, in Table B9, we confirm the reallocation of capital towards initially high productivity firms by estimating Equation (7) with log of capital stock as the outcome variable. We find that the coefficient is positive and significant for the firms in the top quartile of the productivity distribution.

[35]Melitz and Polanec (2015) propose a dynamic extension of the Olley-Pakes framework incorporating the entry and exit of firms in the aggregate productivity decomposition. We, however, do not observe entry and exit of firms in both the ASI as well as the NSS firm level surveys and hence are unable to perform the dynamic decomposition.

is given by:

$$LP_{jt} = \overline{LP_{jt}} + \sum_{i} w_{ijt}(s_{ijt} - \overline{s_{jt}})(LP_{ijt} - \overline{LP_{jt}}) \tag{8}$$

where LP_{jt} denotes the aggregate labor productivity in industry j computed as revenue per worker in year t. $\overline{LP_{jt}}$ is the unweighted mean of firm level labor productivity and is computed as $\frac{\sum_i w_{ijt} LP_{ijt}}{\sum_i w_{ijt}}$, where w_{ijt} denotes the sampling weights in the ASI-NSS firm level surveys. s_{ijt} and LP_{ijt} denote the firm's revenue share in the industry and labor productivity of firm i, respectively. $\overline{s_{jt}}$ is the unweighted mean of firm level revenue shares in industry j, and is calculated as $\frac{\sum_i w_{ijt} s_{ijt}}{\sum_i w_{ijt}}$. Changes in the first term capture the shifts in the labor productivity distribution. The second term is the covariance between market share and labor productivity, and captures changes in aggregate labor productivity due to market share reallocation across firms with differing labor productivity levels. We perform this decomposition for each industry and test for the effect of Chinese import competition on aggregate labor productivity and the underlying components by estimating the specification below:

$$Y_{jt} = \beta_1 IMP^{china}_{jt-1} + \mathbf{Z}_{jt-1}\psi + \alpha_{j(3)t} + \alpha_j + \nu_{jt} \tag{9}$$

where Y_{jt} denotes either aggregate labor productivity or its underlying components. Based on our baseline results, we expect Chinese import competition to increase the aggregate labor productivity driven by a positive effect on the covariance term of the decomposition. Table 8 reports the results. The results in column 1 suggest that Chinese import competition has a significant positive effect on industry level labor productivity. Our results also suggest that Chinese import competition improves allocative efficiency by reallocating resources to high labor productivity firms (column 2) and has a positive albeit insignificant effect on the unweighted mean of labor productivity (column 3). Taken together, these results confirm the importance of reallocation towards high productivity firms as a key mechanism driving productivity gains from Chinese import competition.

6 Reallocation and Aggregate Labor Productivity

In order to quantify the reallocation led aggregate productivity gains from Chinese import competition, we turn to a standard macroeconomic development accounting framework, following Caselli (2005), Gollin et al. (2014), and McCaig and Pavcnik (2018). Our approach closely follows that of McCaig and Pavcnik (2018), who study the aggregate labor productivity gains from within industry formalization induced by export market access for Vietnamese firms. Productivity gains from reallocation can be calculated using information on the share of workers that are reallocated from informal to formal sector (S_f) and the increase in labor productivity for a worker moving from informal to formal sector ($\Delta\omega_f$). Specifically, the gains can then be computed as $\Delta\omega = S_f \Delta\omega_f$. The calculation of S_f is straightforward and we compute it using the coefficient (β) on IMP^{china}_{jt-1} in Table 3. Specifically, $S_f = \sum_{sj} m_{sj}(\beta \times \Delta IMP)$, where m_{sj} is each state-industry's share in overall manufacturing employment and ΔIMP is the industry level change in Chinese import competition between 2000-2001 and 2005-2006. The estimates imply an overall change in formal share of employment by 3.7 percentage points.

Obtaining accurate estimates of labor productivity gap between formal and informal sector, however, is more challenging due to measurement issues and unobserved heterogeneity in characteristics of the two sectors. Below, we describe the procedure to calculate the labor productivity gap between the two sectors, discuss potential issues associated with these calculations, and layout our approach to address them.

6.1 Development Accounting Framework

We consider an industry comprised of two types of firms, formal and informal, that differ in their total factor productivity (TFP). Using standard assumptions of the development accounting framework (Caselli, 2005), it can be shown that the ratio of marginal product of labor between the two sectors equals both the wage ratio and the ratio of the average product of labor. Formally, we assume a Cobb-Douglas production function for each sector given by $Y_s = A_s K_s^{\alpha_s} L_s^{1-\alpha_s}$, where Y_s is real output, K_s and L_s are capital and labor inputs, respectively, A_s denotes the TFP, and α_s is the output elasticity with respect to capital. Under the assumption of perfect competition and homogeneous labor in the two sectors, the wages (w) equal the marginal revenue product of labor (MRPL) which in turn is equal to the product of output elasticity with respect to labor and the average revenue product of labor (ARPL).

$$w_s = MRPL_s = (1 - \alpha_s)ARPL_s$$

Assuming that the output elasticity of labor, $1 - \alpha$, is same across the two sectors, we can represent the MRPL gap between the two sectors in terms of obervables.

$$\frac{w_f}{w_i} = \frac{MRPL_f}{MRPL_i} = \frac{ARPL_f}{ARPL_i} \tag{10}$$

where f and i denote the formal and informal sector, respectively.

Thus, the labor productivity gap between formal and informal sector can be calculated either using revenue per worker or using wages. McCaig and Pavcnik (2018) use both wages and revenue per worker to measure productivity gap between the household and enterprise sector in Vietnam. Gollin et al. (2014) use revenue per worker, while Vollrath (2014) use the wage gap to measure productivity differences between the agricultural and non-agricultural sectors in a cross-country analysis. However, the above approach has some limitations. First, the ARPL gap as measured by revenue per unit labor would also capture price differences arising from markup and demand shocks across the two sectors. To address this, we require data on firm-level prices which is rarely observed in the data, especially in the informal sector. Second, worker characteristics may be significantly different for workers across the two sectors which would contaminate the measure of productivity gap. Finally, the estimates may suffer from measurement issues in output as well as inputs, and the output elasticity with respect to labor may be significantly different across the two sectors. In the following section, we first document the unadjusted labor productivity gap using Equation (10), and then sequentially adjust the productivity gap to address each of the issues discussed above.

6.2 Labor Productivity Gap

We observe wagebill, revenue, and number of workers in our firm level datasets for both the informal and formal sectors, and hence are able to calculate the labor productivity gap using both wages and revenue per worker using Equation (10).[36] Table 9 reports the productivity gap based on revenue per worker in column (1) and wages in column (2). In the first row, we report the unadjusted raw gap in labor productivity between the formal and informal sector. The gap is well above one in both columns, suggesting potentially large productivity gains from reallocation of workers to the formal sector. The average revenue per worker is almost 11 times higher in formal sector compared to the informal sector, while this ratio is only 3.12 using wages. This larger gap in average revenue product of labor compared to wages is consistent with the literature (McCaig and Pavcnik, 2018; Nataraj, 2011). However, as discussed earlier in Section 6.1, this raw productivity gap may be contaminated with measurement error and heterogeneity in characteristics across the two sectors. Next, we discuss the main factors that may be driving the large observed productivity gap and how we address these concerns in our calculations.

Differences in Hours Worked: We adjust the productivity gap for differences in the average number of hours worked across the two sectors. The number of hours worked may not be proportional to the number of workers for two reasons. First, many informal firms do not operate during the entire year, and this would lead to under estimation of actual productivity in the informal sector. Second, informal workers, on average, have lower working hours compared to their formal counterpart. We use information on the number of months in operation and average hours worked per day for informal firms from the NSS, and number of working days and employment reported by the formal firms from the ASI to adjust the raw productivity gap.[37] A detailed description of the adjustment calculations is provided in the Appendix Section C2. The figures after the adjustment are reported in

[36] Wages are calculated as total wages per worker paid by firms in a given year.

[37] This information is available only in the 2005-2006 round of the ASI-NSS surveys. By utilizing this data to correct for differences in hours worked across the two sectors in the 2000-2001 ASI-NSS round, we assume that average number of hours worked across the two sectors did not change significantly between the two survey rounds. Indeed, in the case of Vietnam, McCaig and Pavcnik (2018) find that average number of hours worked do not vary much as workers reallocate from the informal to the formal sector.

row 2. The ARPL gap reduces to 5.09 and the wage gap reduces to 1.45.

Human Capital Differences: Another concern with our measured productivity gap is that we may be capturing differences in human capital between the two sectors. Following Gollin et al. (2014), we adjust for human capital differences in the two sectors using data on the level of education reported in the EUS. The adjustment procedure is described in Appendix Section C3. This adjustment reduces the ARPL gap in column (1) to 4.21, and wage gap in column (2) to 1.21. Thus, differences in hours worked and human capital across the two sectors explain a significant part of the unadjusted labor productivity gap and wage gap.

Besides education and hours of work, there could be other unobserved worker characteristics that could lead to the overestimation of the productivity gap. To check if heterogeneity in worker characteristics other than hours worked and human capital are driving the large productivity gap, we use the EUS survey (worker level) where these details are available. We estimate Mincerian regressions of log wages on an indicator variable for formal enterprise employment, and worker characteristics such as years of education, location, and socio-demographic characteristics. We also include industry and state fixed effects. The coefficient on the indicator variable gives us the wage premium associated with working in the formal sector. Table B10 reports the results. In column (1), without controlling for worker characteristics, we find that there is a 31.4% wage premium for formal sector workers as compared to a wage premium of 24.1% in column (3) which controls for education level of workers. The wage premium further drops to 19.2% for formal sector workers compared to those in the informal sector in the specification including all worker characteristics (column 7). Thus, the wage premium does not drop by much when we control for worker characteristics other than their level of education. This suggests that the observed productivity gap in the firm level surveys between the two sectors are likely not driven by differences in other worker characteristics.

Differences in Prices: Productivity differences between the formal and informal sector using revenue data also captures the differences in prices due to market power and product quality variations across the sectors, in addition to the physical labor productivity differences (Kugler and Verhoogen, 2012; McCaig and Pavcnik, 2018).[38] To adjust for price differences, we first calculate the firm-product level prices (unit values) as sales divided by physical quantity for each firm-product. We compute the firm level price index as sales-share weighted sum of firm product level prices. Next, we calculate the firm level real output by deflating nominal revenue by firm level prices. Finally, we divide the productivity gap based on nominal revenue to the productivity gap based on real revenue, and estimate the adjustment factor to be 1.73.[39] We provide detailed explanation of the procedure employed to correct for price differences in Appendix Section C4. When we adjust the productivity gap for differences in prices using the correction factor of 1.73, the gap drops to 2.18, as reported in column (1) and row (3) of Table 9. Thus, differences in prices explain a significant part of the observed revenue productivity gap across the formal and informal sector, implying that a failure to correct for price differences would lead to significant overestimation of labor productivity gap and the gains from reallocation.

Other adjustments: The estimated productivity gap may be driven by measurement errors in output, particularly because revenues are commonly underreported in the informal sector. As we do not observe the extent of underreporting in India, we follow De Mel et al. (2009), who study firms in Sri Lanka, and assume that revenues were 30% higher than reported in the informal sector, and adjust our productivity gap in column (1) and row (4) to 1.53. A remaining concern is that there may be differences in the output elasticity between the formal and the informal sectors. Again, we do not directly observe these differences for India and following Fernández and Meza (2015), who study Mexican firms, we assume that the output elasticity of labor in the formal and informal sectors are 0.65 and 0.8, respectively. We adjust the productivity gap by a factor of 1.23 and this adjustments reduces the gap in column (1) and row (5) to 1.24.

In Table 9, we consistently find that the wage gap is much lower than the revenue productivity gap. A possible explanation for this is that there are distortions in product or

[38] See De Loecker et al. (2016) for a discussion of issues with estimation of productivity from revenue data.

[39] The data on physical production is available only in the 2005-2006 round of the NSS, and hence we are able to calculate the adjustment factor only for this round. Applying the adjustment factor based on the 2005-2006 round to the data from year 2000 assumes that the average price differences across the two sectors do not change significantly between 2000-2001 and 2005-2006.

labor markets that drive a wedge between the MRPL and the wages received by workers. If the strength of these frictions are different in the formal and informal sector, wage gap is no longer informative about the differences in the MRPL across the two sectors. Thus, we rely on the measured ARPL gap to calculate productivity gains from worker reallocation. The wage gap still enables us to calculate the wage gain that would be experienced by the reallocated workers.

6.3 Productivity Gains from Chinese Import Competition

We estimate the aggregate productivity gains, relative to the baseline average labor productivity in the manufacturing sector, from reallocation in response to Chinese import competition using the formula below:

$$\Delta\omega = \frac{S_f(ARPL_{gap} - 1)ARPL_i}{(1 - s_i)ARPL_f + s_i ARPL_i} \tag{11}$$

where $ARPL_{gap}$ denotes the productivity gap between the two sectors, $ARPL$ denotes the average labor productivity in either the informal or formal sector, and s_i is the share of hours for informal sector in total hours worked. All these variables are defined in the 2000-2001 ASI-NSS survey round.

We report productivity gains from three estimates of labor productivity gap in Table 9. The productivity gap in row (2), which adjusts for hours worked and human capital differences, implies an aggregate productivity increase of 4.62% due to reallocation of workers to the formal sector in response to increased Chinese import competition. Using estimates in row (3) that additionally control for price differences implies an aggregate productivity gain of 2.87%. It is clear from these calculations that failure to correct for price differences greatly overestimates the overall productivity gains due to reallocation. We treat this estimate of 2.87% as the upper bound for productivity gains from Chinese import competition. Finally, we use estimates from row (5) that additionally correct for measurement error and differences in output elasticity of labor across the two sectors which implies an aggregate productivity gain of 0.80% as the lower bound. Using a similar formula as Equation (11) for wages, our estimates suggest a modest gain in wages of 0.25% for workers that would reallocate to the formal sector (based on row (2) of column (2) in Table 9).

7 Conclusion

Extant literature provides mixed evidence on the relationship between import competition and informality. In this paper, we show that higher Chinese import competition increases the employment share in the formal sector in India. The rise in formal sector employment in more productive formal firms is driven by contract workers, who do not carry stringent firing costs and who are typically not a part of trade unions. In contrast, informal sector employment shrinks in response to Chinese import competition. We calculate the labor productivity gap between the two sectors, adjusting for differences in worker characteristics and prices. The adjusted productivity gap between the informal and the formal sectors suggests that the reallocation of workers from the informal to the formal sector due to Chinese import competition leads to aggregate labor productivity gains in the industry.

The relatively large reallocation of workers in a short span of five years that we observe can be attributed to the disruptive effect of Chinese imports on the informal sector. The institution of contract labor enabled the reallocation despite large formal firms in India facing stringent EPLs. Further, the observed reallocation of labor is within an industry, rather than across industries. It is plausible that reallocation across the sectors within an industry is likely to be smoother than cross industry reallocation where the mobility costs could be potentially higher.

While we document an increase in the aggregate share of formal employment in response to Chinese import competition, disentangling the strengths of the extensive margins (exit of informal firms) and intensive margins (changes in formal to informal enterprise employment ratio) is not feasible due to data constraints. Identifying the role of different margins of adjustments in response to import competition remains a fruitful area for future research when such data become available.

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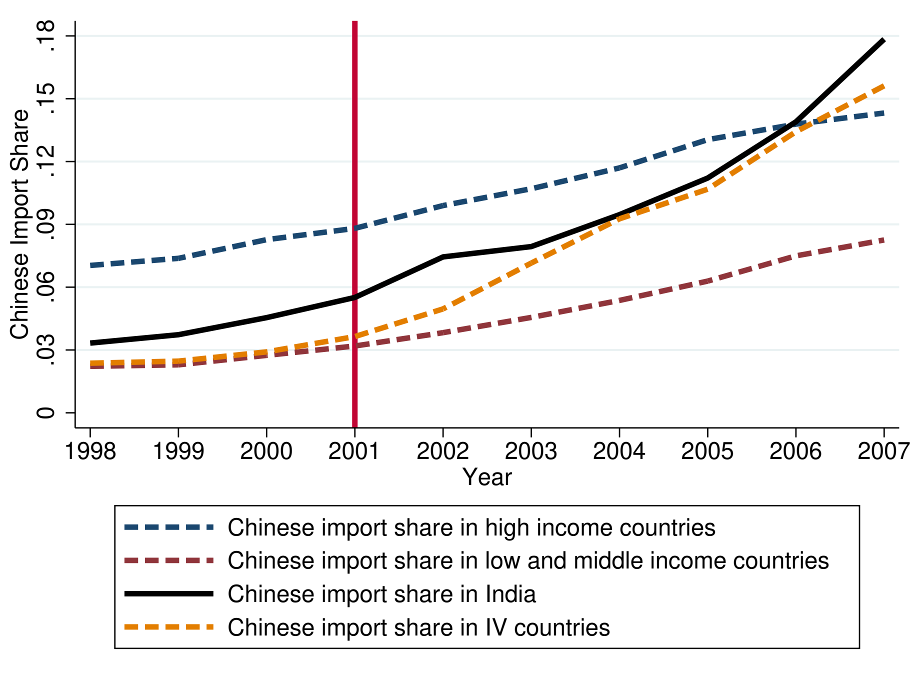
Figure 1: Chinese Import Share in India and Different Country Groups



Note: Chinese import share to a particular country is the ratio of imports from China in that country to all imports in that country. Data are sourced from the UN-COMTRADE database.

Table 1: Summary Statistics

	Formal Sector			Informal Sector		
	Observations	Mean	SD	Observations	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Firm Level Surveys (2000-2001)						
Revenue ('000 INR)	29,550	83,159.95	1,026,358	216,232	100	1,010
Workers	29,550	67.94	402.55	216,232	2.11	1.71
Contract workers	29,550	10.63	238.64	-	-	-
Regular workers	29,550	41.66	228.27	-	-	-
Compensation (Annual, '000 INR)	29,550	21.69	16.27	72131	10.43	9.90
Regular compensation (Annual, '000 INR)	28,269	32.19	25.59	-	-	-
Contract compensation (Annual, '000 INR)	7,058	25.36	18.68	-	-	-
Panel B: Worker Level Survey(1999-2000)						
Below Primary	4,729	0.23	0.42	11,750	0.44	0.5
Below Secondary	4,729	0.3	0.46	11,750	0.35	0.48
Secondary and above	4,729	0.47	0.5	11,750	0.21	0.41
Rural	4,729	0.3	0.46	11,750	0.42	0.49
Unmarried	4,729	0.22	0.41	11,750	0.21	0.41
Female	4,729	0.14	0.34	11,750	0.27	0.44
Disadvantaged social groups	4,729	0.51	0.5	11,750	0.62	0.48
Minority	4,729	0.17	0.38	11,750	0.28	0.45
Age	4,729	35.23	10.91	11,750	34.7	11.5

Note: Panel A describes the firm level characteristics of the formal (columns 1-3) and informal (columns 4-6) enterprises. The firm level data are sourced from Annual Survey of Industries and the National Sample Survey's unorganized sector surveys (ASI-NSS) for the formal and informal sectors, respectively, for the year 2000-2001. Revenue and annual compensation are in thousands of Indian Rupees. Panel B describes the worker characteristics for workers employed in the formal (columns 1-3) and informal (columns 4-6) enterprises. The worker level data are sourced from the NSS employment unemployment survey (EUS) for the year 1999-2000. All variables, except age, are binary variables in Panel B.

Table 2: Within and Between Industry Decomposition of Change in Employment Shares

	Share in 2000	Share in 2005	Change between 2000-2005		
			Total	Within	Between
	(1)	(2)	(3)	(4)	(5)
Formal Share in Employment	0.1407	0.1701	0.0294	0.0248	0.0046
Contract Share in Employment	0.0287	0.0484	0.0197	0.0175	0.0022
Regular Share in Employment	0.1119	0.1217	0.0098	0.0073	0.0024

Notes: The table reports decomposition of the overall change in employment into the within industry and between industry components for the share of formal workers, contract workers, and regular workers in total industry employment between 2000-2001 and 2005-2006. We use data from the Annual Survey of Industries, and NSS's unorganized sector surveys.

Table 3: Chinese Import Competition and Employment: State-industry Level Analysis

	Share in total employment	Log Employment				
		Total	Informal	Formal		
	Formal			Total	Regular	Contract
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS						
Chinese Import Competition (IMP)	1.059**	–6.740**	–12.63***	4.420*	3.000	10.38**
	(0.497)	(3.010)	(2.080)	(2.343)	(1.846)	(4.503)
Panel B: IV						
Chinese Import Competition (IMP)	1.393***	–7.928*	–14.83***	3.881*	2.875*	10.03**
	(0.401)	(4.251)	(3.886)	(2.226)	(1.711)	(4.433)
F-stat	225.77	225.77	480.52	176.28	176.28	176.28
Alternative Trade Channels	Yes	Yes	Yes	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
3-digit-industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,702	3,702	3,182	2,912	2,912	2,912

Note: Analysis is conducted at the 4-digit state-industry-year level. We use Annual Survey of Industries (ASI) to measure formal employment and the NSS's unorganized sector surveys to measure informal employment. We use surveys conducted in 2000-2001 and 2005-2006. In the IV specifications, Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries, and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. Regressions are weighted by total employment (column 1 and 2), informal employment (column 3), and formal employment (columns 4, 5, and 6) in the state-industry in the year 2000-2001. F-stat denotes Kleibergen-Paap first stage F-statistics. Robust standard errors clustered at the 3-digit industry level in parentheses. *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%..

Table 4: Chinese Import Competition and Employment: Worker Level Analysis

	Indicator for Employment in Formal Enterprise					
	(1)	(2)	(3)	(4)	(5)	(6)
Chinese Import Competition (IMP)	0.554***	0.551***	0.510***	0.534***	0.498***	0.457***
	(0.177)	(0.109)	(0.128)	(0.177)	(0.116)	(0.134)
Estimation Method	OLS	OLS	OLS	IV	IV	IV
F-stat	-	-	-	590.87	594.10	615.03
Worker Characteristics	No	Yes	Yes	No	Yes	Yes
Worker Characteristics × Year=2004	No	No	Yes	No	No	Yes
Alternative Trade Channels	Yes	Yes	Yes	Yes	Yes	Yes
3-digit-industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,017	36,017	36,010	36,017	36,017	36,010

Note: The NSS employment-unemployment (EUS) survey for the years 1999-2000 and 2004-2005 are used for analysis. Worker characteristics include age and its squared, marital status indicator, female indicator, education status, rural residence indicator, religious minority status indicator, and disadvantaged social category indicator. In the IV specifications, Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. All regressions are weighted using sample weights from the EUS survey. F-stat denotes Kleibergen-Paap first stage F-statistics. Robust standard errors clustered at the 3-digit industry level in parentheses; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Table 5: The Role of Institutions

	Indicator for Employment in Formal Enterprise				Formal Share in Total Employment				Contract Share in Total Employment			
	Unionization		Labor Laws		Unionization		Labor Laws		Unionization		Labor Laws	
	High	Low	PW==1	PW==0	High	Low	PW==1	PW==0	High	Low	PW==1	PW==0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Chinese Import Competition (IMP)	0.647***	0.351	1.197**	0.186	3.157***	0.185	2.805***	1.329	1.567***	-0.349	1.628**	0.0955
	(0.217)	(0.342)	(0.552)	(0.160)	(0.803)	(0.807)	(0.943)	(0.819)	(0.479)	(0.435)	(0.799)	(0.481)
Data Source	EUS	EUS	EUS	EUS	ASI-NSS	ASI-NSS	ASI-NSS	ASI-NSS	ASI-NSS	ASI-NSS	ASI-NSS	ASI-NSS
Estimation Method	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
F-stat	637.81	710.88	1024.25	618.20	444.01	73.31	175.95	162.19	444.01	73.31	175.95	162.19
Worker Characteristics	Yes	Yes	Yes	Yes	-	-	-	-	-	-	-	-
Alternative Trade Channels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3-digit-industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,141	16,062	7,916	24,836	1,590	1,174	472	2,024	1,590	1,174	472	2,024

Note: The outcome variable in columns (1)-(4) is an indicator variable for employment in a formal enterprise based on the Employment-Unemployment survey (EUS) data (years 1999-2000 and 2004-2005). The outcome variable in columns (5)-(8) and columns (9)-(12) is the share of formal and contract employment in total employment, respectively, and are based on the Annual Survey of Industries (ASI) and unorganized sector surveys (NSS) (years 2000-2001 and 2005-2006). Worker characteristics include age and its squared, marital status indicator, female indicator, education status, rural residence indicator, religious minority status indicator, and disadvantaged social category indicator. Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. Regressions are weighted by the sample weights from EUS survey in columns 1-4, by total employment in the state-industry in columns 5-12. High unionization states and low unionization states are defined respectively based on the unionization index defined by Dougherty (2009), and are classified based on above- and below- median values of the index, respectively. PW = 1 indicates pro-worker states, and PW = 0 indicates non-pro-worker states as per the definition by Besley and Burgess (2004). F-stat denotes Kleibergen-Paap first stage F-statistics. Robust standard errors clustered at the 3-digit industry level in parentheses; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Table 6: Chinese Import Competition and Formal Employment: Firm Level Analysis

	Log Total workers	Log Regular workers	Log Contract workers	Contract worker ratio	Log Total workers	Log Regular workers	Log Contract workers	Contract worker ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chinese Import Competition (IMP)	0.102**	–0.035	0.244***	0.057***	0.200***	0.078	0.345***	0.053***
	(0.047)	(0.040)	(0.075)	(0.012)	(0.071)	(0.060)	(0.109)	(0.018)
Estimation Method	OLS	OLS	OLS	OLS	IV	IV	IV	IV
F-stat					15.54	15.54	15.54	15.54
Alternative Trade Channels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factory FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3-digit Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	196,956	196,956	196,956	196,956	196,956	196,956	196,956	196,956

Note: Analysis uses the Annual Survey of Industries (formal sector survey) at the establishment level for the years 1998-1999 to 2007-2008. In the IV specifications, Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. All regressions are weighted by the sample weights in the ASI survey. F-stat denotes Kleibergen-Paap first stage F-statistics. Robust standard errors clustered at the 4-digit industry level in parentheses; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Table 7: Chinese Import Competition and Employment: Heterogeneity based on Initial Labor Productivity

	Log Total workers	Log Regular workers	Log Contract workers	Contract worker ratio
	(1)	(2)	(3)	(4)
Chinese Import Competition (IMP)	–0.684***	–0.558***	–0.515**	–0.076
	(0.175)	(0.190)	(0.231)	(0.057)
IMP × Qr_2	0.415***	0.286	0.300	0.055
	(0.120)	(0.204)	(0.217)	(0.059)
IMP × Qr_3	0.736***	0.647***	0.337	0.052
	(0.130)	(0.158)	(0.335)	(0.075)
IMP × Qr_4	1.624***	1.088***	1.951***	0.284***
	(0.296)	(0.280)	(0.321)	(0.072)
Estimation Method	IV	IV	IV	IV
SW F-stat (IMP)	142.34	142.34	142.34	142.34
SW F-stat ($IMP \times Q_{r2}$)	319.91	319.91	319.91	319.91
SW F-stat ($IMP \times Q_{r3}$)	362.68	362.68	362.68	362.68
SW F-stat ($IMP \times Q_{r4}$)	227.49	227.49	227.49	227.49
Alternative Trade Channels	Yes	Yes	Yes	Yes
Factory FE	Yes	Yes	Yes	Yes
3-digit Industry × Year FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes	Yes
Observations	196,956	196,956	196,956	196,956

Note: Analysis uses the ASI data (formal sector firms) at the establishment level for the years 1998-1999 to 2007-2008. Qr_i is an indicator variable which is equal to 1 if a firm belongs to the i^{th} quartile of the productivity distribution when it first enters our sample. We calculate firm level labor productivity as revenue per employee. Chinese imports to India, and its interaction with the quartile indicator variables are instrumented with Chinese imports into a set of ten Latin American countries (Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela) and their corresponding interaction with quartiles. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. All regressions are weighted by the sample weights in the ASI survey. SW F-stat denotes Sanderson-Windmeijer first stage F-statistics. Robust standard errors clustered at the 4-digit industry level in parentheses; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Table 8: Decomposition of Effect of Chinese Import Competition on Industry Labor Productivity

	Labor Productivity		
	Overall Effect	Covariance	Mean
	(1)	(2)	(3)
Chinese Import Competition (IMP)	7.305***	7.981***	4.558
	(2.477)	(2.322)	(3.739)
Estimation method	IV	IV	IV
F-stat	143.30	143.30	143.30
Alternative Trade Channels	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
3-digit-industry × Year FE	Yes	Yes	Yes
Observations	108	108	108

Note: Analysis is conducted at the 4-digit industry-year level. Data sources are the Annual Survey of Industries (ASI) and the NSS unorganized sector surveys in 2000-2001 and 2005-2006. Labor productivity is defined as revenue per worker. We decompose aggregate labor productivity using the Olley-Pakes decomposition using employment share as weights. Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. Regressions are weighted by total employment in the industry in the year 2000-2001. F-stat denotes Kleibergen-Paap first stage F-statistics. Robust standard errors clustered at the 3-digit industry level in parentheses. ***, **, * is statistical significance at 1%, 5%, and 10%, respectively.

Table 9: Productivity Gap Between Formal and Informal Enterprises

	Revenue Productivity Gap	Wage Gap
	(1)	(2)
A. Unadjusted	10.95	3.12
B. Adjusted for:		
(1) Hours Worked	5.09	1.45
(2)= (1)+Human Capital Differences	3.77	1.07
(3) = (2)+Differences in Prices	2.18	-
(4)= (3)+Measurement Error in Revenue	1.53	-
(5)= (4)+Difference in Output Elasticity	1.24	-
Productivity Gains(%):		
Using Estimates in (2)	4.62	0.25
Using Estimates in (3)	2.87	
Using Estimates in (5)	0.80	

Note: The table reports the labor productivity gap between the formal and informal enterprises, where labor productivity is measured by revenue per worker in column 1, and earnings per worker in column 2. These calculations use data from the Annual Survey of Industries for the formal sector, and data from the NSS's unorganized enterprises survey for the informal sector for the years 2000-2001 and 2005-2006.

Appendix A

We define the construction of variables used in the analysis below. We define the downstream effect of exposure to Chinese import competition as follows:

$$IMP\_DS_{jt}^{China} = \sum_{s} \alpha_{js} \cdot IMP_{st}^{China} \tag{A.1}$$

where α_{js} is the share of input s in the total output for industry j, and IMP_{st}^{China} is the import penetration ratio for input sector s. Thus, the measure captures the exposure of input industries to industry j to Chinese imports. To obtain this measure for each industry, we used the input-output (IO) table for India for the year 1993-94 (Ministry of Statistics and Programme Implementation, 2000). Input s in Equation (A.1) refers to a sector in this IO table. This input-output table is an $n \times n$ matrix of IO sectors. For each IO sector s in each row, the columns give the share of other IO sectors which are used as inputs, which are represented by α_{js} in Equation (A.1). Using IMP_{jt}^{China} for industry j from (1), we use a simple mapping between industries (j) and the IO sectors (s), to obtain a measure of IMP_{st}^{China} for each IO sector s. This then feeds into Equation (A.1). We instrument for downstream effect of import exposure from China, given by:

$$IVIMP\_DS_{jt}^{China} = \sum_{s} \alpha_{js} \cdot IV_{st}^{China} \tag{A.2}$$

where the instrument is the weighted average of the instrument for import penetration ratio calculated for the input sector s similar to (A.1) above. IV_{st}^{China} is the instrumental variable for import penetration ratio defined in Equation 2.

Similarly, we measure the upstream effect of exposure to Chinese import competition as follows:

$$IMP\_US_{jt}^{China} = \sum_{s} \delta_{js} \cdot IMP_{st}^{China} \tag{A.3}$$

where δ_{js} is the share of sales from industry j in the total output for purchasing sector s, and IMP_{st}^{China} is the import penetration ratio for purchasing sector s. Thus, the measure captures the exposure of buyers of industry j to Chinese import competition. To obtain this measure for each industry, we used the input-output (IO) table for India for the year 1993-94 (Ministry of Statistics and Programme Implementation, 2000).

We also instrument for $IMP\_US_{jt}^{China}$, which is given by:

$$IVIMP\_US_{jt}^{China} = \sum_{s} \delta_{js} \cdot IV_{st}^{China} \tag{A.4}$$

where the instrument is the weighted average of the instrument for import penetration ratio calculated for the purchasing sector s. IV_{st}^{China} is the instrumental variable for import penetration ratio defined in Equation 2.

We proxy for Chinese import competition in foreign markets by Chinese import share in these markets given by the following equation:

$$IS_{jt}^{China,F} = \frac{M_{jt}^{China,F}}{M_{jt}^{World,F}} \tag{A.5}$$

where $IS_{jt}^{China,F}$, $M_{jt}^{China,F}$, and $M_{jt}^{World,F}$ are Chinese import share in the foreign market, imports from China to the foreign market, and total world imports to the foreign markets in industry j and time t respectively. Foreign market, F, is either the set of low and middle income economies except China or the set of high income countries.

We compute the import penetration from other countries into India using Equation (1), where we replace Chinese imports with imports from the set of low and middle income countries (excluding China) or the high income countries. Finally, we use Indian exports to the set of IV countries as a share of total exports from India as a control variable.

Appendix B

Table B1: Chinese Import Competition and Employment: State-Industry Level Analysis, Robustness Checks

	Formal Share in total employment				
	(1)	(2)	(3)	(4)	(5)
Chinese Import Competition (IMP)	1.384***	1.393***	1.204***	1.592***	1.233***
	(0.412)	(0.470)	(0.230)	(0.396)	(0.292)
Downstream Effect (IMP_DS)					–1.897
					(6.767)
Upstream Effect (IMP_US)					–2.091
					(2.079)
Estimation Method	IV	IV	IV	IV	IV
F-stat (IMP)	264.23	251.89	206.50	366.56	97.69
F-stat (IMP_DS)	-	-	-	-	15.34
F-stat (IMP_US)	-	-	-	-	24.19
Alternative Trade Channels	Yes	Yes	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No
3-digit-industry × Trend	Yes	No	No	No	No
3-digit-industry × Year FE	No	Yes	Yes	Yes	Yes
State × Year FE	No	Yes	Yes	Yes	Yes
Two way cluster at 3-digit industry and state	No	Yes	No	No	No
Control for Dereservation	No	No	Yes	No	No
Trends in State and Industry Characteristics	No	No	No	Yes	No
Observations	3,702	3,702	3,702	2,502	3,702

Note: Analysis is conducted at the 4-digit state-industry-year level. We use Annual Survey of Industries (ASI) to measure formal employment and the NSS unorganized sector surveys to measure informal employment. We use surveys conducted in 2000-2001 and 2005-2006. Chinese imports to India is instrumented with Chinese imports into a set of 10 Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. Regressions are weighted by total employment in the state-industry in the year 2000-2001. In column 3, we interact quartiles of formal share in total employment in 2000, and indicator variables for high unionization states and pro-worker states with a linear time trend. F-stat denotes Kleibergen-Paap first stage F-statistics in columns 1-3 and Sanderson-Windmeijer first stage F statistic in column 4. Robust standard errors clustered at the 3-digit industry level in parentheses. ***, **, * is statistical significance at 1%, 5%, and 10%, respectively.

Table B2: Chinese Import Competition and Employment: Industry Level Analysis

	Share in total employment	Log Employment				
		Total	Informal	Formal		
	Formal			Total	Regular	Contract
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS						
Chinese Import Competition (IMP)	2.868***	–4.834	–12.52***	4.002*	2.204	8.490*
	(0.242)	(3.299)	(3.343)	(2.259)	(1.795)	(4.162)
Panel B: IV						
Chinese Import Competition (IMP)	3.004***	–5.330	–13.76***	3.623	1.884	8.000
	(0.411)	(3.945)	(4.256)	(2.209)	(1.612)	(4.596)
F-stat	216.83	216.83	447.91	160.04	160.04	160.04
Alternative Trade Channels	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
3-digit-industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	110	110	110	110	110	110

Note: Analysis is conducted at the 4-digit industry-year level. We use Annual Survey of Industries (ASI) to measure formal employment, and the NSS unorganized sector surveys to measure informal employment. We use surveys conducted in 2000-2001 and 2005-2006. Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. All regressions are weighted by the industry employment in the year 2000-2001. F-stat denotes Kleibergen-Paap first stage F-statistics. Robust standard errors clustered at the 3-digit industry level in parentheses; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Table B3: Chinese Import Competition and Reallocation of Production

	Log(Number of Factories)		Log(Sales)	
	Informal	Formal	Informal	Formal
	(1)	(2)	(3)	(4)
Chinese Import Competition (IMP)	–12.86*	1.847	–6.179	–0.543
	(6.468)	(1.201)	(5.925)	(1.812)
Estimation Method	IV	IV	IV	IV
F-stat	447.91	160.04	447.91	160.04
Alternative Trade Channels	Yes	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes	Yes
3-digit-industry × Year FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
Observations	110	110	110	110

Note: Analysis is conducted at the 4-digit industry-year level. We use Annual Survey of Industries (ASI) and the NSS unorganized sector surveys to measure number of factories and sales for the formal and informal sector, respectively. We use surveys conducted in 2000-2001 and 2005-2006. In the IV specifications, Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. Regressions are weighted by total employment in the industry in the year 2000-2001. F-stat denotes Kleibergen-Paap first stage F-statistics. Robust standard errors clustered at the 3-digit industry level in parentheses. ***, **, * is statistical significance at 1%, 5%, and 10%, respectively.

Table B4: Chinese Import Competition and Employment: District Level

	Log(Employment)			
	Overall	Manufacturing	Services	Agriculture
	(1)	(2)	(3)	(4)
Chinese Import Competition (IMP)	–11.92 (18.14)	–39.73** (19.24)	–13.95 (20.04)	11.05 (23.41)
Estimation Method	IV	IV	IV	IV
F-stat	142.07	142.01	141.51	141.72
Alternative Trade Channels	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	932	924	896	930

Note: The NSS employment-unemployment survey for the years 1999-2000 and 2004-2005 are used for analysis. Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include import penetration from high income countries, and low and middle income countries. All regressions are weighted by the initial employment share of the district in overall employment. F-stat denotes Kleibergen-Paap first stage F-statistics. Robust standard errors clustered at the district level in parentheses; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Table B5: Chinese Import Competition and Formal Sector Employment: Worker Level Analysis, Robustness Checks

	Indicator for Employment in Formal Enterprise					
	(1)	(2)	(3)	(4)	(5)	(6)
Chinese Import Competition (IMP)	0.519***	0.457***	0.455***	0.505**	0.381**	0.408**
	(0.112)	(0.123)	(0.154)	(0.198)	(0.151)	(0.155)
Downstream Effect (IMP_DS)						12.57
						(14.99)
Upstream Effect (IMP_US)						–7.570
						(8.793)
Estimation Method	IV	IV	IV	IV	IV	IV
F-stat (IMP)	573.23	662.97	746.33	1458.37	624.72	795.16
F-stat (IMP_DS)	-	-	-	-	-	18.64
F-stat (IMP_US)	-	-	-	-	-	130.94
Worker Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Worker Characteristics × Year=2004	No	Yes	Yes	Yes	Yes	Yes
Alternative Trade Channels	Yes	Yes	Yes	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No
3-digit-industry × Trend	Yes	No	No	No	No	No
3-digit-industry × Year FE	No	Yes	Yes	Yes	Yes	Yes
State × Year FE	No	Yes	Yes	Yes	Yes	Yes
Two way cluster at 3-digit industry and state	No	Yes	No	No	No	No
Control for Dereservation	No	Yes	No	No	No	No
Trends in State and Industry Characteristics	No	No	Yes	No	No	No
Alternative Criteria for Informality	No	No	No	Yes	No	No
Observations	36,010	36,010	36,010	32,750	35,583	36,010

Note: The analysis uses the NSS Employment-Unemployment survey (EUS) for the years 1999-2000 and 2004-2005. Worker characteristics include age and its squared, marital status indicator, female indicator, education status, rural residence indicator, religious minority status indicator, and disadvantaged social category indicator. Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. In column 3, we interact quartiles of formal share in total employment in 2000, and indicator variables for high unionization states and pro-worker states with a linear time trend. Column 4 defines informal workers using the size threshold in the Factories Act, 1948 irrespective of the registration status of the enterprises. All regressions are weighted using sample weights from the EUS survey. F-stat denotes the Kleibergen-Paap first stage F statistic in columns 1-4 and Sanderson-Windmeijer first stage F-statistics in column 5. Robust standard errors in parentheses are clustered two way at the 3-digit industry and state in column 1 and at the 3-digit industry level in columns 2-5; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Table B6: Chinese Import Competition and Formal Sector Employment: Heterogeneity Based on Worker Characteristics

	Indicator for Employment in Formal Enterprise							
	Age<=30	Age:30-45	Age>45	Lower than Primary Education	Below Secondary Education	Secondary and Higher Education	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Chinese Import Competition (IMP)	0.517**	0.737***	0.554	0.230	0.618**	0.326	0.204	1.003***
	(0.200)	(0.242)	(0.372)	(0.346)	(0.253)	(0.258)	(0.504)	(0.201)
Estimation Method	IV	IV	IV	IV	IV	IV	IV	IV
F-stat	573.37	669.87	628.66	2938.97	964.29	182.73	950.38	325.05
Worker Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Alternative Trade Channels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3-digit-industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,987	14,058	7,196	13,000	12,814	9,488	15,927	19,741

Note: The NSS employment-unemployment survey for the years 1999-2000 and 2004-2005 are used for analysis. Worker characteristics include age and its squared, marital status indicator, female indicator, education status, rural residence indicator, religious minority status indicator, and disadvantaged social category indicator. Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. All regressions are weighted by the sample weights in the NSS survey. F-stat denotes Kleibergen-Paap first stage F-statistics. Robust standard errors clustered at the 3-digit industry level in parentheses; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Table B7: Chinese Import Competition and Production in Formal Sector: Firm-Product Level

	Log(Sales)	Log(Quantity)	Log(Unit Value)
	(1)	(2)	(3)
Chinese Import Competition (IMP)	0.097	1.461***	–1.364***
	(0.171)	(0.373)	(0.316)
F-stat	15.33	15.33	15.33
Alternative Trade Channels	Yes	Yes	Yes
Factory FE	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes
3-digit-industry × Year FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Observations	319,020	319,020	319,020

Note: Analysis is conducted at the firm-product level using the Annual Survey of Industries (ASI) panel data between 1998-1999 and 2007-2008. In the IV specifications, Chinese imports to India is instrumented with Chinese imports into a set of ten Latin American countries — Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. Regressions are weighted by the sample weights in the ASI survey. F-stat denotes Kleibergen-Paap first stage F-statistics. Robust standard errors clustered at the 4-digit industry level in parentheses. ***, **, * is statistical significance at 1%, 5%, and 10%, respectively.

Table B8: Chinese Import Competition and Employment: Heterogeneity based on Initial Total Factor Productivity (TFP)

	Log Total workers	Log Regular workers	Log Contract workers	Contract worker ratio
	(1)	(2)	(3)	(4)
Chinese Import Competition (IMP)	0.102	0.122	0.188	–0.006
	(0.102)	(0.104)	(0.138)	(0.024)
IMP × Qr_2	–0.022	-0.111	0.0523	0.040
	(0.108)	(0.116)	(0.142)	(0.030)
IMP × Qr_3	0.215	–0.043	0.340*	0.111**
	(0.169)	(0.193)	(0.201)	(0.050)
IMP × Qr_4	0.259*	–0.020	0.292	0.107***
	(0.131)	(0.115)	(0.178)	(0.032)
Estimation Method	IV	IV	IV	IV
SW F-stat (IMP)	70.62	70.62	70.62	70.62
SW F-stat ($IMP \times Q_{r2}$)	42.01	42.01	42.01	42.01
SW F-stat ($IMP \times Q_{r3}$)	36.31	36.31	36.31	36.31
SW F-stat ($IMP \times Q_{r4}$)	33.03	33.03	33.03	33.03
Alternative Trade Channels	Yes	Yes	Yes	Yes
Factory FE	Yes	Yes	Yes	Yes
3-digit Industry × Year FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes
State × Industry FE	Yes	Yes	Yes	Yes
Observations	196,956	196,956	196,956	196,956

Note: Analysis uses the ASI data (formal sector firms) at the establishment level for the years 1998-1999 to 2007-2008. Qr_i is an indicator variable which is equal to 1 if a firm belongs to the i^{th} quartile of the productivity distribution when it first enters our sample. We calculate TFP using the methodology of Ackerberg et al. (2015). To estimate TFP, we use output and input deflators from Allcott et al. (2016) and capital deflators from Reserve Bank of India (RBI) publications. Chinese imports to India, and its interaction with the quartile indicator variables are instrumented with Chinese imports into a set of ten Latin American countries (Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela) and their corresponding interaction with quartiles. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. All regressions are weighted by the sample weights in the ASI survey. SW F-stat denotes Sanderson-Windmeijer first stage F-statistics. Robust standard errors clustered at the 4-digit industry level in parentheses; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Table B9: Heterogeneous effects on fixed assets based on Initial Labor Productivity

	Log(Fixed Assets)
Chinese Import Competition (IMP)	0.256
	(0.290)
IMP × Qr_2	0.0222
	(0.204)
IMP × Qr_3	0.198
	(0.205)
IMP × Qr_4	0.645***
	(0.182)
Estimation Method	IV
SW F-stat (IMP)	142.34
SW F-stat ($IMP \times Q_{r2}$)	319.91
SW F-stat ($IMP \times Q_{r3}$)	362.68
SW F-stat ($IMP \times Q_{r4}$)	227.49
Alternative Trade Channels	Yes
Factory FE	Yes
3-digit Industry × Year FE	Yes
State × Year FE	Yes
State × Industry FE	Yes
Observations	196,956

Note: Analysis uses the ASI data (formal sector firms) at the establishment level for the years 1998-1999 to 2007-2008. Qr_i is an indicator variable which is equal to 1 if a firm belongs to the i^{th} quartile of the labor productivity distribution (revenue per employee) when it first enters our sample. Fixed assets are measured as the gross value of capital in the beginning of the year. Chinese imports to India, and its interaction with the quartile indicator variables are instrumented with Chinese imports into a set of ten Latin American countries (Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, Paraguay, Peru, Uruguay, and Venezuela) and their corresponding interaction with quartiles. Alternative trade channels include output and input tariffs, import penetration from high income countries and low and middle income countries, Chinese import share in high income countries, Chinese import share in low and middle income countries, and India's export share in the total exports to the set of Latin American countries used to create the instrument. All regressions are weighted by the sample weights in the ASI survey. SW F-stat denotes Sanderson-Windmeijer first stage F-statistics. Robust standard errors clustered at the 4-digit industry level in parentheses; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Table B10: Wage Difference Between Formal and Informal Workers: Worker-Level Analysis

	Log(wages)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Indicator for Formal Employment	0.314***	0.273***	0.241***	0.245***	0.293***	0.209***	0.192***
	(0.042)	(0.039)	(0.038)	(0.031)	(0.041)	(0.030)	(0.029)
Controls:							
Years of Education	-	Yes	-	-	-	Yes	-
Education Categories	-	-	Yes	-	-	-	Yes
Demographic Characteristics	-	-	-	Yes	-	Yes	Yes
Location	-	-	-	-	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	-	-	-	-	Yes	Yes	Yes
Observations	8,888	8,888	8,888	8,888	8,888	8,888	8,888

Note: The analysis uses the NSSO's employment-unemployment survey at the worker-level for the years 1999-2000 and 2004-2005. Daily wages, the outcome variable are reported by the workers based on a 7-day recall period, and are calculated based on earnings in the last week and the number of half-days worked in the last week. Education categories include below primary (omitted), below secondary, and secondary and higher. Years of education for a worker is derived from the standard number of years taken to complete each level of education. Demographic characteristics for workers include age and its squared, marital status indicator, female indicator, rural residence indicator, religious minority status indicator, and disadvantaged social category indicator. All regressions are weighted by the sample weights in the NSSO survey. Robust standard errors clustered at the 4-digit industry level in parentheses; *** - statistical significance at 1%; **- statistical significance at 5%; *- statistical significance at 10%.

Appendix C: Labor Productivity Gap

C1 Calculating the Unadjusted Productivity Gap

Using Equation 10 in the main text, we calculate labor productivity gap using both revenue per worker and wages using data from the ASI-NSS firm level surveys. For calculating revenue per worker, we aggregate revenue and employment for all firms in each sector and take the ratio. The productivity gap is then given by the ratio of revenue per worker between the formal and informal sector. We perform similar calculations to get the wage gap. We sum up the total compensation paid to employees as well the number of employees for each sector and take the ratio to arrive at the average wage per worker in a sector. We take the ratio of the average wage for the formal and informal sector to get the wage gap across the two sectors.

C2 Adjusting for Differences in Hours Worked

A major concern with the observed labor productivity gap is that it may be driven by differences in average number of hours worked across the two sectors. If informal workers on average work fewer hours, we would overestimate the labor productivity gap. To adjust the gap based on these differences, we indirectly infer the total number of hours worked for workers in each sector. For the informal sector, we utilize availability of information on average number of hours worked per day and the number of months in operation for the enterprise. However since this information is only available for the 2005 round of the NSS survey, we use the ASI-NSS 2005 round to measure differences in hours worked across the two sectors. We assume that the average number of hours worked across the two sectors does not change significantly across the two sectors between the two rounds.

We calculate the total number of hours worked by all employees for each firm as:

$$H_i = 30 \times n \times h_i$$

where n is number of months in operation, and h_i is average number of hours worked per day as reported by the firm. For the formal sector, we utilize data on number of mandays for each firm in that year. We calculate the total number of hours worked for each formal sector firm as $H_f = 8 \times mandays$, assuming a 8 hour working shift for the formal firms. We sum H_i and H_f across all firms to arrive at the total number of hours worked for the informal and formal sector, respectively. Next, we adjust the raw productivity and wage gap by dividing the ratio of employees to the ratio of hours worked across the two sectors. Our estimates provide an adjustment factor of 2.15 suggesting that differences in hours worked account for a significant portion of the large unadjusted productivity gap.

C3 Adjusting for Difference in Human Capital

There may be significant differences in the human capital for workers in the two sectors that may lead to overestimation of the productivity gap. To account for this heterogeneity, we follow Gollin et al. (2014), who adjust for differences in average years of education across the agriculture and non-agriculture sectors, and compute average human capital in a sector as $e^{r \times ed_s}$ where r is the rate of return on each year of education and ed_s is the average years of education in each sector s. The EUS worker level survey provides details about the education level of each worker but does not report the years of education. We infer the years of education for each worker based on the level of education qualification using the standard number of years required to complete that level of education in the Indian education system. We assign 5 years to primary education, 8 years to middle, 10 years to secondary, 12 years to higher secondary, and 15 years to undergraduate and above. We assume a rate of return of 10% for each year of education following Gollin et al. (2014). Using the above approach, we estimate that the average human capital in formal sector is 1.35 times that in the informal sector.

C4 Adjusting for Difference in Prices

The labor productivity gap, as measured by revenue per unit labor, may reflect differences in demand shocks and markup in addition to the true labor productivity gap. The ASI-NSS data is unique in that we observe sales and quantity produced for all products (upto 10 products) produced by each firm. Firms producing more than 10 products report revenue from all products but do not specify the quantities for some products. Thus, we restrict our sample to firms that produce 10 or fewer products.

These surveys assign each product produced by the firm to a 5 digit ASICC product code. Our approach for correcting for price differences involves comparing average prices across the two sectors. We start by calculating the firm level prices (unit values) by dividing the firm product sales by quantity produced. Then we calculate the firm level prices as the sales share weighted sum of firm product level prices. Next, we calculate the real sales of a firm as the nominal sales deflated by the firm level prices calculated above. We divide the nominal sales per worker gap between the formal and informal sectors to the real sales per worker gap to arrive at a correction factor of 1.73. We adjust the labor productivity gap by this factor and report the adjusted gap in row (3) of Table 9. The labor productivity gap in column 1 drops from 3.77 to 2.18 due to this adjustment, suggesting that there are significant differences in average firm-level prices across the two sectors. Ignoring these price differences would have greatly overestimated the labor productivity gap between the two sectors.

We also follow an alternative procedure to adjust for price differences across the two sectors and find similar results. We utilize the availability of information on physical quantities at the firm product level and calculate the physical quantity per worker for both sectors. We allocate workers to each firm-product in proportion to the revenue share of the firm product in total firm revenues. Then we take the ratio of revenue per worker gap to quantity per worker gap in each product category to arrive at the adjustment factor. Note that we need the quantity to be reported in same units across firms to be able to perform this calculation. Thus, this calculation is based on a subset of 1600 product lines for which both formal and informal sector datasets report quantities in the same units. We take a sales share weighted sum of the product level adjustment factor and arrive at the overall adjustment factor for differences in prices. The calculations suggest an adjustment factor of 1.67.