The China Shock in India: Input Linkages and Output Competition*

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Abstract

This paper studies how the impact of a trade shock depends on a country's production structure and its position in the global supply chain. I decompose the effect of the China Shock on Indian manufacturing into two channels - direct output competition and higher intermediate input availability. The input channel dominates, in part because Indian manufacturers were predominantly buyers of Chinese intermediates rather than competitors in final-goods markets at the time of the shock. Using district-level data and a shift-share IV methodology, I find that a 1 standard deviation higher exposure to Chinese inputs per worker slows the decline of the manufacturing employment share by 0.62 percentage points. Within manufacturing sub-sectors, the direct competition effect is associated with a lower share of intermediate goods employment and leads to a reallocation of employment toward consumer goods sectors. I quantify aggregate welfare and employment effects using a quantitative trade model with input-output linkages in production and state-level geography. The model implies higher welfare gains in industrial states that were more reliant on Chinese intermediate inputs.

Keywords: Local Labor Markets, Input Output Linkages, General Equilibrium, Shift Share, International Trade
JEL codes: D57, F16, O14, R13, R15

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1 Introduction

The impact of the China Shock, following China's accession to the WTO in 2001, has been extensively studied since the seminal paper by Autor et al. (2013) (henceforth, ADH). Across a range of economies, local labor markets exposed to the shock have witnessed declines in manufacturing employment shares, in large part due to the competition that domestic manufacturing producers faced from Chinese imports, which grew exponentially after the China Shock. This paper estimates and quantifies the impact of the China Shock on India. Using the identification strategy and methodology of ADH, I study the impact of the shock on manufacturing employment shares across Indian districts, and find that contrary to the US, more exposed labor markets saw a slower decline in manufacturing employment shares. Figure 1 supports this finding by comparing manufacturing employment trends between India and the US during the period of the China Shock and beyond. While Chinese import penetration grew more sharply in India relative to the US, the share of manufacturing in aggregate employment did not decline in the same manner as the US.

One reason for this difference could be that while imports from China grew around the world, there was substantial variation in the composition of these imports as seen in Figure 2. Based on the classification of commodities into broad economic categories defined by end use in Nations (2002)'s BEC Rev. 4, between 2000-2011, Chinese imports in advanced economies were split almost equally between intermediate and consumer goods, while capital goods represented around 26% of total imports. For emerging economies, on the other hand, more than 50% of imports from China were in the intermediate goods category, followed by consumer goods and then capital goods. In India, the difference in composition of the Chinese import basket was even more pronounced. Intermediate goods represented almost 70% of total Chinese imports, followed by capital goods at 24%.

Countries that import intermediate or capital goods which they use as inputs in production potentially face a different trade shock than those that import goods for which domestic producers must compete in final output markets. To investigate how the composition of imports from China and the domestic production technology affected the impact of the China Shock in India, I decompose exposure to the shock into two channels. The

output channel measures the direct output competition that Indian districts faced in their product markets if they produced the same goods whose imports from China increased. A district with higher exposure would have faced more direct competition with Chinese imports, leading to downward pressure on manufacturing production and employment. I construct a shift-share instrument for districts' output channel exposure to the China Shock, using their shares in national employment per manufacturing sub-sector and the change in China's exports to India's peer countries. The input channel measures the extent to which a district's manufacturing sector used goods that were imported from China after the shock as inputs in production. A district facing higher exposure would benefit from increased availability of intermediate input goods, which in turn can boost production and employment in the manufacturing sector. To capture input channel exposure, I construct a shift-share instrument based on a district's share in national demand for each input and the change in Chinese imports in peer countries for the input sector.

My main empirical finding is that in the Indian context, the input exposure channel of the China Shock dominated, and once the input channel is controlled for, the effect of the direct output competition channel is not statistically distinguishable from zero. A one standard-deviation increase in input exposure per worker is associated with a 0.62 percentage point slower decline in the share of manufacturing in total employment. The finding is robust to controls for other socioeconomic characteristics of the district such as baseline manufacturing employment shares and labor force participation rates, as well as exposure to India's tariff liberalization that had started in 1991, and state and decade fixed effects.

Second, I split manufacturing employment shares by goods types to evaluate if the output competition channel affected intermediate goods producers differently than the rest of the manufacturing sector, given the concentration of imports in intermediate goods sectors. Using the same measures of output and input channel exposure, I find that the output competition effect is observable and concentrated in intermediate goods manufacturing. A one-standard deviation increase in the output exposure channel is associated with a 0.61 percentage point higher decline in the share of intermediate goods sectors in total employment. However, an almost equal and opposite effect is observed for consumer goods

sectors, where higher exposure to the output channel is associated with a slower decline in employment share. The China Shock substantially increased the import of intermediate and capital goods and displaced workers from the intermediate goods sector in Indian districts. However, instead of market exit, the shock led to a reallocation of production and employment toward consumer goods sectors. The output channel had no detectable effect on capital goods employment, while the input exposure channel, as in the aggregate case, boosted employment shares of all goods types. Figure 3 shows that across districts, consumer goods sectors represented the majority share of manufacturing employment throughout the sample period. Higher employment in consumer goods sectors, which were somewhat shielded from competition with Chinese imports, can explain why aggregate manufacturing employment shares did not decline sharply in response to the China Shock.

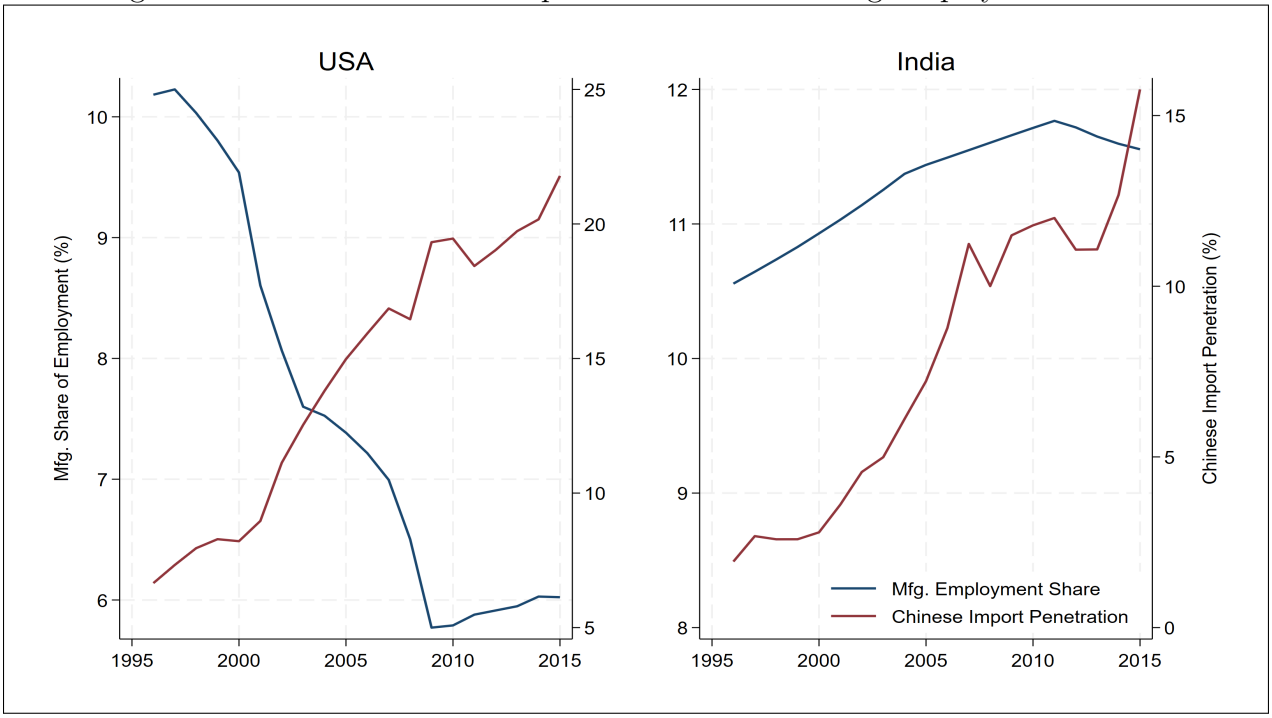
To quantify the general equilibrium effects of the China Shock on the Indian economy, I then build a multi-sector multi-region quantitative trade model with input-output (I-O) linkages in production as in Caliendo and Parro (2015), with 30 Indian states trading with China and the rest of the world. The model features two producer types: intermediate goods producers combine labor as the only factor of production and material from all sectors; and composite goods producers purchase intermediate goods within their own sector from the lowest cost supplier to produce a CES aggregate good. Composite goods are non-tradable and used either for final consumption or as materials for intermediate goods production in the region. The China Shock is modeled as a shock to productivity that lowers production costs. As the price of intermediate goods in China falls, composite goods producers in India can purchase these cheaper goods, which reduces the price of materials for Indian producers as well as of consumption goods. I-O linkages amplify these gains by lowering prices for composite goods producers who purchase intermediate goods from Indian producers.

Using inter-state trade flows data for India and international trade flows, I calibrate the model to match the real economy in 2011. I, then, construct a counterfactual economy in which the China Shock did not happen to quantify the impact of the shock. To do so, I estimate the change in Chinese import penetration ratio in India between 2001-2011 that can be attributed to the China Shock (similar to Caliendo et al. (2019) and Galle et al. (2023)). Next, I use the

model to compute the productivity change in China for each sector that matches the level of Chinese import penetration that can be attributed to non-China Shock factors. I define the amount by which productivity falls to match lower import penetration ratio targets for each sector as the productivity increase due to the China Shock. Finally, using exact hat algebra (as in Dekle et al. (2008)), I compute the overall effect of the China Shock on welfare across Indian states, and the contribution of lower prices to welfare. Overall, the model implies that the China Shock led to a 0.2 percentage point gain in aggregate welfare. States that had higher manufacturing shares in the no-shock counterfactual economy see higher welfare gains after the shock. This is a departure from Caliendo et al. (2019), who find that labor markets producing services gained more than those producing in manufacturing sectors. In part, this is because more industrial Indian states had higher reliance on Chinese intermediate inputs before the shock, such that prices fell more in these states. I also show that the contribution of lower material prices is greater than the contribution of lower consumption prices in the total price reduction.

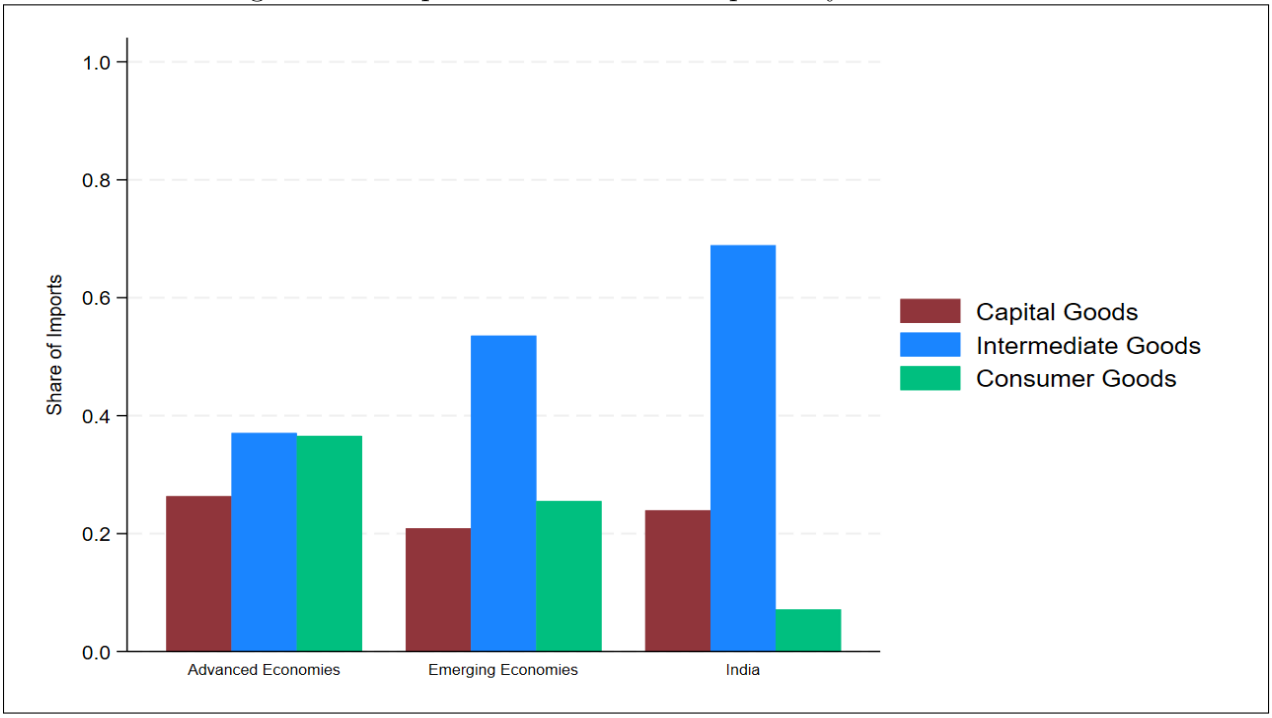
These results establish that the impact of the China Shock on the Indian economy was meaningfully different compared to advanced economies. By splitting the exposure to the shock into the direct output competition effect and the intermediate input availability effect, I show that the input channel was dominant in India. The China Shock reduced employment shares in intermediate goods sectors, given that imports from China, and hence the competition effect, was concentrated in these sectors. However, there was a reallocation of production toward consumer goods sectors, which prevented a sharper decline in the employment shares of the manufacturing sector as a whole. Lower prices and higher availability of intermediates also increased welfare, especially in more industrial states. The rest of the paper is structured as follows. The next section provides an overview of the relevant literature. In section 3, I explain the data sources and concordance exercises required for the project. Section 4 presents the empirical specification and results. The quantitative model and counterfactual exercise are presented in section 5. Section 6 concludes.

Figure 1: Growth in Chinese Imports and Manufacturing Employment Share



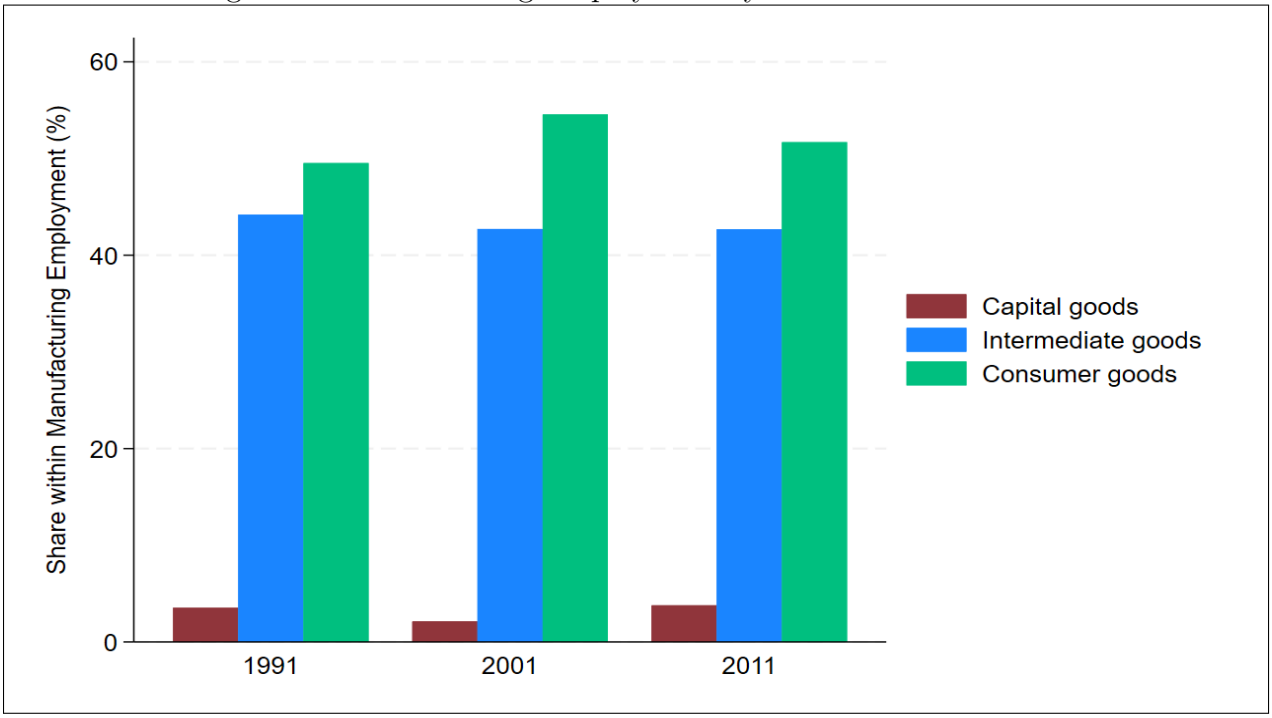
Sources: COMTRADE, US Bureau of Labor Statistics, and Reserve Bank of India

Figure 2: Composition of Chinese Imports by Income Level



Source: COMTRADE (average share over 2000-2011)

Figure 3: Manufacturing Employment by End-Use Sub-Sectors



Source: Population Census of India (average share across districts)

2 Literature

The paper contributes to two strands of literature on the impact of trade shocks on firms and labor markets. First, I add to the work on estimating the impact of the China shock on labor markets and manufacturing employment. Since Autor et al. (2013) (henceforth ADH), many studies have examined the impact of the China shock on manufacturing employment and output in various countries (Malgouyres (2017), Yang et al. (2021), Hauptmann and Schmerer (2020), and Flückiger and Ludwig (2015)). Similar work on emerging markets includes Branstetter et al. (2019) studying Portugal; Moreira et al. (2020) studying Brazil; Mendez (2015) studying Mexico; Álvarez and Claro (2009) studying Chile; and Hanson and Robertson (2008)) evaluating the impact of the shock on ten developing countries that specialize in manufacturing. Saha (2024) examines the impact of the China shock on the gender wage gap in Indian districts, and finds that the shock led to a higher wage gap, particularly in rural areas. Shi (2025) also examines district-level labor market responses to

the China shock, reporting higher manufacturing employment but lower wages in response to the China shock. Other studies on the impact of the China shock on India include Verma and Jin (2025), who evaluate the impact of intermediate imports from China on the employment of permanent and contract workers in formal manufacturing firms, and Chakraborty et al. (2024), who show that increased competition from Chinese exports led to a 3.5% decline in firm-product prices. I add to this work by studying the input channel of the China Shock as a potential explanation for the surprising lack of decline in manufacturing employment shares in India, and establishing that the impact of the shock differs based on the import composition and production structure of the receiving country.

Second, the effect of increased access to intermediate inputs, or the input channel of the China Shock, has been documented in recent work such as Aghion et al. (2024), who study the effect of output competition and intermediate input access at the firm level in France. Pierce et al. (2026) analyze the input and output channels based on industry exposure of workers in the US, and find that the downstream gains of the input channel raise earnings especially for workers in non-manufacturing sectors. Acemoglu et al. (2016) extend the ADH analysis to incorporate the input channel of the China shock on US local labor markets and find that the output competition effect dominates, with inter-industry linkages amplifying the negative effect of the China shock on employment. Caliendo et al. (2019) and Galle et al. (2023) study the effect of input-output linkages in the transmission of the China Shock on the US economy with labor mobility frictions and heterogeneous workers in a quantitative trade model. I contribute to this strand of literature with a comparison of the intermediate input and output competition channels in an emerging economy context, which can differ substantially from advanced economies based on its production structure and position in global supply chains.

My work also adds to the literature on the transmission of trade shocks in emerging economies through intermediate inputs and labor market effects of trade shocks. Goldberg et al. (2010) discuss how the 1991 trade liberalization reforms in India affected the manufacturing sector. They study how the introduction of imported intermediate inputs increased the product scope of domestic firms, and highlight substantial gains from trade through the input channel.

Topalova (2010) provides a comprehensive review of the Indian economy leading up to the sweeping reforms that started in the 1980's but were sped up by the external crisis of 1991. She demonstrates how districts that were more exposed to tariff reduction experienced slower poverty reduction, and the impact that the trade reforms had on the income distribution in India. Topalova and Khandelwal (2011) also examine the impact of the reforms on firm productivity. They find that lower tariffs on imports, which increased competition on final goods and the availability of inputs, led to higher firm productivity. Amiti and Konings (2007) evaluate the productivity effects of tariff reduction on output and intermediate inputs for Indonesian manufacturing, and find a significant gain in productivity from input tariff liberalization. With newly available data on inter-state trade flows in India (Zheng et al. (2026)), my paper is the first to quantify the general equilibrium impact of the China Shock on India with state-level geography.

3 Data

The data used for this project combines trade data for China, India and peer countries, socioeconomic and manufacturing production data for the Indian economy at the district level, and input-output data for production in India. The sample period is 1991-2011. Details on mapping across different waves of industrial classifications and district boundaries is presented in Appendix B.

Trade data is collected from COMTRADE for exports from China to all reporting partners in the period from 1992 to 2011. This is used for the selection of peer countries and the measurement of export changes from China. I map all trade data to the NIC-2004 Indian industry codes for manufacturing sub-sectors at the 4-digit level. I use 4789 HS-6 digit categories that have export data from China to India and from China to at least one peer country, mapped to 127 NIC-04 categories (of which there are 102 manufacturing sub-sectors).

Data for **employment** at the district level is taken from the 1991, 2001 and 2011 waves of the Population Census conducted by the Indian National Statistics Office. For data on district-level **manufacturing output**, I use the Annual Survey of Industries (ASI). The ASI

was launched in 1960 and is conducted annually by surveying formal manufacturing-sector firms in India. For the 1990-91 wave, only aggregate results were published, while the 2000-01 wave included firm-level data, which are aggregated up to the district level for this paper.

Data for **input and intermediate shares** in production is obtained from the long-run World Input-Output Database (WIOD, Timmer et al. (2015)). This data is reported at a 2-digit aggregation of ISIC Rev. 3 product categories, which have been mapped to the Indian industrial classification system.

For the quantitative section, data on **inter-state trade flows** is taken from Zheng et al. (2026), who created input-output tables for 32 Indian states from 2011-2019. These tables comprise data on trade flows across 66 sectors, of which 10 sectors are classified as agriculture, 30 sectors are manufacturing and the remaining 26 are service sectors. The dataset also contains aggregate data on state-level final consumption, exports and imports.

4 Empirical Analysis

4.1 Main Specification

For each district, I construct two channels of exposure to the China Shock, direct output competition and cheaper intermediate inputs. The direct competition effect or "output channel" measures the exposure of districts to Chinese imports in their output markets. This is similar to the exposure measure in Autor et al. (2013) (henceforth ADH), using baseline employment structure of a district and its share in national employment per sector. A district with a higher share of employment in sectors in which Chinese imports grew faced more direct competition in output markets, and should be adversely affected by Chinese import growth. The district-level output exposure as a shift-share variable is defined as follows:

$$\Delta Exposure_{d,t}^{Output} = \sum_{j} \left(\frac{L_{d,j,t_0}}{L_{Ind,j,t_0}} . \frac{\Delta M_{CI,j,t}}{L_{d,t_0}} \right) \tag{1}$$

$\Delta M_{CI,j,t}$ is the decadal change in imports from China into India in 4-digit NIC sector j,

weighted by the ratio of employment in district d ($L_{d,j,t}$) as a share of employment across India ($L_{Ind,j,t}$) in sector j at the start of the period. Given that trade data is only available at the country level, the weight component approximates the share of the import change that is apportioned to each district, based on the share of the national labor market that the district captures. The product is divided by the total employment of district d at the baseline ($L_{d,t}$) to compute exposure per worker in each district. This district-sector level variable is aggregated across all sectors, j, to obtain the district level exposure-per worker.

The cheaper intermediate inputs or "input channel" measures how much a district used Chinese import sectors as inputs in production. A district with high input exposure had a higher demand as input for sectors in which Chinese imports grew, and should benefit from increased imports from China. The district-level input channel is defined as follows:

$$\Delta Exposure_{d,t}^{Input} = \sum_{j} \left(\frac{D_{d,j,t_0}}{D_{Ind,j,t_0}} . \frac{\Delta M_{CI,j,t}}{L_{d,t_0}} \right) \tag{2}$$

District d's share in national demand for sector j as an input at the baseline captures the share of national imports of sector j apportioned to d. D_{d,j,t_0} in Equation 2 is the demand for sector j as input in total production in district d at the start of the period. It is constructed using total production in the district and India's Input-Output table from the World Input Output Database. Total production per sector k in d, given by (Y_{d,k,t_0}), is multiplied by the share of intermediates goods in the production of that good ($\eta_{k,t}$) and the share of each input, j, in the intermediates basket for k ($\psi_{k,j,t}$).

$$D_{d,j,t} = \sum_{k} (Y_{d,k,t} \cdot \eta_{k,t} \cdot \psi_{j,k,t}) \tag{3}$$

Input-output tables at a more disaggregated level are not available for the complete list of NIC sectors for 1991 and 2001, thus restricting the input channel definition to the 2-digit NIC sector level. The variation in the input channel across districts arises from differences in total output of using sectors across districts.

The baseline specification then becomes:

$$\Delta \left(\frac{L_M}{L} \right)_{d,t} = \alpha + \beta_1 \Delta Exposure_{d,t}^{Output} + \beta_2 \Delta Exposure_{d,t}^{Input} + \mathbf{X'}_{d,t} + \gamma_{s,t} + \varepsilon_{d,t} \quad (4)$$

The outcome is the decadal change in the share of manufacturing in district employment. $\mathbf{X'}_{d,t}$ captures start-of-period socioeconomic district-level controls. Similar to ADH, when estimating Equation 4 for the entire sample period, I stack the ten-year first-differences for 1991-2001 and 2001-2011. All observations are weighted by the start-of-period population in the district. The control vector includes the share of manufacturing in district employment, labor force participation trends, the sum of shares for the input channel ($\sum_j \frac{D_{d,j,t_0}}{D_{Ind,j,t_o}}$), and district exposure to tariff reductions that occurred in the same time period (constructed as in Topalova (2010)).

Since the shares in the instruments refer to a district's share in national employment per industry (output channel) or a district's share in national demand for input sector j (input channel), the sum of shares across sectors within a district does not equal one for either channels. Controlling for the sum of shares makes the results robust to the "incomplete shares" concern discussed in Borusyak et al. (2022) (BHJ). As BHJ explain, by isolating the overall sum of shares for each district, I adjust for the fact that districts with a higher sum of shares, denoting higher level of industrialization, will have a higher value of the instrument as long as the shift is positive. By including the control, the remaining variation in the exposure instruments can then be attributed to randomness among sectors in which the shock hits. [1]

Following India's trade liberalization in 1991, import tariffs on almost all sectors fell sharply. The control for district-level exposure to tariff reductions accounts for the change in imports into India from all countries, including China, that can be attributed to the change in Indian trade policy. This ensures that the contribution of the import shock from the input and output exposure instruments is precisely due to the China Shock. Further, as presented in Topalova (2010), most of the tariff reduction had already happened in the first

[1] BHJ show that in the context of ADH, the share of manufacturing in district employment at the start of the period is a suitable proxy for the sum of shares control for the output channel. The sum of shares for the input channel is explicitly controlled for, thus addressing the concern for both instruments.

decade of my sample period. The average nominal tariff rate had fallen from 80 percent in 1990 to 37 percent by 1996, with intermediate and capital goods being liberalized before consumer goods. Thus, the change in Chinese imports into India, especially in the decade following 2001 and for intermediate goods, can be confidently attributed to the China Shock. District-level exposure to tariff reductions is constructed as below:

$$Exposure_{dt}^{Tariff} = \sum_{i} \frac{L_{d,j,t_0}}{L_{d,M,t_0}} \cdot \Delta\tau_{j,t} \tag{5}$$

where $\tau_{j,t}$ is the tariff rate for sector j, L_{d,j,t_0} is the employment in district d, sector j at baseline and L_{d,M,t_0} is baseline manufacturing employment in each district.

Finally, the specification includes state-decade fixed effects to account for state-level changes such as industrial policy and other government schemes that could affect employment trends in all districts within a state in the same decade.

4.2 Identification

4.2.1 Selection of Peers

However, as detailed in ADH, measuring the change in Chinese exports to India introduces endogeneity concerns about the demand conditions in India affecting the performance of the manufacturing sector in addition to the change in supply conditions of China. To isolate the effect of Chinese supply-side changes, I follow ADH's identification strategy to instrument the growth of Chinese imports into India with that of imports into India's peer countries. I select ten peer countries based on similarity in income and production - Bangladesh, Cameroon, Indonesia, Kenya, the Philippines, Nicaragua, Senegal, Tanzania, Viet Nam and Zambia.

There is no obvious reason why demand conditions in India should affect Chinese exports to these countries, such that I can use peers' imports as an instrument for imports into India to capture the impact of the change in Chinese supply capabilities. Then, both the exposure variables in Equation 4 are instrumented with a change in exposure variable defined for peer countries such that the shares are still baseline state values but the shift is the change in Chinese imports into peers ($\Delta M_{CP,j,t}$) instead of into India:

$$\Delta \hat{Exposure}_{d,t}^{Output} = \sum_j \left(\frac{L_{d,j,t}}{L_{Ind,j,t}} . \frac{\Delta M_{CP,j,t}}{L_{d,t}} \right) \tag{6}$$

$$\Delta \hat{Exposure}_{d,t}^{Input} = \sum_j \left(\frac{D_{d,j,t}}{D_{Ind,j,t}} . \frac{\Delta M_{CP,j,t}}{L_{d,t}} \right) \tag{7}$$

4.2.2 Instrumental Variable Estimation

Using this set of peer countries to isolate the exogenous component of Chinese supply-side shocks, I estimate the causal impact of combining the output competition effect and cheaper inputs effect on Indian districts. The 2SLS specification is:

$$\Delta \left(\frac{L_M}{L} \right)_{d,t} = \alpha + \beta_1 \Delta \hat{Exposure}_{d,t}^{Output} + \beta_2 \Delta \hat{Exposure}_{d,t}^{Input} + \mathbf{X'}_{d,t} + \gamma_{s,t} + \varepsilon_{d,t} \tag{8}$$

The Kleibergen-Paap F-stat values are well over 10, implying that the instrument is strong. First-stage results are shown in the appendix (Table A1). The estimates are robust to running the specification leaving one peer out at a time, ensuring that no single peer country is driving the results.

4.3 Results

Table 1 presents the OLS and IV estimates for the baseline specification for the full sample period with stacked decade-wise long differences. The dependent variable is the change in manufacturing employment share. Columns 1 and 3 report the results for the OLS and IV specification of testing only the output channel in the Indian context. In column 3, we see that a one standard deviation increase in output competition exposure per worker is associated with a 0.28 percentage point slower decline in the share of manufacturing in total employment. However, this positive coefficient becomes statistically insignificant and close to zero after controlling for the input channel effect. According to the preferred specification in column 4, which presents the second-stage IV estimates, the positive impact of the China Shock on district-level manufacturing employment shares is driven by the input channel effect. Column 4 shows that a one standard deviation increase in exposure to the

input channel effect, of being downstream to Chinese imports, is associated with a 0.62 percentage point slower decline in the share of manufacturing in district employment. The change in significance and magnitude for the output channel coefficient between columns 3 and 4 can in part be explained by the fact that many sectors have high diagonal values in the input-output matrix, that is the output sector has high demand for itself as an input. Therefore, districts with higher production in sectors whose imports from China grew, or more exposed to the output competition channel, may also be using these same sectors as inputs in their production, which the input channel separates out in columns 2 and 4.

Table 1: Baseline Import Exposure and Manufacturing Shares: 2SLS Stacked

	(1)	(2)	(3)	(4)
	Dep. Var. $= \Delta\left(\frac{L_M}{L}\right)_{d,t}$			
	Output channel	Combined	Output channel	Combined
	OLS	OLS	IV	IV
$\Delta Exposure_{d,t}^{Output}$	0.234*	0.023	0.284*	0.055
	(0.135)	(0.169)	(0.147)	(0.175)
$\Delta Exposure_{d,t}^{Input}$		0.600***		0.622***
		(0.208)		(0.212)
Socioeconomic controls	✓	✓	✓	✓
Borusyak Correction	✓	✓	✓	✓
State x Decade FE	✓	✓	✓	✓
No. of Districts	810	810	810	810
KP F			394.49	
Joint KP F				182.43
SW F - Output				517.12
SW F - Input				1831.55

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the district level. Observations are weighted by start-of-period population. Exposure measures are in standard-deviation units. One SD=$89/worker for input and $66/worker for output exposure. The mean change in manufacturing employment share was 1.48pp in 1991-2001 and -1.24pp in 2001-2011. SW-F is the Sanderson-Windmeijer conditional F for each instrument. Socioeconomic controls include baseline share of manufacturing in employment, female labor force participation rate, and exposure to tariff reductions. Borusyak correction includes the sum of shares for the input channel.

As Figure 1 shows, imports from China into India were comprised mainly of intermediate and capital goods, which supports the hypothesis that the China Shock increased access to intermediate inputs. The results in Table 1 show that this input channel explains the positive effect of the shock on Indian manufacturing employment. Since the shock was not evenly felt across all manufacturing sectors, I disaggregate manufacturing employment into intermediate, capital and consumers goods sectors defined according to the Broad Economic

Categories (BEC) Rev. 4, and separately investigate the impact of the shock on employment shares for each sub-sector.

In Table 2, I show results for the specification below:

$$\Delta\left(\frac{L_{M,i}}{L}\right)_{d,t} = \alpha + \beta_1 \Delta \hat{Exposure}_{d,t}^{Output} + \beta_2 \Delta \hat{Exposure}_{d,t}^{Input} + \mathbf{X'}_{d,t} + \gamma_{s,t} + \varepsilon_{d,t} \quad (9)$$

Relative to the specification in Equation 8, the outcome variable now represents the share of manufacturing sub-groups, i. Column 1 shows the impact of the output and input channels on the share of intermediate goods in total district employment. Consistent with the fact that the composition of Chinese imports leaned heavily toward intermediate goods, the standard competition effect is evident here, with a one standard deviation increase in exposure to the output competition channel leading to a 0.61 percentage point decline in the share of intermediate goods employment. In contrast, in column 2, there is an almost equal and opposite effect of the output competition channel for consumer goods employment shares. A one standard deviation increase in output exposure is associate with a 0.63 percentage point higher share of consumer goods employment.

The positive effect on consumer goods employment reflects a reallocation of producers from intermediate goods to consumer goods in the face of Chinese competition. While imports from China mainly included intermediate and capital goods, district employment within manufacturing was on average higher in consumer goods sectors (Figure 3). Higher employment in consumer goods sectors, which were somewhat shielded from competition with Chinese imports, and competition being concentrated in intermediate goods sectors, can explain the lack of the standard negative effect of output competition on manufacturing employment shares. The input cost channel remains significant and contributes positively to employment shares of each sub-sector within manufacturing.

Table 2: Import Exposure and Manufacturing Sub-sector Employment Shares: 2SLS Stacked

	(1)	(2)	(3)
	Dep. Var. $= \Delta\left(\frac{L_{M,i}}{L}\right)_{d,t}$		
	i = Intermediate goods	Consumer goods	Capital goods
$\Delta Exposure_{d,t}^{Output}$	-0.608***	0.630***	0.038
	(0.159)	(0.125)	(0.041)
$\Delta Exposure_{d,t}^{Input}$	0.285**	0.254**	0.086***
	(0.115)	(0.127)	(0.027)
Socioeconomic controls	✓	✓	✓
BHJ correction	✓	✓	✓
State x Decade FE	✓	✓	✓
No. of Districts	810	810	810
Mean Dep. Var. (1991-2001, %)	0.583	1.27	-0.247
Mean Dep. Var. (2001-2011, %)	-0.756	-0.582	0.089

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors, in parentheses, are clustered at the district level. Observations are weighted by start-of-period population. Exposure measures are in standard-deviation units. One SD=$89/worker for input and $66/worker for output exposure. The Sanderson-Windmeijer conditional F for the output instrument is 517 and for the input instrument is 1831.5. The joint Kleibergen-Paap Wald F is 182.43. Socioeconomic controls include baseline share of manufacturing in employment, female labor force participation rate, and exposure to tariff reductions. Borusyak correction includes the sum of shares for the input channel. The dependent variable is the change in employment share of each category within manufacturing sectors, defined by BEC-end use classifications.

4.4 Robustness

4.4.1 Correlation between input and output channels

The fact that many sectors use themselves as inputs in production, in part, explains why the coefficient on the output exposure channel is positive and significant in columns 1 and 3 of Table 1. Districts competing in output markets with imports from China also potentially benefited from the same imports being used as inputs in their production. Once the input exposure channel is controlled for, the coefficient on the output channel becomes

insignificant. This mechanism implies a degree of correlation between the input and output exposure channel instruments in each specification. If the regressors are highly collinear, the coefficients may be unstable and imprecise. Moreover, omitting either regressor may bias the coefficient for the other channel. I measure the correlation between the instruments after including all fixed effects and control variables, and the change in each coefficient when the other channel is excluded. The correlation between the input and output channel is 0.43 for the two exposure measures, and 0.41 for their instrument values. Accounting for all fixed effects and controls, the variance inflation factor (VIF) for the fitted exposure measure is approximately 1.7 for the output channel and 1.6 for the input channel. With the conventional threshold of 4 for the VIF, this indicates that the multi-collinearity between the input and output exposure channels is not a major concern. The input exposure channel coefficient is stable with and without the control for the output exposure channel, while the results for the output exposure channel are seen in Table 1 and suggest omitted variable bias from excluding the input channel.

4.4.2 Mechanics of higher manufacturing employment shares

In appendix table Table A2, I present results for the growth rate of manufacturing and total employment across districts, expressed as difference in logs. The coefficients for both the output and input exposure channels are small but positive and statistically significant. Column 2 of table Table A2 shows that a one standard deviation increase in input channel exposure was associated with a 0.02 percentage point higher growth rate of total employment. This shows that higher exposure to the China Shock was associated with higher growth in manufacturing employment, and that higher shares of manufacturing employment cannot be attributed to the mechanics of a falling denominator (since more exposed districts did not witness lower total employment).

4.4.3 Test for Pre-Trends

Finally, a concern for the identification is if districts that were more exposed to the China Shock were experiencing a rising trend in manufacturing employment before the shock, such as the trade liberalization in the previous decade. I report results for a falsification exercise

in Table 3, where I check for such pre-trends by regressing the change in manufacturing shares of employment over the period 1991-2001 on the future change in import exposure per worker in the period 2001-2011, including both the input- and output-channel instruments. I find no significant correlation between either instrument on changes and manufacturing employment shares in the prior decade, suggesting that districts that were more exposed to import competition after the China shock in the second decade were not already on a rising trajectory in manufacturing employment in the period from 1991 to 2001.

Table 3: Future Import Exposure and Baseline Manufacturing Shares: 2SLS Stacked

	(1)	(2)
		Dep. Var. $= \Delta(\frac{L_M}{L})_t$
	OLS	IV
$\Delta Exposure^{Output}_{d,t+1}$	0.143	0.388
	(0.206)	(0.249)
$\Delta Exposure^{Input}_{d,t+1}$	0.011	-0.054
	(0.120)	(0.115)
Socioeconomic controls	✓	✓
BHJ correction	✓	✓
State x Decade FE	✓	✓
No. of Districts	405	405
Joint KP F		124.08
SW F - Output		291.29
SW F - Input		1565.55

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are clustered at the district level. All observations are weighted by the 1991 population. SW-F is the Sanderson-Windmeijer conditional F for each instrument. Exposure measures are in standard-deviation units. One SD=$118/worker for input and $84/worker for output exposure in the second decade, 2001-2011. Socioeconomic controls include 1991 values of manufacturing employment share, female labor force participation and exposure to tariff reductions. Borusyak correction includes the sum of shares for the input channel. The dependent variable is the change in manufacturing employment shares over 1991-2001.

5 Quantification

The empirical analysis shows that the input channel was the main propagation mechanism for the China shock in India. Chinese imports to India over the period of the shock leaned heavily toward intermediate and capital-sector goods, benefiting downstream production and slowing the decline of manufacturing employment. To quantify the general equilibrium effects of the China shock on India, combining the output and input channel effect, I adapt the general equilibrium model from Caliendo and Parro (2015), which incorporates trade in intermediate goods and input-output (IO) linkages in production, for an economy comprising 30 Indian states, China and the rest of the World.

Every region produces intermediate goods and composite goods. The composite good in each sector is an aggregate of intermediate goods purchased from the lowest-cost region, and can be used as material for the production of intermediates or for final consumption. Regions include households that produce labor, which is the only factor of production. Labor is assumed to be perfectly mobile across sectors but not regions. There are 18 sectors in total, of which one sector represents all agricultural activity, one sector represents the services sector and the rest are manufacturing sub-sectors.

The China shock increases productivity in Chinese manufacturing sectors, lowering production cost and prices. Through IO linkages, lower costs propagate to downstream sectors not only in China but also in India and the rest of the world, further driving down prices. As a first-order effect, states that were already buying inputs from China benefit from lower prices. States in which output is higher for sectors in which Chinese productivity rises also benefit from lower prices if China becomes their lowest-cost supplier after the shock. Finally, lower prices in states whose inputs are sourced from China propagate along the supply chain to downstream states who purchase inputs from the former set of states.

5.1 Environment

5.1.1 Households

A representative household in region n has Cobb-Douglas preferences and maximizes:

$$\max\ U(C_n) = \prod_{j=1}^{J} (C_n^j)^{\alpha_n^j} \tag{10}$$

$$\text{s.t. } \textstyle\sum_j P_n^j C_n^j = w_n L_n + D_n, \text{ and } \sum_j \alpha_n^j = 1$$

C_n^j denotes consumption of composite good j in each region. For a measure of households, L_n, household income comprises of factor income at wage, w_n and trade deficit in the region, D_n. The trade deficit is taken as fixed and exogenous at the regional level. The price index for consumption in region n is given by:

$$P_n = \prod_j \left(\frac{P_n^j}{\alpha_n^j} \right)^{\alpha_n^j} \tag{11}$$

5.1.2 Intermediate Goods Production

In each sector j, a continuum of intermediate goods $\omega^j \in [0,1]$ is produced using labor and composite intermediate goods from all sectors as material:

$$q_n^j(\omega_j) = z_n^j(\omega^j) \cdot (L_n^j(\omega^j))^{\gamma_n^j} \cdot \prod_{k=1}^{J} (Q_n^{kj}(\omega^j))^{\gamma_n^{kj}} \tag{12}$$

$z_n^j(\omega^j)$ is the efficiency parameter for producing ω^j, which varies by region, and is drawn from a Fréchet distribution, with location parameter, λ_n^j and dispersion parameter, θ^j. Q_n^{kj} is the quantity of sector-k composite good used as material in the production of a sector-j intermediate good. γ_n^j is the share of value added in production in region n (since labor is the only factor of production), and γ_n^{kj} is the expenditure share of input k used to produce sector j. With perfectly competitive markets and constant returns to scale in production, the price of an intermediate good equals the unit cost of the input bundle, which can be expressed as $\frac{c_n^j}{z_n^j}$ where:

$$c_n^j = \phi_n^j w_n^{\gamma_n^j} \prod_{k=1}^{J} \left(P_n^k\right)^{\gamma_n^{kj}} \tag{13}$$

where P_n^k is the price index faced by region n to purchase the composite intermediate good of sector k. ϕ_n^j is a region-sector constant equal to $\gamma_n^{j^{-\gamma_n^j}} . \prod_k \gamma_n^{kj^{-\gamma_n^{kj}}}$. A fall in P_n^k lowers the price of intermediate goods, $p_n^j(\omega^j), \forall j$, as a function of k's cost share in the production of j. Regions that use k more intensively in production across using sectors j thus benefit more from the productivity increase in sector k.

5.1.3 Composite Intermediate Goods Production

In every region n and sector k, composite intermediate goods are produced as a CES aggregate over the continuum of intermediate goods produced in sector k:

$$Q_n^k = \left[\int r_n^k(\omega^k)^{1-\frac{1}{\sigma^k}} \cdot d\omega^k \right]^{\frac{\sigma^k}{\sigma^k - 1}} \tag{14}$$

σ^k is the elasticity of substitution over sector k intermediate goods. Composite goods are produced by demanding each intermediate good from the lowest cost supplier at quantity $r_n^k(\omega^k)$, and can be used for final consumption in region n or as material for intermediate goods production. The cost minimization problem for composite goods producers implies that demand for each intermediate good is given by:

$$r_n^k(\omega^k) = \left[\frac{p_n^k(\omega^k)}{P_n^k} \right]^{-\sigma^k} \cdot Q_n^k \tag{15}$$

where $p_n^k(\omega^k)$ is the lowest price at which ω^k is sold across suppliers, and P_n^k is the price index of sector k in region n. From the CES production function, the price index equals:

$$P_n^k = \left[\int_0^1 p_n^k(\omega^k)^{1-\sigma^k} \cdot d\omega^k \right]^{\frac{1}{1-\sigma^k}} \tag{16}$$

Higher productivity of manufacturing sector k in China lowers the unit cost of production for intermediate goods, which lowers p_{Ch}^k. For Indian producers of sector k composite goods, there are states, n, who were already purchasing inputs from China whose input prices fall and hence, P_n^k falls. On the extensive margin, some states, m, switch to the Chinese input after the shock, and lower prices also result in lower P_m^k. Producers of composite goods in

states, m, switching to Chinese inputs displaces domestic producers in sector k. This is the direct output competition effect of higher productivity in China.

On the other hand, higher productivity in China propagates through production in India, given the input-output linkages embedded in the use of materials. As shown above, when composite goods become cheaper to produce in Indian states, lower P_n^k reduces costs for intermediate goods producers in n using material from k. If the state uses material k intensively enough in a sector, j, p_n^j may fall enough such that n becomes the lowest cost supplier for composite goods in sector j among other Indian states. This increases demand for n's production of intermediate goods in sector j. The intermediate input channel captures the higher availability of cheaper intermediates from China in sector k raising the profitability of Indian producers in sectors j, which is increasing in the cost share of sector k. As the propagation continues, the fall in P_n^k lowers p_n^j, which lowers P_s^j for all states, s, sourcing input j from n, and consequently p_s^i for all using sectors i in state, s.

5.2 Equilibrium

Trade of goods across regions incurs standard iceberg trade costs, $\tau_{in}^j \geq 1$ to ship 1 unit of sector j goods from region i to region n, and $\tau_{ii}^j = 1$. Intermediate goods are traded across all regions, while the composite intermediate good is non-tradable. The unit price at which sector j goods produced in region i are sold to region n is given by:

$$p_n^j(\omega^j) = \frac{c_i^j \cdot \tau_{in}^j}{z_i^j(\omega^j)} \tag{17}$$

Given the productivity term, $p_n^j(\omega^j)$ is governed by a Fréchet distribution as explained above, following Eaton and Kortum (2002), the unit price of a composite intermediate good in region n can be denoted as:

$$P_n^j = \Gamma^j \left[\sum_i \lambda_i^j (c_i^j \cdot \tau_{in}^j)^{-\theta^j} \right]^{-\frac{1}{\theta^j}} \tag{18}$$

Γ^j is a sector-specific constant, and $\theta^j > \sigma^j - 1$ guarantees a solution for prices, P_n^j.

Finally, the expenditure share of region n on region i with the properties of the Fréchet distribution can be denoted as:

$$\pi_{in}^{j} = \frac{\lambda_{i}^{j} \cdot (c_{i}^{j} \tau_{in}^{j})^{-\theta^{j}}}{\sum_{i'} \lambda_{i'}^{j} (c_{i'}^{j} \cdot \tau_{i'n}^{j})^{-\theta^{j}}} \tag{19}$$

Expenditure shares, π_{in}^{k}, for Indian producers in state i will fall if China replaces them as the lowest cost supplier in region n. This leads to lower output and demand for labor in sector k. For producers in sector j who use sector k more intensively as material, if c_{n}^{j} falls enough, region n may remain or become the lowest cost supplier of intermediate goods in sector j, such that π_{ni}^{j} rises. This would increase Y_{n}^{j} and, hence, demand for labor, L_{n}^{j} in state, n, sector j.

5.2.1 Definition

Given parameters α_{n}^{j}, θ^{j}, λ_{n}^{j}, γ_{n}^{j}, γ_{n}^{kj} and τ_{in}^{j}, the equilibrium is a wage vector $w_{n} \in \mathbf{R}^{N}$ and a price matrix $P_{n}^{j} \in R^{[N \times J]}$ such that for all regions and sectors:

Labor markets clear: $w_{n} L_{n} = \sum_{j} \gamma_{n}^{j} Y_{n}^{j}$

Goods markets clear: $Y_{n}^{j} = \sum_{i} \pi_{ni}^{j} X_{i}^{j}$

Expenditure $X_{n}^{j} = \alpha_{n}^{j}(w_{n} L_{n} + D_{n}) + \sum_{k} \gamma_{n}^{jk} . Y_{n}^{k}$; and

Trade balance: $\sum_{j} \sum_{i} \pi_{in}^{j} X_{n}^{j} - D_{n} = \sum_{j} \sum_{i} \pi_{ni}^{j} X_{i}^{j}$

where X_{n}^{j} is total expenditure in region n on sector j and Y_{n}^{j} is the total output in region n, sector j, and Equation 13, **??** and Equation 18 hold.

5.3 Counterfactual

5.3.1 Calibrating the China Shock

To quantify the impact of the China Shock, I conduct a counterfactual exercise by calibrating the model to match the actual 2011 economy for 30 Indian states, China and the rest of the

world, and then "undoing" the China Shock from this economy.[2] As explained below, I use exact hat algebra as in Dekle et al. (2008) to solve the model. Then, to conduct the counterfactual, I first estimate the change in productivity in China that can be attributed to the China Shock, and introduce the calibrated lower productivity to construct a 2011 economy without the China Shock.

My strategy to estimate the change in productivity is similar to Caliendo et al. (2019). The total change in Chinese import penetration ratio for India between 2001-2011 would have been a combination of Indian demand-side and Chinese supply-side factors, of which the China Shock would be one part. I use an ADH-type first-stage regression to estimate how much of the change in China's import penetration ratio per sector j in India can be attributed to the China Shock. To do so, I regress China's change in import penetration in India over the period of the shock on the change in China's import penetration ratio among India's peer countries:

$$\Delta\Big(\frac{M_{Ch,India}}{\sum_i M_{i,India}}\Big)_{j,2011-2001} = \alpha + \beta\Delta\Big(\frac{M_{Ch,Peers}}{\sum_i M_{i,Peers}}\Big)_{j,2011-2001} + \varepsilon_j \tag{20}$$

I use the same peer countries as in the empirical section. The counterfactual import penetration ratio for 2011 is then defined as

$$\left(\frac{M_{Ch,India}}{\sum_i M_{i,India}}\right)'_{j,2011} = \left(\frac{M_{Ch,India}}{\sum_i M_{i,India}}\right)_{j,2011} - \beta\Delta\Big(\frac{M_{Ch,Peers}}{\sum_i M_{i,Peers}}\Big)_{j,2011-2001} \tag{21}$$

where $\beta\Delta\big(\frac{M_{Ch,Peers}}{\sum_i M_{i,Peers}}\big)_{j,2011-2001}$ is the component of total change in China's import penetration ratio that can be attributed to the China Shock. I then calibrate the model over values of λ^j_{Chn} that match the counterfactual penetration ratios per sector with other fundamentals remaining unchanged. This exercise gives me a vector of productivity parameter values, $\boldsymbol{\lambda'^j_{Chn}}$, such that $\hat{\lambda}^j_{Chn} = \frac{\lambda'^j_{Chn}}{\lambda^j_{Chn}}$ is the decline in productivity in China needed for each sector j to undo the China Shock from the 2011 economy.

[2] Alternatively, I could calibrate the model to match the 2001 state of the world and only introduce the China Shock to estimate the impact. However, the earliest data on inter-state trade flows in India is only available 2011 onward.

5.3.2 Equilibrium in Hat Algebra

The equilibrium defined above in section 5.2 is expressed in hat algebra notation[3], where for any variable x, hat notation denotes relative changes, or the ratio of the counterfactual value of a variable to its baseline value. There are no changes to trade costs, so that $\hat{\tau}_{in}^{j} = 1$ for all i, n, and $\hat{\lambda}_{i}^{j} = 1$ for all regions $i \neq$China. The productivity shock affects only the 16 manufacturing sub-sectors, such that $\hat{\lambda}_{Chn}^{j} = 1$ for $j =$ agriculture, services. Using hat algebra eliminates the need to estimate prices or productivity parameters to solve for the equilibrium. Given data for trade flows across regions, labor and production, I can solve for the vectors of wages and prices such that the model baseline exactly matches the data.

5.4 Taking the Model to the Data

To conduct the counterfactual analysis, I first construct the baseline 2011 economy to match the data. For inter-state trade flows, I use the Multi-Region Input Output (MRIO) tables constructed by Zheng et al. (2026). The data disaggregates trade flows for each state-sector pair at the destination and origin level. I combine this with data from the World Input-Output Table (WIOT) to record trade flows between India, China and the Rest of the World (ROW). This gives me a bilateral flows matrix across 32 regions (30 Indian states, China and ROW) and 18 sectors, comprising 16 manufacturing sub-sectors, agriculture and services. Bilateral trade flows are used to compute trade shares in the baseline economy, π_{in}^{j}, denoting expenditure share of region n on region i in sector j.

The MRIO dataset also provides information on value added in each sector-state pair, and the corresponding value added data for China and ROW are obtained from WIOT. Gross output in region n and sector j, Y_{n}^{j} is computed as the row sum of the bilateral flows matrix, summing over all domestic and foreign exports. Total expenditure, X_{n}^{j} is correspondingly the column sum of the matrix, summing over all domestic and foreign imports and value added. For Indian states, sectoral labor data, L_{n}^{j}, is taken from the 2011 population census, same as the data used for the empirical analysis. Labor force per sector for China is obtained from WIOD's Socioeconomic accounts (SEA). The SEA database only contains employment data

[3] All equations for the hat algebra notation are included in Appendix C

for 43 countries, so I take world employment data from the World Development Indicators. I then compute shares from SEA's non-China non-India countries for employment in each sector, and apply this to the WDI aggregate. Finally, I measure the share of value added, γ_n^j, input-output coefficients, γ_n^{kj}, and consumption shares, α_n^j, from the bilateral flows matrix. The IO coefficients are then rescaled to ensure that $\gamma_n^j + \sum_k \gamma_n^{kj} = 1$. For China and ROW, corresponding values of $\gamma_n^j, \gamma_n^{kj}$ and α_n^j are obtained from WIOT. Values for the dispersion parameter of the Fréchet distribution, θ^j are borrowed from Caliendo and Parro (2015).

Table 4: Calibration

Parameter	**Description**	**Source**
γ_n^j	Labor cost share	IO tables (WIOD, MRIO)
γ_n^{kj}	Intermediate input shares	IO tables (WIOD, MRIO)
α_n^j	Consumption shares	IO tables (WIOD, MRIO)
θ^j	Trade elasticity	Caliendo and Parro (2015)

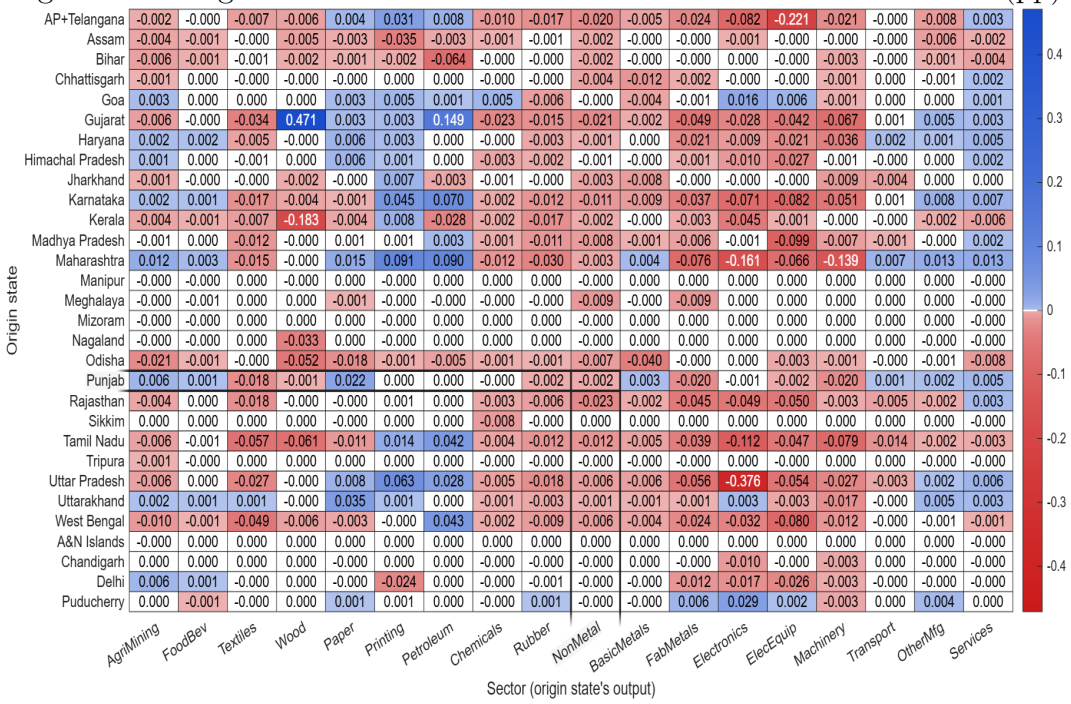
5.5 Impact of the China Shock

With parameter values computed as explained above and baseline expenditure shares per sector for every region-pair, the hat algebra methodology can be applied to estimate the impact of the China Shock once I calibrate the counterfactual Chinese productivity values.

In Figure 4, I present the average loss in an Indian state's share of expenditure across all destination regions by sector due to the China Shock. The hat algebra notation explained above uses the non-shock counterfactual values in the numerator, such that $\hat{\pi}_{in}^j$ would represent the change in share of region i in region n's total expenditure on sector j if the shock had not happened. However, to illustrate the impact of the China Shock more directly,

the results below are expressed as the inverse of that magnitude, or $\frac{1}{\hat{\pi}^j_{in}}$, averaged over all destination regions $n \neq i$. The largest losses in market share, in red, are concentrated in sectors in which Chinese productivity grew more, such as electronics and electrical equipment, fabricated metals, machinery and textile. These sectors are similar to the ones identified as the most affected by the shock in Caliendo et al. (2019). Market losses are also higher for India's more industrial states in the pre-shock period, including Andhra Pradesh, Gujarat, Karnataka, Maharashtra, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal.

Figure 4: Change in Market Share for Indian states due to China Shock (pp)



5.5.1 Change in Welfare

I define welfare, W_n, as real income in region n, such that changes in welfare can be expressed as:

$$\hat{W}_n = \frac{\hat{I}_n}{\hat{P}_n} \tag{22}$$

where $I_n = w_n L_n + D_n$ and $P_n = \prod_j \left(\frac{P^j_n}{\alpha^j_n}\right)^{\alpha^j_n}$

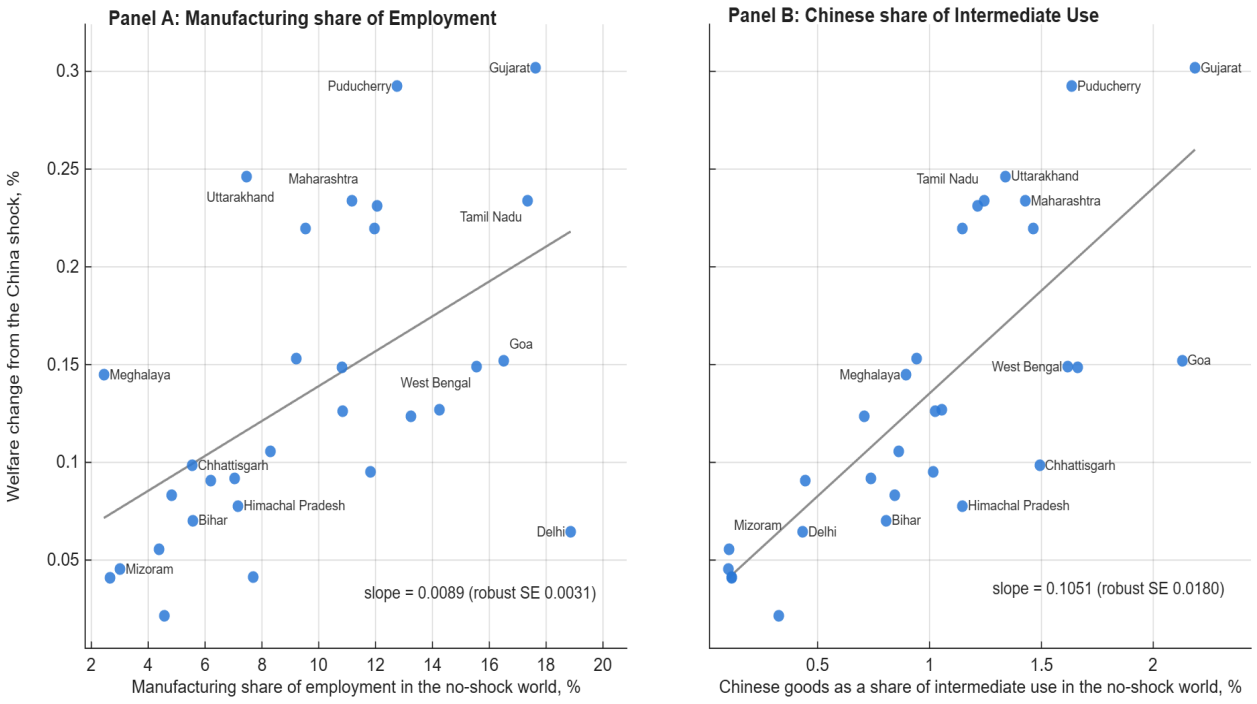
From Equation 22, we can split the change in welfare as:

$$\log \hat{W}_n = \log \hat{I}_n - \sum_j \alpha_n^j \log \hat{P}_n^j, \tag{23}$$

where the first term is the income channel and the second term is the price channel. The income channel of welfare change depends on the direction of change in wages per region as I hold total labor endowment of the region fixed. Regional deficit, D_n is considered exogenous and does not change from the shock. The full mechanisms of the price channel are explained below.

Heterogeneity in welfare change The aggregate gain in welfare for all Indian states, weighted by total income share before the shock, is 0.2 percentage points. In Figure 5, I plot the change in welfare against each state's no-shock share of manufacturing in total employment (Panel A) and against each state's no-shock reliance on Chinese intermediate inputs (panel B). The positive relationship in panel A shows that states that had a higher share of manufacturing employment before the China Shock gained more from the shock. The results are robust to weighting welfare change by state population. This is a departure from Caliendo et al. (2019), who find that labor markets in the US that gained in welfare were more likely to be producing service goods rather than those producing in manufacturing sectors. Panel B shows that the result for India partly reflects the strength of the intermediate input channel. States that were more reliant on Chinese inputs in the no-shock counterfactual had higher welfare gains after the China Shock. This suggests that even if states with a higher industrial base faced direct competition from Chinese imports, the price channel, through lower input prices, led to net higher welfare gains.

Figure 5: Heterogeneity in Welfare Change



Price channel of welfare change The relationship between more industrial states and those reliant on Chinese intermediate inputs achieving higher welfare gains can be explained in part by the price channel. Cheaper Chinese intermediates lower the price index that a state's consumers face, and states that use more Chinese inputs should see larger price reductions. To test how much of the welfare effect this channel can account for, I decompose the change in the price index, $\sum_j \alpha_n^j \log \hat{P}_n^j$, which is positive if the China shock lowered the consumer price index in state n. The decomposition separates the direct effect of cheaper Chinese goods from the effect that works through supply chains, in which suppliers buy cheaper Chinese inputs and pass the lower costs on, and it takes account of the circularity this creates with a Leontief inverse. By log-linearizing Equation 18, I get:

$$\sum_j \alpha_n^j \log \hat{P}_n^j \approx \underbrace{-\sum_j \alpha_n^j \frac{1}{\theta^j} \log(1 + \pi_{Ch,n}^j (\hat{\lambda}_{Ch}^j - 1))}_{(A)\text{Higher cons. of Chinese goods}} + \underbrace{\sum_j \alpha_n^j \sum_i \pi_{in}^j \log \hat{c}_i^j}_{(B)\text{Higher cons. from regions with lower costs}} \tag{24}$$

and $\log \hat{c}_i^j = \gamma_i^j \log \hat{w}_i + \sum_k \gamma_i^{kj} \log \hat{P}_i^k$; $\hat{\lambda}_i^j = 1 \forall i \neq Ch$.

Linearizing further:

$$\log \hat{P}_n^j = a_n^j + \sum_i \pi_{in}^j \log \hat{c}_i^j \tag{25}$$

where $a_n^j = -\frac{1}{\theta^j} \log(1 + \pi_{Ch,n}^j (\hat{\lambda}_{Ch}^j - 1))$

The term a_n^j is the first-round effect of an increase in Chinese productivity on P_n^j when costs are still unchanged. It is higher when region n buys more from China in sector j at the baseline.

The second term in Equation 25 combines the changes in input costs in all source regions. Substituting the expression for input bundle cost change into Equation 25 gives:

$$\log \hat{P}_n^j \;=\; a_n^j \;+\; \underbrace{\sum_i \pi_{in}^j \gamma_i^j \log \hat{w}_i}_{\tilde{w}_n^j} \;+\; \sum_i \sum_k \pi_{in}^j \, \gamma_i^{kj} \, \log \hat{P}_i^k. \tag{26}$$

P_n^j depends on the price indices $\hat{P}_i^k$ of the inputs of its suppliers, which depend in turn on the inputs of their own suppliers, and so on. As prices feed into each other at every step, I solve the circularity with the Leontief inverse calculation to capture input-output (I-O) linkages.

Leontief inverse decomposition. I stack the log price indices of all state-sector pairs in the vector $\mathbf{p}$, and define vectors $\mathbf{a}$ and $\tilde{\mathbf{w}}$ with elements a_n^j and $\tilde{w}_n^j$ and the matrix $\mathbf{M}$ with elements $M_{(n,j),(i,k)} = \pi_{in}^j \gamma_i^{kj}$. Equation 26 becomes $\mathbf{p} = \mathbf{a} + \tilde{\mathbf{w}} + \mathbf{M}\mathbf{p}$, and therefore

$$\mathbf{p} \;=\; \mathbf{Q}\,(\mathbf{a} + \tilde{\mathbf{w}}), \qquad \text{where } \mathbf{Q} \;\equiv\; (\mathbf{I} - \mathbf{M})^{-1} \;=\; \mathbf{I} + \mathbf{M} + \mathbf{M}^2 + \cdots. \tag{27}$$

The element $M_{(n,j),(i,k)}$ is the share of n's sector-j spending that goes to region i, multiplied by the share of sector k in i's costs of producing j. Each row of $\mathbf{M}$ is a weighted average of intermediate-input shares, which are below one because part of every sector's cost is value added. $\mathbf{Q}$ is the Leontief inverse of the multi-region input-output system: the r-th term $\mathbf{M}^r$ is the effect that arrives after r rounds of supply chains, and $\mathbf{Q}$ sums all rounds at once.

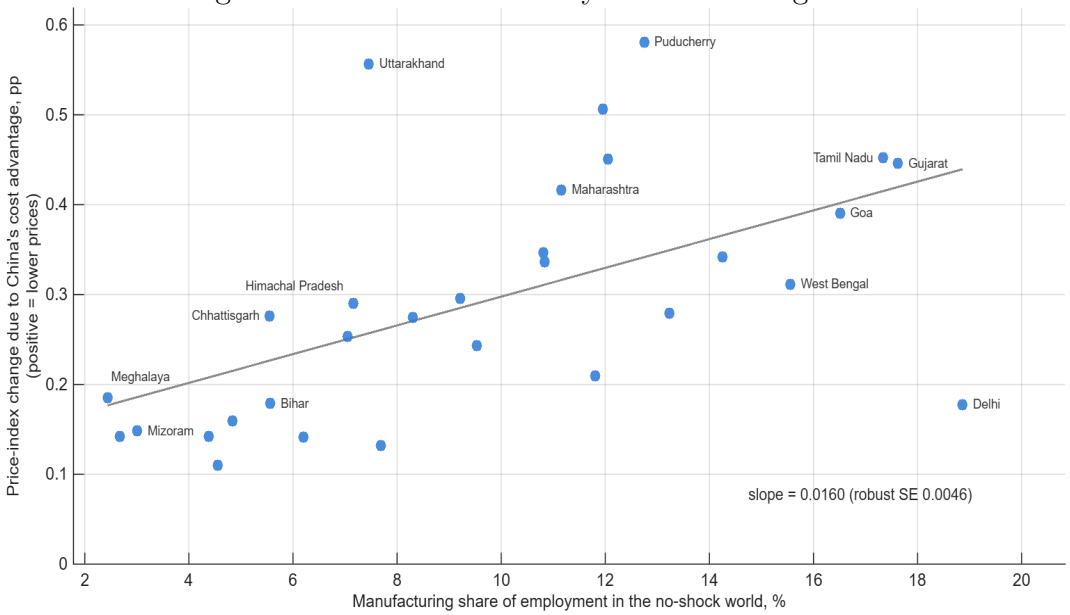
Let $\boldsymbol{\alpha}_n$ be the vector of state n's consumption shares. The price channel of state n is then

$$\sum_j \alpha_n^j \log \hat{P}_n^j = \underbrace{\boldsymbol{\alpha}_n' \mathbf{Q}\, \mathbf{a}}_{\text{China cost effect}} + \underbrace{\boldsymbol{\alpha}_n' \mathbf{Q}\, \tilde{\mathbf{w}}}_{\text{wage response}} . \tag{28}$$

The first term is the numeraire-invariant cost reduction effect of China's productivity gain at unchanged wages, including every round of the supply chain, and can be expressed as $\boldsymbol{\alpha}_n'\mathbf{a}+\boldsymbol{\alpha}_n'(\mathbf{Q}-\mathbf{I})\mathbf{a}$. The first component in this equation reflects the effect of cheaper Chinese goods on the price index in state n (term (A) of Equation 24). $\boldsymbol{\alpha}_n'(\mathbf{Q}-\mathbf{I})\mathbf{a}$ captures the effect of suppliers of n buying cheaper Chinese inputs, as well as I-O linkages since suppliers of n purchase intermediates from other suppliers whose costs also fall if they buy Chinese inputs. The second term in Equation 28 is the price effect of the equilibrium wage changes, carried through the same supply chains. Wages are measured relative to the rest-of-world wage, which is the numeraire, $\hat{w}_{ROW} = 1$. $\boldsymbol{\alpha}_n' \mathbf{Q}\, \tilde{\mathbf{w}}$ captures the effect of wage changes on the price index.

Figure 6 plots the cost component of the price channel (the first term of Equation 28) in Indian states against their share of manufacturing in total employment in the no-shock world. The positive relationship is consistent with the welfare result that more industrial states achieved higher welfare gains, in part because they had higher reliance on Chinese intermediate inputs, which led to lower prices through cost reductions.

Figure 6: Price Reductions by Manufacturing Share

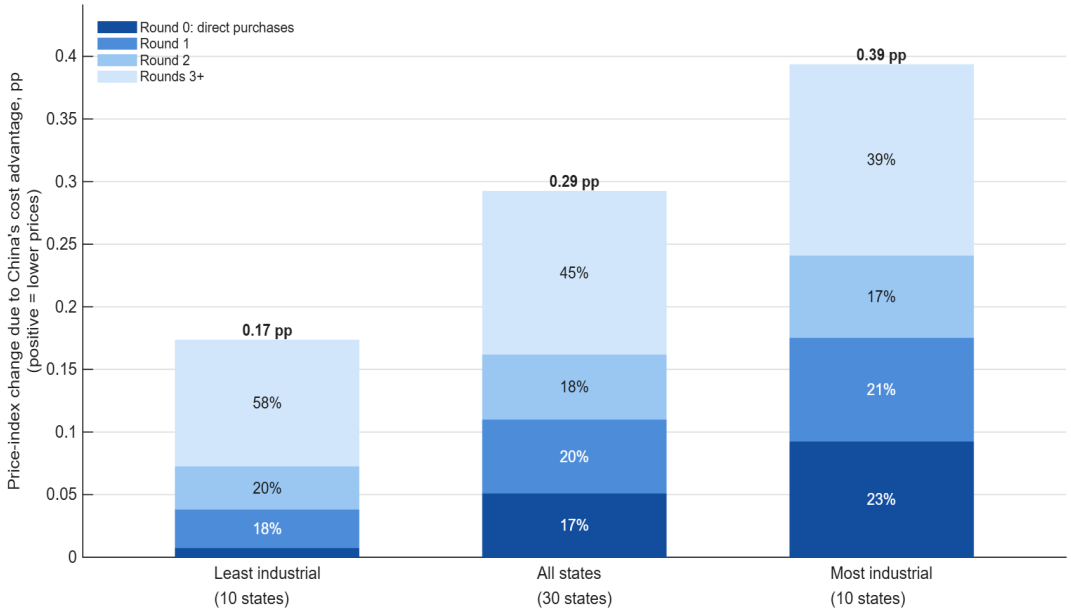


Contribution of I-O linkages to price channel. Next, I show that the majority of the cost effect in the price channel was felt through supply-chain linkages instead of the direct effect. I express the Leontief inverse term, $\mathbf{Q}$, as a sum of rounds:

$$\boldsymbol{\alpha}_n'\mathbf{Q}\mathbf{a} = \underbrace{\boldsymbol{\alpha}_n'\mathbf{a}}_{r=0\text{: direct purchases}} + \underbrace{\boldsymbol{\alpha}_n'\mathbf{M}\mathbf{a}}_{r=1\text{: cheaper inputs for suppliers of } n} + \underbrace{\boldsymbol{\alpha}_n'\mathbf{M}^2\mathbf{a}}_{r=2} + \cdots \tag{29}$$

In Figure 7, I plot the effect of the China Shock on prices in each of these rounds of supply-chain linkages. Round 0 includes the direct effect of the change in Chinese productivity on the price index in state n. Rounds 1 and higher reflect the I-O linkages and transmission of lower prices for all upstream suppliers of state n producers. While prices fell for all states, the overall price reduction was higher in more industrial states. In all states, the majority of the price reduction was due to the supply-chain linkages, relative to the direct effect of cheaper Chinese goods.

Figure 7: Direct vs Supply Chain contribution to Lower Prices



To summarize, in the Indian context, welfare gains due to the China Shock were higher in more industrial states. This is in part explained by the fact that these states were more reliant on Chinese intermediate inputs before the shock occurred, which led to larger price reductions in these states. Input-output linkages amplified the gains from lower prices and made up the majority of the cost reductions, which lowered the price index and raised welfare.

6 Conclusion

This paper shows how the impact of a trade shock can differ across economies based on its production structure, what it imports from the rest of the world, and its position in the global supply chain. I study the impact of the China Shock in India through the output channel, in which local labor markets compete with Chinese imports in their output sectors, and the input channel, in which labor markets benefit from higher intermediate input availability as imports from China grow. Using the shift-share IV methodology of Autor et al. (2013) for Indian districts over 1991-2011, I find that, in aggregate, the input channel dominates and higher exposure to the China Shock was associated with a positive effect on the share of manufacturing in district employment. I also find that the competition

effect is concentrated in the intermediate goods sectors, which represented the lion's share of Chinese imports into India, unlike advanced economies who import an almost equal share of intermediate and consumer goods. There is evidence of production reallocation away from intermediates and into consumer goods sectors, thus alleviating the negative effect on the share of manufacturing in total employment. Interstate trade data enables the first general equilibrium quantification of the impact of the China Shock on India. I estimate aggregate welfare effects of the shock with a theoretical trade model featuring input-output linkages in production to capture the transmission of Chinese imports and falling input prices through the Indian manufacturing sector and beyond. Overall, the China Shock led to welfare gain in India, with higher gains in more industrial states, which benefited from more direct linkages with Chinese imports and a higher reduction in prices.

The results establish that the impact of a trade shock can differ substantially across countries, and even flip to positive, based on import composition and production technology. The analysis lends to the discussion on the impact of new technologies on labor markets and firms, based on sub-national variation in production structures and technology. A natural extension of this research question is to study how firms adapted to the China Shock, based on their exposure to output competition and input availability. This connects to the literature on firm product scope and trade shocks (Goldberg et al. (2010)) as well as structural change at the firm level as firms pivot to downstream production (Ding et al. (2022)).

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A Tables

A.1 First-stage Regressions

Table A1: Baseline Import Exposure and Manufacturing Shares: First Stage

	(1) $\Delta Exposure^{Output}_{India,d,t}$	(2) $\Delta Exposure^{Input}_{India,d,t}$
$\Delta Exposure^{Output}_{Peers,d,t}$	0.916***	0.016
	(0.048)	(0.014)
$\Delta Exposure^{Input}_{Peers,d,t}$	0.024**	0.776***
	(0.014)	(0.016)
Socioeconomic controls	✓	✓
Borusyak Correction	✓	✓
State x Decade FE	✓	✓
No. of Districts	810	810
R-squared	0.96	0.98

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the district level. Observations are weighted by start-of-period population. Exposure measures are in standard-deviation units. Socioeconomic controls include baseline share of manufacturing in employment, female labor force participation rate, and exposure to tariff reductions. Borusyak correction includes the sum of shares for the input channel.

A.2 Growth Rate in Employment

Table A2: Baseline Import Exposure and Log Employment Change: 2SLS Stacked

	(1)	(2)
	$\Delta \log L_{M,d}$	$\Delta \log L_d$
$\Delta Exposure_{d,t}^{Output}$	0.047***	0.002
	(0.014)	(0.008)
$\Delta Exposure_{d,t}^{Input}$	0.043***	0.016**
	(0.016)	(0.008)
Socioeconomic controls	✓	✓
Borusyak Correction	✓	✓
State x Decade FE	✓	✓
No. of districts	810	810

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the district level. Observations are weighted by start-of-period population. Exposure measures are in standard-deviation units. exposure. The average growth rate of manufacturing employment was 0.32pp in 1991-2001 and -0.012pp in 2001-2011. The average growth rate of total employment was 0.11pp in 1991-2001 and 0.13pp in 2001-2011. The dependent variable is the log change in employment over the decade. Socioeconomic controls include baseline share of manufacturing in employment, female labor force participation rate, and exposure to tariff reductions. Borusyak correction includes the sum of shares for the input channel.

B Data construction

B.1 Data for Empirical Analysis

Trade data is collected from COMTRADE for exports from China to all reporting partners in the period from 1992 to 2011. This is used for the selection of peer countries and the measurement of export changes from China. I map all trade data to the NIC-2004 Indian industry codes for manufacturing sub-sectors at the 4-digit level. There are in total 5028 HS-1992 categories at the 6-digit level in COMTRADE. Of these, I use 4789 categories that have export data from China to India and from China to at least one peer country, mapped to 127 NIC-04 categories (of which there are 102 manufacturing sub-sectors).

Data for **employment** at the district level is taken from the 1991, 2001 and 2011 waves of the Population Census conducted by the Indian National Statistics Office. For every district, the census reports population and employment statistics by age group and gender across sectors. For data on district-level **manufacturing output**, this paper relies on the Annual Survey of Industries (ASI). The ASI was launched in 1960 and is conducted annually by surveying formal manufacturing-sector firms in India. For the 1990-91 wave, only aggregate results were published, while the 2000-01 wave included firm-level data, which are aggregated up to the district level for this paper.

Data for **input and intermediate shares** in production is obtained from the long-run World Input-Output Database (WIOD, Timmer et al. (2015)). This data is reported at a 2-digit aggregation of ISIC Rev. 3 product categories, which have been mapped to the Indian industrial classification system.

Industrial sub-sectors in India are classified according to the National Industrial Classification (NIC). The 1991 population census uses NIC 1987, while the 2001 census uses NIC 1998 and the 2011 census uses NIC 2008. For ASI data, the 1990-91 wave uses NIC 1987 and the 2000-01 wave is published according to NIC 2004 definitions. I create a concordance between the different waves of the NIC to ensure consistency across all data sources. There is an exact match between ISIC-Rev 4 and the 2008 revision of the NIC classification. Using this concordance, I map trade data from the 6-digit HS-1992 classification to the 4-digit NIC

2008 codes, and then concord all data (trade, employment and production) to the NIC 2004 classification at the 4-digit level. The choice for the NIC classification is based on the most comprehensive categories available, as some sectors in NIC 2004 were split into multiple categories for NIC 2008.

The names and **boundaries of states and districts** in India have also changed multiple times over the sample period. State and district lists changed in 1987, 1991, 1998, 2005 and 2011. To ensure consistent coverage across years, I match all state and district names to the 1990 definitions. New districts within states have been mapped to the districts that they were carved out of as of the 1990 wave.

For the output channel, there are 450 districts and 206 unique NIC-04 4-digit level codes for which Population Census data is available across all three waves. For the input channel, there are 410 districts across India with production data in both waves of the ASI and socioeconomic data in all three waves of the Population Census. For input and intermediate shares in the WIOD, mapping can only be done at the 2-digit NIC level, and so all production data from the ASI and export data from COMTRADE are aggregated up to the NIC 2004 2-digit level. There are 31 NIC 2-digit categories with input-output details corresponding to 56 sectors in the WIOD database, of which there are 12 manufacturing sub-sectors. To use the national input shares from WIOD, I assume that technology is the same across districts.

Table A3 below provides summary statistics on the main outcome and independent variables in the empirical section.

Table A3: Descriptive Statistics

		1991-2001	2001-2011
Manufacturing Share (%)	Mean	10.22	11.89
(of total emp. at baseline)	SD	7.62	7.19
Capital goods (%)	Mean	0.55	0.32
(of total emp. at baseline)	SD	0.91	0.46
Consumer goods (%)	Mean	4.73	6.07
(of total emp. at baseline)	SD	3.76	3.97
Intermediate goods (%)	Mean	4.72	5.41
(of total emp. at baseline)	SD	4.00	4.17
Δ Manufacturing Share (% points)	Mean	1.48	-1.24
	SD	2.72	1.86
Δ Import Exposure per Worker	Mean	2.97	60.13
(Output channel, USD)	SD	5.06	84.27
Δ Import Exposure per worker	Mean	3.4	59.4
(Input channel, USD)	SD	6.02	118.4

Notes: Each decade has 405 district observations, weighted by start of period population. Change variables are calculated as decadal change, while baseline values are noted at start of each decade. Employment data is obtained from Population Censuses of India, trade data is obtained from COMTRADE, and output data to compute input exposure uses the 1991 and 2001 waves of the Annual Survey of Industries.

B.2 Constructing the Baseline Economy in the Model

To conduct the counterfactual analysis, I first construct the baseline 2011 economy to match the data. For inter-state trade flows, I use the Multi-Region Input Output (MRIO) tables constructed by Zheng et al. (2026). The data disaggregates trade flows for each state-sector pair at the destination and origin level, covering 66 sectors and 32 Indian states. The dataset also contains data on state-level final consumption, exports and imports. I combine this with data from the World Input-Output Table (WIOT) to record trade flows between India, China and the Rest of the World (ROW). This gives me a bilateral flows matrix across 32 regions (30 Indian states, China and ROW) and 18 sectors, comprising 16 manufacturing sub-sectors, agriculture and services. Bilateral trade flows are used to compute trade shares in the baseline economy, π_{in}^{j}, denoting expenditure share of region n on region i in sector j. The MRIO dataset also provides information on value added in each sector-state pair, and the corresponding value added data for China and ROW are obtained from WIOT. Gross output in region n and sector j, Y_n^j is computed as the row sum of the bilateral flows matrix, summing over all domestic and foreign exports. Total expenditure, X_n^j is correspondingly the column sum of the matrix, summing over all domestic and foreign imports and value added.

The MRIO table only contains import and export data at the destination state-origin sector level. For instance, it can tell us how much Andhra Pradesh imports in the textile sector, but it cannot tell us which sectors in Andhra Pradesh use these textile imports, and it also does not provide a breakdown of origin region of the imports. To compute state and destination sector-level imports, I combine information on state-level trade with WIOD data. As an illustrative example, I calculate how much textile is imported by the chemicals sector in Andhra Pradesh. WIOD data provides the quantity of Chinese textile imports used by India's chemicals sector, and MRIO data provides the share of Andhra Pradesh in national textile imports. Then, Chinese imports of input sector k (textile in the example above) in Andhra Pradesh's using sector j (chemicals above) are:

$$M_{Ch,AP}^{kj} = M_{Ch,Ind}^{kj} \times \frac{M_{AP}^{k}}{M_{Ind}^{k}}$$

Exports from every state-sector pair to China and analogously, ROW, are computed using

state shares in national exports by input sector and China (or ROW's) imports from India as in WIOT. So, Chinese imports of input sector k for using sector j from Andhra Pradesh can be expressed as:

$$M^{kj}_{AP,Ch} = M^{kj}_{Ind,Ch} \times \frac{Exp^{k}_{AP}}{Exp^{k}_{Ind}}$$

For Indian states, sectoral labor data, L^j_n, is taken from the 2011 population census, same as the data used for the empirical analysis. Labor force per sector for China is obtained from WIOD's Socioeconomic accounts (SEA). The SEA database only contains employment data for 43 countries, so I take world employment data from the World Development Indicators. I then compute shares from SEA's non-China non-India countries for employment in each sector, and apply this to the WDI aggregate.

Finally, I measure the share of value added, γ^j_n, input-output coefficients, γ^{kj}_n, and consumption shares, α^j_n, from the bilateral flows matrix. State-level value added from MRIO is divided by gross output to compute γ^j_n for all states. The bilateral flows matrix also provides expenditure from each using state-sector pair for every origin sector (from domestic and international sources), which is used to compute the share of input k in production of using sector j in region n, γ^{kj}_n. The IO coefficients are then rescaled to ensure that $\gamma^j_n + \sum_k \gamma^{kj}_n = 1$. The MRIO dataset also contains expenditure on final use for every state-origin sector pair, which feeds into the bilateral flows matrix separately from intermediate input flows. The share of total income spent on final consumption use, α^j_n, is then computed as total expenditure - total intermediate expenditure (implied by the rescaled γ^{kj}_n and divided by regional income. For China and ROW, corresponding values of γ^j_n, γ^{kj}_n and α^j_n are obtained from WIOT. Values for the dispersion parameter of the Fréchet distribution, θ^j are borrowed from Caliendo and Parro (2015).

C Hat Algebra notation

The equilibrium defined in section 5.2 is expressed in hat algebra notation, where for any variable x, hat notation denotes relative changes, or the ratio of the counterfactual value of a variable to its baseline value. There are no changes to trade costs, so that $\hat{\tau}_{in}^{j} = 1$ for all i, n, and $\hat{\lambda}_{i}^{j} = 1$ for all regions $i \neq$China. The productivity shock affects only the 16 manufacturing sub-sectors, such that $\hat{\lambda}_{Chn}^{j} = 1$ for $j =$ agriculture, services.

Change in the price index,

$$\hat{P}_{n}^{j} = \Big[\sum_{i} \pi_{in}^{j} \hat{\lambda}_{i}^{j} . (\hat{c}_{i}^{j})^{-\theta^{j}} \Big]^{-\frac{1}{\theta^{j}}} \tag{30}$$

Change in the input bundle cost for sector k intermediate goods in region n,

$$\hat{c}_{n}^{k} = \hat{w}_{n}^{\gamma_{n}^{k}} \prod_{j} (\hat{P}_{n}^{j})^{\gamma_{n}^{j,k}} \tag{31}$$

Change in expenditure shares for region i in region n's total expenditure on sector j:

$$\hat{\pi}_{in}^{j} = \frac{\hat{\lambda}_{i}^{j} . (\hat{c}_{i}^{j})^{-\theta^{j}}}{\pi_{Ch,n}^{j} \hat{\lambda}_{Ch}^{j} (\hat{c}_{Ch}^{j})^{-\theta^{j}} + \pi_{ROW,n}^{j} (\hat{c}_{ROW}^{j})^{-\theta^{j}} + \Sigma_{i} \pi_{in}^{j} (\hat{c}_{i}^{j})^{-\theta^{j}}} \tag{32}$$

Change in the wage in region n:

$$\hat{w}_{n} = \sum_{j} \gamma_{n}^{j} \Sigma_{i} \hat{\pi}_{ni}^{j} \hat{X}_{i}^{j} \tag{33}$$

New total output in region n for sector j:

$$(Y')_{n}^{j} = \sum_{n} (\pi')_{ni}^{j} (X')_{i}^{j} \tag{34}$$

New expenditure in region i on sector j:

$$(X')_{i}^{j} = \alpha_{i}^{j} (w_{i}' L_{i} + D_{i}) + \sum_{k} \gamma_{i}^{jk} Y_{i}'^{k} \tag{35}$$

Labor demand in region n, sector j after the shock:

$$(\ell')_n^j = \frac{\gamma_n^j . (Y')_n^j}{w'_n} \tag{36}$$