Imports, Exports, and Employment: India's Trading Relationship with China

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November 9, 2023

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Abstract

This paper examines the effect of increased import competition and export demand on local labor markets in the context of India's trading relationship with China. Using an instrumental variables approach, I find that labor markets exposed to Chinese imports decrease their manufacturing employment growth relative to their positive preexisting trend. On average, manufacturing employment does not grow in response to export demand shocks, but sufficiently literate, developed, or urban labor markets see positive manufacturing growth in response to export demand increases. These same districts are also able to increase their service sector employment in response to increased export demand.

Keywords: Local Labor Markets, International Trade, Manufacturing, Employment
JEL: F16, F66, J21, J23, O10

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1 Introduction

There is robust empirical evidence that import competition coming from developing countries, such as China, has lowered manufacturing employment for developed countries (Autor, Dorn, and Hanson 2013; Pierce and Schott 2016). This evidence suggests that there are substantial adjustment frictions that prevent workers from reallocating to new jobs (Autor, Dorn, Hanson, and Song 2014; Kondo 2018). Yet for many countries, the rise of China has been both a source of import competition and export demand. In these cases, increased export demand may offset the negative labor demand shock coming from import competition, leading to increased manufacturing employment. Increased export demand even has the potential to create positive spillover effects in the service sector of the economy.

Despite the understanding that the rise of China has led to both increased import competition and export demand for many countries, we know significantly more about the local labor market effects of import competition relative to the effects of increased export demand.[1] In addition, we know less about how developing countries responded to the China trade shock. Specifically, we know little about the characteristics which allow developing local labor markets to withstand import competition or take advantage of export demand.

To shed light on these questions and investigate how increased trade impacts the local labor markets of a developing country, I examine the trading relationship of the two most populous countries in the world, China and India.[2] The setting is well suited to address this issue as India experienced both an increase in import competition and export demand from China. Panel (a) of Figure 1 shows the value of Indian exports to China and India's imports of Chinese goods over time. After China's accession to the World Trade Organization (WTO) in 2001 there was a large but balanced increase in India's trading relationship with China. Panel (b) confirms that this is not simply the result of India increasing their trade with the rest of the world (ROW). The share of India's total imports that were Chinese and share of total exports that were sent to China increased substantially.

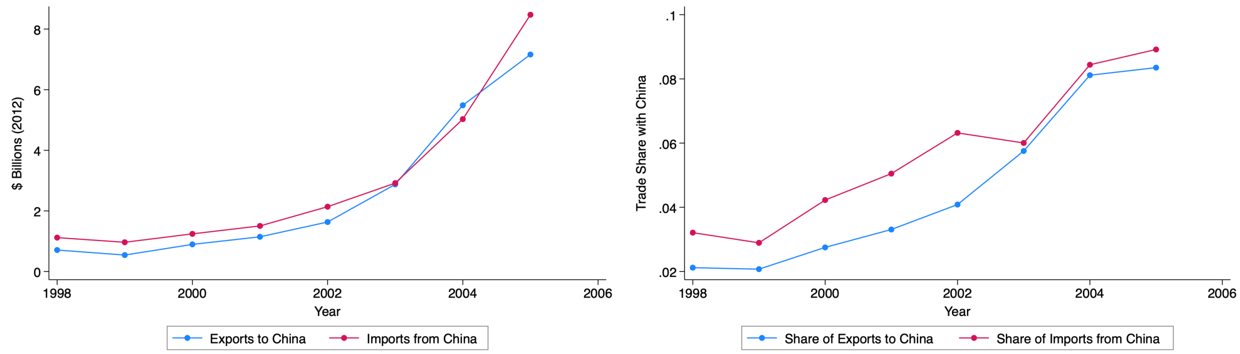
My empirical strategy involves dividing India into 506 local labor markets based on

[1]Three notable exceptions are Feenstra et al. 2019, Dauth et al. 2014, and Costa et al. 2016 who respectively study the effect of Chinese import competition and export demand in the U.S., Germany, and Brazil. They all find positive effects of increased export demand on local labor markets.

[2]In 2020, China and India comprised 36% of the world's population.

Figure 1: India-China Trade

(a) Imports/Exports (b) Import/Export Share



Notes: Panel (a) plots aggregate Indian exports to China and imports from China while Panel (b) plots the share of total imports to India that are from China and the share of total Indian exports that are to China.

1998 district definitions. I then apportion imports from China and exports to China to these local labor markets based on the 1998 distribution of workers across industries in each district. Next, I estimate a stacked first-differences equation via Ordinary Least Squares (OLS) to examine the association between increased imports and exports and local labor market outcomes. I find that districts which would experience large growth in Chinese imports from 1998-2005, experienced higher growth rates of manufacturing employment from 1990-1998, before there was a large trading relationship between India and China. In my preferred specification, a $100 (2012 USD) increase in Chinese imports per worker from 1998-2005, was associated with a 9% increase in manufacturing employment from 1990-1998. When the Chinese imports were realized, the growth in manufacturing employment stalled from 1998-2005 as every $100 in Chinese imports per worker was associated with a 2% decline in local manufacturing employment.[3] These results suggest that increased imports from China had a negative effect on India's local labor markets. On average, I also find no association between increased export demand and local labor market outcomes.

Since the value of India-China trade is an endogenously determined value, I instrument for imports and exports using the methodology of Costa et al. 2016. The instrument is constructed using growth rates of Chinese trade with all countries except India, after remov-

[3]This constitutes an 11% decline relative to the positive pre-trend of 9% growth in manufacturing employment. The relative effect is calculated as: -2% - 9% = -11%.

ing the mean worldwide growth rate of trade in industries through an auxiliary fixed effect regression. By removing the mean growth rate of an industry, the instrument exploits variation in the growth of China's imports and exports with other countries that departs from worldwide growth rates. The instrument is highly predictive of growth in Chinese imports and exports to China, and the results are very similar when I estimate my regressions via Two Stage Least Squares (2SLS) in order to address the endogeneity of imports and exports.

Next, I turn to examining whether Chinese imports or export demand had an effect on employment in the services sector. I find no evidence that import or export exposure had an effect on the growth of services employment, suggesting that in this context there were limited spillovers from manufacturing to the service sector. I then examine whether the China trade shock led to geographic mobility. Consistent with other evidence on trade in developing countries, I find precisely estimated null effects of trade exposure on district population (Costa et al. 2016; Dix-Carneiro and Kovak 2017; Erten et al. 2019). This suggests that individuals face substantial mobility frictions, highlighting a mechanism for why I find that Chinese imports negatively affect manufacturing employment.

Finally, I explore heterogeneity in the effect based on districts' pre-existing characteristics. This analysis sheds light on how local labor markets can remain resilient in the face of import competition and take advantage of increased export demand. I find evidence that the negative effect of imports on manufacturing employment is stronger in more educated, developed, or urban districts. This runs against the evidence in Topalova 2010 who use the 1991 Indian trade liberalization to document that the declines in tariffs most negatively affect the consumption of poor households. My results are consistent with a story where adjustment is costlier for high skilled manufacturing. Further, I find that sufficiently educated, developed, or urban districts see positive effects from export demand on manufacturing employment. This result contrasts McCaig 2011 who find that in response to a positive export demand shock unskilled Vietnamese workers benefit the most relative to skilled workers. My results suggest that sufficient education, development, and density are necessary in order for a local labor market to be able to exploit export demand opportunities.

My results contribute to a literature studying the effects of trade on developing labor markets. My work is mostly closely related to Costa et al. 2016 who study the impact of

Chinese import competition and export demand on local labor markets in Brazil. Costa et al. 2016 find a positive effect of export demand on wages and employment, while they find that import competition from China has a negative effect on manufacturing wages. My results provide new evidence in the Indian context and examine characteristics of local labor markets that make them more resilient to import competition or better able to take advantage of increased export demand. Other studies separately study the labor market effects of import competition or export demand. In a wide variety of developing country contexts, several studies examine the effects of import tariff reductions on outcomes such as employment (Dix-Carneiro and Kovak 2017; Erten et al. 2019) and poverty (Topalova 2010; Kis-Katos and Sparrow 2015). These studies consistently find adverse effects of tariff reductions on employment and poverty. McCaig 2011 addresses the effect of export demand and finds that a positive export demand shock reduces poverty in Vietnam. This paper also address the topic of export demand and highlights that sufficiently educated, developed, or urban districts are most able to take advantage of increased export demand.

2 Data

The data on trade flows comes from the BACI database, maintained by the Centre d'Etudes Prospectives et d'Informations Internationales. The BACI database contains information from COMTRADE on bilateral trade flows at the harmonized system six digit (HS6) level. Indian industrial data is most commonly categorized using the 1987 Indian national industry classification system (NIC87). In order to translate HS6 products to NIC87 industries, I digitized a concordance provided by Debroy and Santhanam 1993. There are cases in the concordance where NIC87 codes match to multiple HS6 codes with no weights provided. In order to consistently map HS6 trade flows into NIC87 codes, I assign a weight of one to each HS6-NIC87 pair. In the end, this gives me bilateral trade flows at the NIC87 $\times$ country-pair $\times$ year level for the years 1998-2009.[4]

Local labor market data comes from several sources. First is the Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG) database provided by Asher

[4]Bilateral trade flows are converted to 2012 USD using the US GDP deflator.

et al. 2021. I follow Imbert and Papp 2015 and use Indian districts as my measure of a local labor market. Since the number of Indian districts has been growing over time, the boundaries of districts are not consistent.[5] The SHRUG database addresses this issue by mapping nearly 600,000 towns and villages into geographic areas called SHRIDs which are consistent across the 1990-2013 Indian Economic and Population Censuses. The SHRUG database contains data taken from the 1990, 1998, and 2005 Indian Economic Censuses (EC) and data from the 1991, 2001, and 2011 population censuses (PC) provided by the Ministry of Statistics and Programme Implementation. Although the SHRUG's coverage of data in the 1990-2013 Indian Economic and Population Censuses is good, it is not perfect. Although the SHRUG's coverage of data in the 1990-2013 Indian Economic and Population Censuses is good, it is not perfect. The SHRUG data covers 70%, 89%, and 93% of all employment in the respective 1990, 1998, and 2005 economic censuses.[6]

I use data from these censuses to create my primary local labor market outcomes. The economic censuses provide an enumeration of most Indian enterprises, but they do not include enterprises which exist for the 'sole purpose of own consumption.' They also do not include enterprises related to agricultural crop production & plantation. For this reason, agricultural activity is underrepresented in any given EC with significantly better coverage of manufacturing and services, leading me to focus my analysis on the manufacturing and services sectors. The economic censuses provide a count of the total number of workers in a district $\times$ year observation, along with the number of workers in manufacturing and services. Changes in employment from 1990-1998 are used to examine whether districts facing differential exposure to Chinese trade were on different trends before the rise of China. Changes in outcomes from 1998-2005 are used to capture the effect of India-China trade on local labor markets. Since each SHRID uniquely matches to a district definition at any point in time, I aggregate SHRID level data on employment up to the district level. I also supplement data that can readily be found in the SHRUG database with data that I construct from the economic censuses and then merge to the SHRUG data. For example, I use the 1998 EC to measure the distribution of workers across NIC87 industries in each district. This

[5] There were 593 districts recorded in the 2001 census, that number grew to 640 by the 2011 census and stood at 748 by 2021.

[6] See Asher et al. 2021 for more details.

distribution of workers is used to allocate aggregate Chinese imports and exports to China to each district.

The data from the population censuses is used to assess whether India's trading relationship with China led to changes in population or migration. Population growth from 1991-2001 is used to assess population trends before the rise in India's trading relationship with China while population growth from 2001-2011 is used to examine whether India's trading relationship with China had an effect on population growth and migration. The 1991 PC is also used to construct the share of literate persons in a district, which I use as a proxy for the education level of the district. The SHRUG database also provides data on nightlights running from 1994 through 2013. I use nightlights as a proxy for the amount of economic activity and development in a district (Henderson et al. 2011). These literacy and nightlight characteristics are used to examine whether the effect of imports and exports on local labor market outcomes varied by the initial amount of education and development a district had.

3 Empirical strategy

To measure each district's exposure to Chinese imports and exports I use the following apportionment rule where L denotes the number of workers, d subscripts district, year t, and NIC87 j:

$$\text{Exports}_{dt} = \frac{1}{L_{d,98}} \sum_{j} \frac{L_{dj,98}}{L_{j,98}} \text{Exports}_{jt} \tag{1}$$

Intuitively, each industry's aggregate exports to China are apportioned to districts based on the share of industry employment found in the district. Aggregating across all industries in a district gives the total value of exports to China for the district in a given year. Finally, I divide through by the size of the total workforce in the district ($L_{d,98}$). Exports_{dt} can be interpreted as the export value in hundred 2012 U.S. dollars per worker. Imports_{dt} is defined analogously. Importantly, I use a district's 1998 employment distribution to apportion import and export exposure. I do this to avoid using outcomes that could be endogenously influenced by Chinese trade in order to construct exposure to the shock. 1998 sufficiently pre-dates the rise of the India-China trade relationship and China's entry into the WTO, making it unlikely that the 1998 district employment distribution reflects any anticipation of the rise in India-China trade.

Table 1 presents summary districts for several of the main variables used in the analysis. All statistics, excluding total employment in 1998, are calculated by using each district's total 1998 employment as weights. The weighted average change in exports (imports) per worker from 1998-2005 is \$96 (\$102) 2012 USD. Given that 1998 GDP per capita in India was \$366 2012 USD, this represents a meaningful economic shock. Manufacturing makes up a sizeable share of employment with the average district having about 30% of its employment in manufacturing.

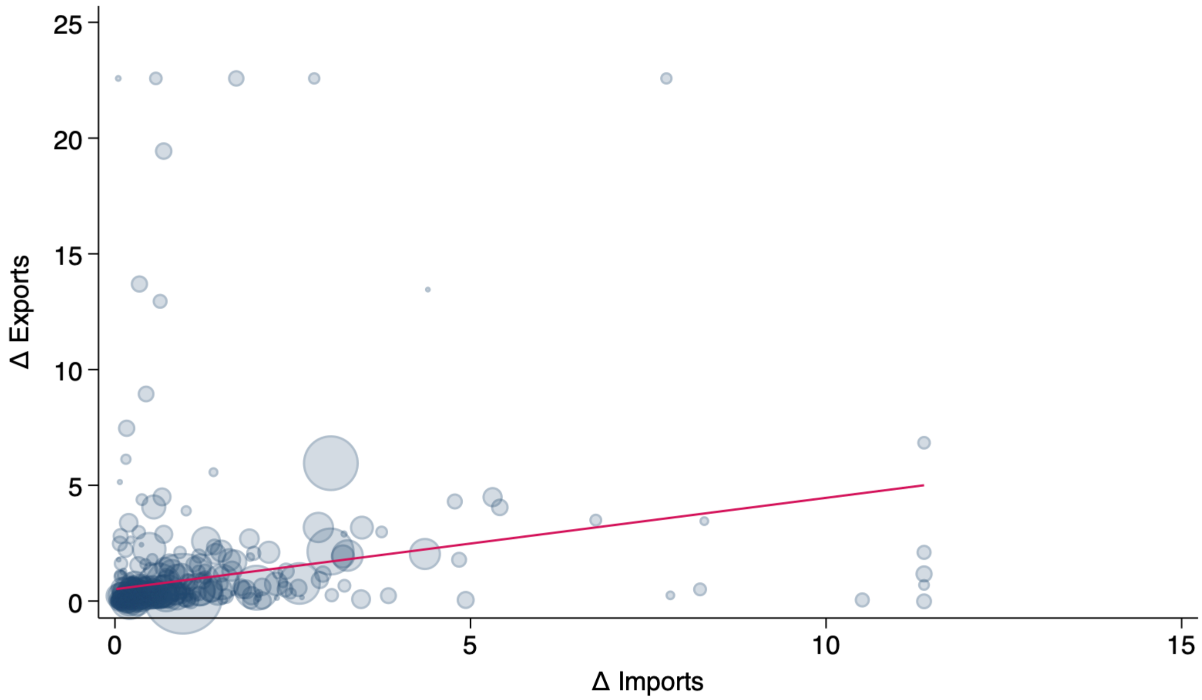
Table 1: Summary Statistics

	Mean	St. Dev.	Min	Median	Max	N
ΔExports	0.96	2.17	-0.02	0.32	22.58	506
ΔImports	1.02	1.40	0.02	0.52	11.38	506
Rural Share_{98}	0.49	0.25	0.00	0.51	1.00	506
Mfn Share_{98}	0.29	0.11	0.04	0.27	0.69	506
Δ ln(Mfn Emp)	0.05	0.31	-1.51	0.08	3.14	506
Δ Mfn Share	-0.02	0.06	-0.24	-0.02	0.21	506

Notes: This table presents results summary statistics at the district level for districts which are in the sample for Table 2. All statistics are calculated using weights where weights are the number of individuals recorded as employed in the 1990 EC. Districts are based on the 1998 EC definitions.

In order to separately identify the effects of import and export exposure on local labor markets, there needs to be independent variation in import and export exposure. Figure 2 plots the change in import penetration from 1998-2005 in a district against the change in exports per worker along with the regression line resulting from regressing the change in 1998-2005 import exposure on the 1998-2005 change in export exposure. While there is a positive and statistically significant relationship between the two variables, there is significant variation between import and export exposure with the two measures having a correlation of 0.31.

Figure 2: Correlation Between Import/Export Exposure



Notes: This figure displays a scatterplot of the change in Chinese export and import penetration from 1998-2005 across districts, weighted by total district employment in 1990 along with the line of best fit. The coefficient on $\Delta\text{Imports}_{dt}$ is .48 with a t-statistic of 3.19. R^2 is 0.09.

3.1 *Instrumental variables*

Using the change in a district's import or export penetration from 1998-2005 as my main explanatory variable, I would like to estimate the following stacked first-differences model where the two stacked time periods are the period before the rise of China (1990-1998) and the period after the rise of China (1998-2005).

$$\Delta\text{Y}_{d\tau} = \alpha_x \Delta\text{Exports}_{d,(98-05)} + \alpha_m \Delta\text{Imports}_{d,(98-05)} \tag{2}$$

$$+\beta_x(\Delta\text{Exports}_{d,(98-05)} \times \mathbb{1}\{\text{Post}\}) + \beta_m(\Delta\text{Imports}_{d,(98-05)} \times \mathbb{1}\{\text{Post}\}) + \delta_\tau + \varepsilon_{d\tau}$$

ΔY_{dt} is the change in a labor market variable of interest for district d over time period

τ. $\Delta\text{Exports}_{d,(98-05)}$ and $\Delta\text{Imports}_{d,(98-05)}$ are measured as described in Equation (1) and are the difference between 2005 and 1998 district imports and exports. Notice that in both time periods the 1998-2005 change in export and import penetration is used, similar to the specification in Autor, Dorn, Hanson, Pisano, et al. 2020. This is for several reasons. First, this allows me to examine any differential trends that exposed districts were on before the rise of China. These pre-trends are captured by α_x and α_m. In addition, China and India's trade was at low and constant levels before China's entrance into the WTO and rise as a manufacturing superpower, making the pre-trends test relevant since the true change in exports and imports was approximately zero (Copestake and Zhang 2023). $\mathbb{1}\{\text{Post}\}$ is an indicator for the 1998-2005 time period. β_x and β_m capture the effect that a \$100 2012 USD change in export and import penetration have on labor market outcome Y during the 1998-2005 time period τ relative to the 1990-1998 pre-trend.

Unfortunately, the estimates on β_x and β_m are likely biased for several reasons. First, Chinese demand for a district's products could be correlated with worldwide demand for a district's products. This would bias the OLS coefficient on exports upwards since I would be conflating the rise in Chinese demand for a districts goods with worldwide changes in demand. Second, exports to China may not be related to a Chinese demand shock, but could be related to Indian supply shocks. For example, one of India's main exports to China is iron ore. Indeed, Table A.2 shows that the Goldsmith-Pinkham et al. 2020 Rotemberg weight on the iron ore mining industry is approximately 90%, indicating that exposure to the iron ore industry plays a leading role in determining the overall estimate of the effect of Chinese exports on local labor markets. This aligns with the findings of Costa et al. 2016 who report that in 2005 nearly 70% of Brazil's exports to China were in the agricultural and extractive sectors. If India experienced productivity improvements in the iron extraction industry then this could be a source of increased iron exports to China independent of a Chinese demand shock. This would bias β_x upwards as I would be conflating Chinese demand with Indian supply shocks. Likewise, import supply shocks from China could be correlated with Indian demand shocks that have little to do with increases in China's comparative advantage in manufacturing certain goods. To the extent that import supply shocks represent competition for Indian manufacturing workers, then the correlation between demand shocks and foreign supply shocks is likely to attenuate my estimates towards zero (Autor, Dorn, and Hanson 2013).

In order to make causal claims about the effect of Chinese export demand and import supply shocks, I attempt to isolate variation in Chinese supply or demand that is exogenous with respect to the outcomes I am interested in. To do this I follow Costa et al. 2016 and construct instruments for Chinese imports to India and Indian exports to China. The starting point is inspired by the insight of Autor, Dorn, and Hanson 2013, the trading relationship between China and countries besides India is reflective of the comparative advantages of China and the goods that China demands from other countries, but these trade flows are likely unrelated to idiosyncratic features of the Indian economy. As stated earlier, one of India's main exports to China is iron ore. To capture the component of Indian exports of iron ore to China that come from increased Chinese demand and not Indian supply shocks I can use Chinese imports of iron ore from other countries to instrument for Chinese imports of iron ore coming from India. This is likely to remove much of the idiosyncratic changes to Indian supply. This story still leaves a worrying possibility, there could be worldwide changes to the supply of iron ore which may be correlated with increases in Chinese demand. For example, if a new and more efficient method of extracting iron ore was discovered, I would likely observe increased Chinese imports of iron ore not due to a demand shock from China, but due to the worldwide supply shock. The instruments of Costa et al. 2016 improve upon those of Autor, Dorn, and Hanson 2013 by removing these aggregate industry shocks.

To construct the instruments I start by translating HS6 products to NIC87 industries in the trade data using the concordance I described earlier. Next, for each country $\times$ year observation I calculate the total value of imports (exports) from (to) all countries except India. Then for each time period in my analysis I estimate regressions of the form outlined in Equation (3) with an analogous regression for exports. I weight all regressions by base year imports (exports) to avoid undue influence from observations with low levels of trade volume which can cause growth rates to be very large in absolute value terms:

$$\frac{\Delta \text{Imports}_{cj\tau}}{\text{Imports}_{cj,t_0}} = \alpha_j + \psi(\alpha_j \times \mathbb{1}\{\text{China}_c\}) + \varepsilon_{cj\tau} \tag{3}$$

The dependent variable is the country's growth rate of imports in NIC87 industry j over time period τ. The NIC87 fixed effects, α_j, capture the weighted mean growth rate in imports in industry j over time period τ. This effectively absorbs world level supply or demand shocks for the goods of industry j which may confound identification of the China trade shock. The coefficient, ψ, on the interaction between NIC87 fixed effects and a China dummy captures Chinese deviation from world level growth rates in the imports of goods in industry j. This Chinese deviation from world growth rates is the variation I exploit to capture the rise of China's integration into world trade and the specific comparative advantages in production and demand for certain goods in world markets.

To do this, I use the estimated $\hat{\psi}_j$ to construct predicted changes in Indian exports to China as outlined in Equation (4). For a given period of time, I use the industry exports to China in the starting year t_0 and multiply them by $\hat{\psi}_j$ in order to arrive at the predicted change in Indian exports to China during time period τ for a particular industry j. Summing across all industries j brings me to the total predicted change in export penetration at the district level. These predicted changes in imports and exports are then used to instrument for endogenous district level imports and exports in Equation (2). Notice that in Equation (3) the growth rate of imports is the dependent variable. I use imports to construct instruments for Indian exports because Chinese imports from other countries provide information on Chinese demand for goods which corresponds to Indian exports to China. Similarly, I calculate instruments for Indian imports from China replacing the growth rate of imports in Equation (3) with the growth rate of exports and then performing an analogous calculation as in Equation (4).

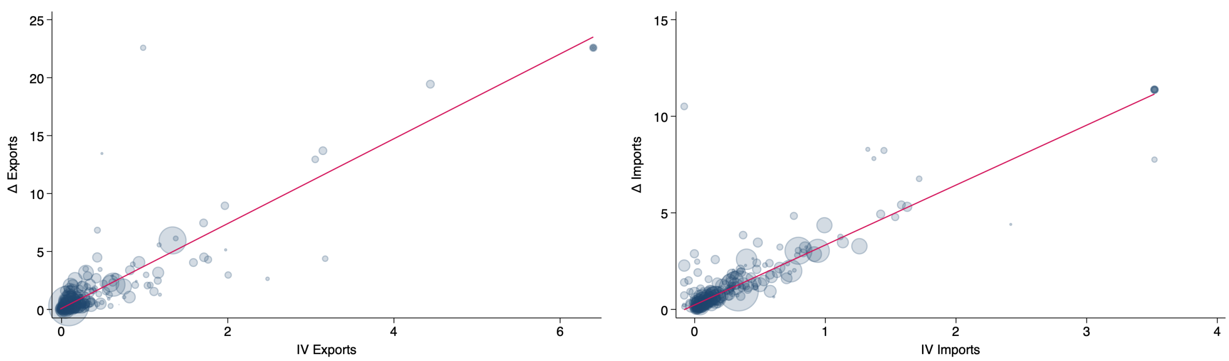
$$\Delta \text{IV Exports}_{d\tau} = \sum_j \hat{\psi}_j \times \text{Exports}_{djt_0} \tag{4}$$

To examine the ability of the instruments to explain India's change in trade with China from 1998-2005, Figure 3 plots the change in exports and imports against the instrument values with the size of each circle corresponding to number of workers in the district in

1998. There is a strong positive correlation between the instruments and the change in exports and imports, suggesting that the instruments will have strong explanatory power for the endogenous variables. In addition, Table A.1 and Table A.2 respectively display the Goldsmith-Pinkham et al. 2020 Rotemberg weights for the import and export instruments. For the import exposure instrument, the industry associated with the manufacture of apparatuses for broadcasting radio, TV, and radar signals received the highest Rotemberg weight at 45%. Eleven other industries received Rotemberg weights above 1%, indicating that the estimates of the import exposure effect are being driven by a variety of industries.

Figure 3: First Stage

(a) $\Delta \text{Exports}_{dt}$ (b) $\Delta \text{Imports}_{dt}$



Notes: Panels (a) plots the change in district exports per worker from 1998-2005 against the instrument value of exports along with the line of best fit. Panels (b) plots the change in district imports per worker from 1998-2005 against the instrument value of imports along with the line of best fit. The size of the circle is the total employment of the district in the 1990 EC.

4 Main results

4.1 *Employment*

My first set of results examines how increased trade with China impacted the growth of a district's manufacturing employment. I estimate the stacked first-differences specification in Equation (2) via OLS and 2SLS (using the instruments described previously) with the change in the natural log of a district's total manufacturing employment as the dependent variable. Changes are over the 1990-1998 and 1998-2005 periods, while changes in import and export penetration are only calculated over the 1998-2005 time period.

A potential concern is that pre-existing characteristics of districts which are related to other shocks may be correlated with the India-China trading relationship. For example, districts who have a high share of their workforce in manufacturing may be differentially exposed to structural change, which could cause me to conflate the effect of structural change with Chinese trade. To address this issue, I augment Equation (2) with a vector of controls that includes: the share of 1990 employment in manufacturing, the natural log of the district's total 1990 employment, and the share of the 1990 workforce in rural areas. The 1990 manufacturing share is a demanding control as it holds the district's overall manufacturing exposure constant and forces identification to come from comparing district's who have similar manufacturing shares but have differing distributions of their workforce across detailed NIC87 industries. I also include state $\times$ time period fixed effects in some specifications. While there are 506 1998 EC districts in my data, there are only 28 states. The inclusion of state $\times$ time period fixed effects forces comparisons to be made within states. I winsorize outcome and trade variables at the 1st and 99th percentile to mitigate the influence of any outliers, although Table A.3 shows robustness of my results to not winsorizing. In all regressions, I weight by the district's 1990 employment and cluster standard errors at the district level. Weighting makes results representative of aggregate effects and helps reduce the influence of large changes coming from districts with little employment. Standard errors are clustered at the district level to account for correlation over time in the error term.

The first two rows of Table 2 display the coefficients on the change in district import and export penetration interacted with a post indicator, along with their standard errors. The coefficients can roughly be interpreted as percent changes in district manufacturing employment that correspond with an \$100 2012 USD increase in district imports or exports per worker. In columns (1)-(3) I estimate the specifications via OLS, leaving the coefficients on imports or exports subject to concerns about endogeneity. The point estimate on the change in import penetration in the first row is positive and significant, indicating that districts which would receive a large import shock from China were on a positive trend before the rise of India's trading relationship with China. In my most basic specification in column (1) this positive pre-trend was completely eliminated by the arrival of Chinese

Table 2: Manufacturing Employment

	Δ ln(Mfn Emp)					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
ΔImports	0.056**	0.090***	0.091***			
	(0.023)	(0.025)	(0.023)			
ΔImports $\times$ Post	-0.075**	-0.111***	-0.106***	-0.066*	-0.119***	-0.106**
	(0.033)	(0.035)	(0.036)	(0.038)	(0.045)	(0.046)
ΔExports	0.002	0.003	0.024			
	(0.014)	(0.010)	(0.016)			
ΔExports $\times$ Post	0.012	0.012	-0.012	0.009	0.013	-0.013
	(0.020)	(0.013)	(0.018)	(0.020)	(0.014)	(0.018)
Mfn Share$_{90}$ $\times$ Post		0.340	-0.066		0.353	-0.066
		(0.354)	(0.319)		(0.356)	(0.320)
ln(Emp$_{90}$) $\times$ Post		0.186***	0.161***		0.186***	0.161***
		(0.035)	(0.041)		(0.035)	(0.041)
Rural Share$_{90}$ $\times$ Post		-0.158	-0.339*		-0.166	-0.339*
		(0.156)	(0.175)		(0.158)	(0.177)
Mfn Share$_{90}$		-0.637**	-0.261			
		(0.295)	(0.258)			
ln(Emp$_{90}$)		-0.152***	-0.132***			
		(0.028)	(0.028)			
Rural Share$_{90}$		0.156	0.258*			
		(0.132)	(0.155)			
Observations	1,012	1,012	1,012	1,012	1,012	1,012
KP *F*-Stat				165.5	160.1	104.6
District FE				✓	✓	✓
State $\times$ Year FE			✓			✓

Notes: This table presents results from estimating Equation (2) where the dependent variable is the change in the log of manufacturing employment in period τ. The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{d\tau}$ is defined similarly. In columns (4)-(6), $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Regressions are weighted by the number of workers in the district according to the 1990 EC and standard errors are clustered at the 1998 EC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

imports. The point estimates suggest that a \$100 increase in Chinese imports per worker is associated with a 7.5 percent decline in manufacturing employment over the 1998-2005 time period relative to the counterfactual of manufacturing employment increasing 5.6%, as it did from 1990-1998. In column (2), I add controls which address the concern that districts with different pre-existing characteristics may trend differently for reasons unrelated to China's trading relationship with India. When I add controls, the estimate on the change in imports interacted with the post indicator becomes larger in absolute value. In column (3), using state fixed effects does little to change the result, suggesting that even within the 28 Indian states the results hold. In contrast to the results on imports, the point estimates for β_x are much smaller and imprecisely estimated both in the pre-period and during the exposure period of 1998-2005.

To address concerns of endogeneity, I instrument for the change in exports and imports interacted with a post dummy by interacting the instruments I described earlier with a post indicator. In my IV specifications, I use district fixed effects to remove the main effects of all control variables and import and export exposure. This increases the joint explanatory power of the instruments. District fixed effects control for the mean level of manufacturing employment growth over the two time periods, along with any other time-invariant district characteristics. Across all specifications, the instruments produce a strong first stage with a Kleibergen-Paap F-statistic that exceeds 100 across all specifications. The point estimates are similar to what I found in the OLS specifications and precisely estimated. Columns (4)-(6) indicate that a \$100 increase in imports per worker causes somewhere between a 7-12% decline in manufacturing employment. Adão et al. 2019 and Borusyak et al. 2022 find that traditional standard errors are often too small because they fail to take into account the correlation of regression residuals across districts with similar distributions of workers across industries. Following the procedure in Borusyak et al. 2022, Table A.4 shows that the exposure-robust standard errors are smaller than the conventional standard errors clustered at the district level.[7] Overall, the results suggest that the arrival of Chinese import competition caused a significant decline in Indian manufacturing employment

[7] The point estimates and standard errors found in Table A.4 should be compared to the point estimates and standard errors found in Table A.3 as both tables use variables which are not winsorized.

while increased export demand likely had little effect.

Table 3 uses the same empirical strategy as before, but examines the change in the share of enumerated employment in the manufacturing sector as the dependent variable. The results indicate that the observed changes in manufacturing employment are not an artifact of overall changes in district employment. India's trading relationship with China had an impact on the composition of district employment. Using my preferred estimates in column (5), a \$100 increase in Chinese imports per worker leads to a 2 percentage point decline in the manufacturing share of employment. While export demand had no effect on the growth of manufacturing employment, it did have an effect on the share of employment in manufacturing. In column (5), a \$100 increase in Chinese exports per worker leads to a 0.05 percentage point increase in the manufacturing share of employment. These effects are sizeable. A \$100 per worker increase in import penetration leads to a $\frac{2}{29} = 6.9\%$ decrease in the manufacturing share off the weighted mean manufacturing share.[8] While changes in export demand had a positive impact on the manufacturing share, their impact is a quarter of the effect that imports had.[9]

Increased import competition should have a direct negative effect on manufacturing employment, but the effect on non-tradeable employment is less clear. There may be negative spillovers to services employment as lower manufacturing employment may lower the demand for services employment. On the other hand, to the extent that labor is mobile across sectors, workers may substitute from manufacturing employment to services. To empirically distinguish between these two opposing forces, I examine the effect that import penetration and export demand have on the growth in services employment. Note, that manufacturing and services employment together make up the vast majority of recorded employment, the average district has 97.8% of its EC employment in either manufacturing or services.

Table 4 presents the results, showing small and statistically insignificant coefficients on all trade exposure measures. The general lack of pre-trends and any subsequent change in trend during the 1998-2005 time period indicate that services employment did not respond to import competition or export demand. These results suggest that any negative spillovers

[8] Weights are the district's 1990 population

[9] Table A.5 and Table A.6 respectively show that the results are robust to not winsorizing and estimating exposure-robust standard errors according to Borusyak et al. 2022.

Table 3: Manufacturing Share of Employment

	Δ Mfn Share					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
ΔImports	0.007^{**}	0.012^{***}	0.010^{***}			
	(0.003)	(0.003)	(0.003)			
ΔImports × Post	-0.014^{***}	-0.020^{***}	-0.016^{**}	-0.012^{*}	-0.021^{***}	-0.016^{**}
	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)
ΔExports	-0.002	-0.002^{*}	-0.001			
	(0.001)	(0.001)	(0.002)			
ΔExports × Post	0.005^{**}	0.005^{**}	0.002	0.004^{*}	0.005^{**}	0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Mfn Share_{90} × Post		0.197^{***}	0.170^{**}		0.198^{***}	0.170^{**}
		(0.071)	(0.078)		(0.073)	(0.079)
$\ln(\text{Emp}_{90})$ × Post		0.007	0.004		0.007	0.004
		(0.011)	(0.015)		(0.011)	(0.015)
Rural Share_{90} × Post		-0.063^{*}	-0.080^{*}		-0.064^{*}	-0.081^{*}
		(0.034)	(0.045)		(0.034)	(0.045)
Mfn Share_{90}		-0.319^{***}	-0.308^{***}			
		(0.052)	(0.056)			
$\ln(\text{Emp}_{90})$		-0.001	0.012			
		(0.006)	(0.008)			
Rural Share_{90}		0.042^{*}	0.079^{**}			
		(0.023)	(0.031)			
Observations	1,012	1,012	1,012	1,012	1,012	1,012
KP F-Stat				165.5	160.1	104.6
District FE				✓	✓	✓
State × Year FE			✓			✓

Notes: This table presents results from estimating Equation (2) where the dependent variable is the change in the manufacturing share in period τ. The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{d\tau}$ is defined similarly. In columns (4)-(6), $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Regressions are weighted by the number of workers in the district according to the 1990 EC and standard errors are clustered at the 1998 EC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table 4: Services Employment

	Δ ln(Services Emp)					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
ΔImports	0.008	0.018	0.031**			
	(0.015)	(0.015)	(0.014)			
ΔImports $\times$ Post	0.009	0.004	-0.015	0.010	0.001	-0.017
	(0.017)	(0.018)	(0.017)	(0.020)	(0.022)	(0.020)
ΔExports	0.011	0.012	0.020*			
	(0.013)	(0.008)	(0.011)			
ΔExports $\times$ Post	-0.012	-0.012	-0.016	-0.012	-0.013	-0.013
	(0.014)	(0.010)	(0.013)	(0.014)	(0.010)	(0.013)
Mfn Share$_{90}$ $\times$ Post		-0.484	-0.700**		-0.479	-0.697**
		(0.312)	(0.328)		(0.311)	(0.329)
ln(Emp$_{90}$) $\times$ Post		0.137***	0.123*		0.137***	0.123*
		(0.046)	(0.068)		(0.046)	(0.068)
Rural Share$_{90}$ $\times$ Post		0.187	0.070		0.184	0.069
		(0.144)	(0.207)		(0.144)	(0.208)
Mfn Share$_{90}$		0.661**	0.921***			
		(0.301)	(0.286)			
ln(Emp$_{90}$)		-0.132***	-0.178***			
		(0.028)	(0.048)			
Rural Share$_{90}$		-0.036	-0.130			
		(0.109)	(0.190)			
Observations	1,012	1,012	1,012	1,012	1,012	1,012
KP *F*-Stat				165.5	160.1	104.6
District FE				✓	✓	✓
State $\times$ Year FE			✓			✓

Notes: This table presents results from estimating Equation (2) where the dependent variable is the change in the log of services employment in period τ. The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{d\tau}$ is defined similarly. In columns (4)-(6), $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Regressions are weighted by the number of workers in the district according to the 1990 EC and standard errors are clustered at the 1998 EC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

from the decline in manufacturing labor demand were likely offset by movement into services occupations.[10]

4.2 *Population Flows*

If labor is mobile, workers are likely to move away from occupations and geographies that were hit by increased Chinese import competition. This could result in changes in district population as workers reallocate themselves to to arbitrage away differences in employment opportunities. Studies examining the effect of trade on local labor markets have generally found that import competition or export demand have no effect on local population. This finding has generally held in developed (Autor, Dorn, and Hanson 2013) and developing contexts (Costa et al. 2016; Dix-Carneiro and Kovak 2017; Erten et al. 2019). These results suggest that there are strong frictions which keep workers from reallocating across geographic space.

To examine this in my context, I use the 1991, 2001, and 2011 population censuses to measure changes in district population.[11] I employ a similar empirical strategy as in Equation (2), but I use the 1991-2001 time period as my pre-period and the 2001-2011 period as my exposure time period. Changes in district import and export penetration are measured over the 2001-2011 time period.

Table 5 displays the results. Across the first three columns, districts that would receive high levels of import competition from 2001-2011 were on a small but precisely estimated positive pre-trend from 1991-2001. Using the estimates in column (2), a district that would receive \$100 more imports per worker from 2001-2011 saw a 0.2% increase in 1991-2001 population relative to a district receiving no increase in imports per worker. In columns (4)-(6) I instrument for the endogenous trade exposure variables. The point estimates on the interaction between imports and a post indicator continue to be very small and precisely estimated indicating that the positive pre-trend continued during the 2001-2011 time period. The 95% confidence interval on Δ Imports $\times$ $\mathbb{1}\{\text{Post}\}$ in column (5) rules out increases

[10] Table A.7 and Table A.8 respectively show that the results are robust to not winsorizing and estimating exposure-robust standard errors according to Borusyak et al. 2022.

[11] Districts and states are defined using 2001 PC geographic definitions.

(decreases) in population greater than .08% (.22%). The first stage F statistics weakly exceeds the conventional rule of ten in all specifications except column (6). Changes in exports also produce precisely estimated null effects across all specifications. Overall, the small size of the point estimates and the lack of change in the pre-trend indicate that district populations did not respond to trade exposure.[12] These results are in line from the literature's consensus that migration decisions are not affected by trade shocks (Costa et al. 2016; Dix-Carneiro and Kovak 2017; Erten et al. 2019).

One implication of this result is that the employment results in Table 2 are not likely to be caused by migration or population changes. This provides evidence that the estimated effects on manufacturing employment are likely to represent aggregate changes in Indian manufacturing employment and not simply reallocation of individuals across districts. These results also shed light on a reason why I observe declining manufacturing employment in response to Chinese imports. If workers are slow to reallocate themselves, the adjustment to import competition will be sluggish and there will be persistent negative effects of import competition on local labor markets.

5 Heterogeneity in effects

The effects of Chinese import competition and export demand may have differentially affected districts based on their characteristics. Understanding if the effects are concentrated amongst districts with specific characteristics will help identify populations that were particularly impacted by the rise of India-China trade. In addition, it has the potential to shed light on the mechanisms through which trade had an impact on local labor markets. To explore heterogeneity in the effect, I augment Equation (2) by including interactions between the trade exposure variables, the post dummy, and various district characteristics measured before the rise of China. I instrument for all endogenous variables by interacting my trade exposure instrument with a post dummy and the corresponding district characteristics if necessary.[13] I also modify the controls slightly to include each district characteristic I am

[12] Table A.9 and Table A.10 respectively show that the results are robust to not winsorizing and estimating exposure-robust standard errors according to Borusyak et al. 2022.

[13] For each equation I have four endogenous variables and four excluded instruments.

Table 5: Population

	Δ ln(Pop)					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
ΔImports	0.003***	0.002***	0.002***			
	(0.001)	(0.001)	(0.001)			
ΔImports × Post	-0.001	-0.000	0.000	-0.001*	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
ΔExports	-0.000	-0.000	-0.000			
	(0.000)	(0.000)	(0.000)			
ΔExports × Post	0.000	0.000	-0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Mfn Share_{90} × Post		-0.025	-0.064**		-0.022	-0.060**
		(0.028)	(0.030)		(0.029)	(0.030)
$\ln(\text{Pop}_{91})$ × Post		0.011	0.015*		0.011	0.014
		(0.007)	(0.009)		(0.007)	(0.009)
Rural Share_{91} × Post		0.076**	0.080**		0.070*	0.075**
		(0.035)	(0.036)		(0.036)	(0.037)
Mfn Share_{90}		0.013	0.042			
		(0.032)	(0.032)			
$\ln(\text{Pop}_{91})$		-0.018**	-0.010			
		(0.008)	(0.010)			
Rural Share_{91}		-0.081***	-0.122***			
		(0.030)	(0.034)			
Observations	1,034	1,034	1,034	1,034	1,034	1,034
KP *F*-Stat				10.6	11.3	6.6
District FE				✓	✓	✓
State × Year FE			✓			✓

Notes: This table presents results from estimating Equation (2) where the dependent variable is the change in the . The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 2001-2011. $\Delta\text{Imports}_{d\tau}$ is defined similarly. In columns (4)-(6), $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Regressions are weighted by 1991 population and standard errors are clustered at the 2001 PC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

interested in measuring interacted with a post dummy. This removes any main effects which would cause districts with different underlying characteristics to evolve differently in the 1998-2005 time period. Further, I add district fixed effects, controlling for the time invariant characteristics of the district as well as average growth rates in the dependent variable.

I am interested in examining how educated and rural districts responded differently to the trade shock. Districts with a more educated population are likely engaging in high skilled and capital intensive manufacturing. This may make them particularly vulnerable to Chinese competition as high skilled manufacturers are more likely to be producing goods that can compete in the global market. Further, capital intensive manufacturing may be particularly hard to substitute away from in the presence of capital adjustment costs. These arguments favor the idea that manufacturing employment in more educated districts would respond more negatively to Chinese import competition. At the same time, higher education may make the workforce more mobile as their skills are broader and more useful across a variety of industries. This argument cuts in the opposite direction. Which of these two forces dominate is an empirical question that I will answer in my context.

To proxy for the education level of a district, I use the 1991 PC to calculate the share of literate persons in the district and standardize the variable to have mean zero and standard deviation of one for ease of interpretation. Column (1) of Table 6 presents the results when the change in the log of manufacturing employment is the dependent variable. Despite instrumenting for two additional endogenous variables relative to my main specification, the instruments still strongly predict the endogenous variables with an F-stat of over 140. The negative coefficient on Δ Imports $\times$ $\mathbb{1}\{\text{Post}\}$ aligns with the main result, high import penetration from 1998-2005 caused lower manufacturing employment, relative to the earlier pre-trend.

Is this effect stronger or weaker for more educated districts? The negative coefficient on ΔImports $\times$ $\mathbb{1}\{\text{Post}\}\times$ Z answers that question, showing that the negative effect of imports is stronger in districts with a high share of the population who are literate. An increase in the 1991 literate share of one standard deviation leads to an additional 8% reduction in manufacturing employment for every \$100 in import penetration. Given the positive correlation between education and urban status, we would expect that more developed and urban districts may demonstrate similar heterogeneity. In column (2), I use the same specification as in column (1) but use the 1998 average night luminosity per grid cell as my characteristic of interest. Districts with higher luminosity per grid cell should have greater population density and economic development. Again, we see a strong negative coefficient on the interaction between import penetration exposure, a post dummy, and the luminosity measure. This suggests that more populated and economically developed districts saw larger impacts from import penetration exposure. Column (3) uses the share of workers who work in urban areas as my characteristic of interest. While less precisely estimated, the magnitude on the interaction effect is comparable to columns (1) and (2). Table A.11 shows that the results are robust to using changes in the manufacturing share of employment as the dependent variable. Taken together, these results suggest that more educated, more developed, and more urban districts saw larger declines in response to the same increases in import penetration. This is consistent with adjustment being costlier in higher skilled manufacturing which is more prevalent in urban settings and employs skilled labor.

While more educated, urban districts were more responsive to import competition shocks, they also appear to respond more to export demand shocks. In column (1) when I add the coefficient on $\Delta\text{Exports} \times \mathbb{1}\{\text{Post}\}$ and $\Delta\text{Exports} \times \mathbb{1}\{\text{Post}\} \times$ Z together I arrive at the conclusion that a district one standard deviation above the mean literate share increases their manufacturing employment by 1.39 + 1.51 = 2.9% (p=0.273) in response to a \$100 export demand shock. Columns (2) and (3) indicate similar but larger and more precisely estimated results. Districts one standard deviation above the mean level of luminosity [urban share] respond to a \$100 export demand shock with a 3.7% (p=0.025) [6.4% (p=0.033)] increase in manufacturing employment. These are in comparison to small effects at the mean. The results are consistent with education and economic development being necessary conditions for taking advantage of an export demand shock. This is reminiscent of Melitz 2003 where only the most productive firms enter the export market.

Table 7 examines whether there is heterogeneity in spillover effects to service employment. There are no robust effects relating to imports, but there are effects with exports. At the mean levels of all three characteristics, a \$100 increase in exports per worker lowers services employment by approximately 2%. This fits with a story where, in response to

Table 6: Manufacturing Employment (Heterogeneity)

	Δ ln(Mfn Emp)		
	(1)	(2)	(3)
	Lit Share$_{91}$	Lights$_{98}$	Urban Share$_{98}$
ΔImports $\times$ Post	-0.052	-0.027	-0.043
	(0.034)	(0.039)	(0.034)
ΔExports $\times$ Post	0.014	-0.003	0.003
	(0.014)	(0.015)	(0.014)
ΔImports $\times$ Post $\times$ Z	-0.080**	-0.061***	-0.085*
	(0.033)	(0.008)	(0.050)
ΔExports $\times$ Post $\times$ Z	0.015	0.040***	0.061**
	(0.018)	(0.011)	(0.029)
Mfn Share$_{98}$ $\times$ Post	-1.836***	-1.563***	-1.729***
	(0.452)	(0.425)	(0.455)
Urban Share$_{98}$ $\times$ Post	-0.058	-0.145	0.032
	(0.210)	(0.194)	(0.268)
Lit Share$_{91}$ $\times$ Post	-0.045	-0.818**	-0.580*
	(0.428)	(0.333)	(0.336)
Lights$_{98}$ $\times$ Post	0.010	0.023***	0.011*
	(0.006)	(0.004)	(0.006)
Observations	1,020	1,020	1,020
KP F-Stat	141.1	76.3	73.0

Notes: This table presents results from estimating augmented versions of Equation (2) via 2SLS where I include interactions with changes in imports/exports a post dummy and various characteristics. Z denotes the standardized version (mean zero, st. dev. one) of the column header (in column (1) Z is Lit Share$_{91}$). The change in ΔExports$_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. ΔImports$_{dBStau}$ is defined similarly. District fixed effects are included in all regressions and regressions are weighted by the number of workers in the 1990 EC. Standard errors are clustered at the 1998 EC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

an export demand shock, the average district simply substitutes workers from services to manufacturing, with limited role for spillovers back to the demand for services employment. But as districts become more literate, luminous, or urban, this negative effects reverses and exports may even have a positive effect on services employment. This is consistent with more educated and urban districts being able to generate new services that can take advantage of higher demand coming from the export demand shock. The results suggest that education and development play a role in the ability of a local labor market to propagate positive labor demand shocks to industries that were not directly affected.

Table 7: Services Employment (Heterogeneity)

	Δ ln(Services Emp)		
	(1)	(2)	(3)
	Lit Share_{91}	Lights_{98}	Urban Share_{98}
ΔImports $\times$ Post	0.008	0.009	0.008
	(0.014)	(0.019)	(0.015)
ΔExports $\times$ Post	-0.023**	-0.026**	-0.021**
	(0.010)	(0.011)	(0.010)
ΔImports $\times$ Post $\times$ Z	0.017	-0.009*	-0.004
	(0.015)	(0.005)	(0.014)
ΔExports $\times$ Post $\times$ Z	0.017	0.038***	0.047**
	(0.014)	(0.007)	(0.019)
Mfn Share_{98} $\times$ Post	0.153	0.237	0.171
	(0.250)	(0.257)	(0.261)
Urban Share_{98} $\times$ Post	-0.233	-0.252	-0.387**
	(0.158)	(0.157)	(0.176)
Lit Share_{91} $\times$ Post	-0.436	-0.332	-0.281
	(0.302)	(0.296)	(0.297)
Lights_{98} $\times$ Post	0.002	0.002	0.003
	(0.003)	(0.003)	(0.003)
Observations	1,020	1,020	1,020
KP F-Stat	141.1	76.3	73.0

Notes: This table presents results from estimating augmented versions of Equation (2) via 2SLS where I include interactions with changes in imports/exports a post dummy and various characteristics. Z denotes the standardized version (mean zero, st. dev. one) of the column header (in column (1) Z is Lit Share_{91}). The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{dBStau}$ is defined similarly. District fixed effects are included in all regressions and regressions are weighted by the number of workers in the 1990 EC. Standard errors are clustered at the 1998 EC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

6 Conclusion

This paper contributes to our understanding of how opening to trade affects the labor market of developing countries by examining how local labor markets in India respond to increased trade with China. I find that in response to an increase in imports, local labor markets see their manufacturing employment growth decline. This effect is stronger for more educated, developed, and urban labor markets. While import penetration has a strong negative effect on manufacturing employment, I find no effect on services employment suggesting that there are limited spillovers between manufacturing and services employment.

On average, I find that the negative effects of import penetration on manufacturing employment are not offset by increased export demand. Districts who receive positive export demand shocks do not experience manufacturing employment growth. Despite a limited average response, the effect of exports on employment displays significant heterogeneity. Districts that are sufficiently educated, developed, or urban see increases in manufacturing employment in response to an export demand shock. Further, less educated, under-developed, or rural districts see negative service employment growth in response to an export demand shock while more educated, developed, or urban districts see positive service employment growth. These results suggest that in sufficiently developed labor markets, export demand can increase employment in both the manufacturing and service sector.

The results suggest that the negative effects of import competition on manufacturing employment are not simply a developed world phenomenon, but are large and important even for a developing country such as India. My findings paint a more subtle picture regarding export demand and suggest that a sufficient level of development is necessary in order for a labor market to be able to take advantage of export demand. This is reminiscent of poverty traps where poverty begets poverty (Kraay and McKenzie 2014). Further, I find that educated, developed, or urban districts have another important advantage: they are not only able to translate increased export demand into higher manufacturing employment, but they are also able to increase their services employment. This suggests that sufficient education and development is an important factor in being able to move beyond simply reallocating workers across sectors to aggregate job creation. Further investigation into how development of a local labor market allows it take advantage of increased export demand would be a valuable contribution.

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A Appendix

Table A.1: Rotemberg Weights for Import Exposure IV

NIC 87 Code	NIC 87 Description	(1)	(2)	(3)
365	radio, TV, radar apparatus	.421	.448	.469
367	computers	.106	.095	.103
300	industrial organic/inorganic chemicals	.081	.079	.076
338	processing of metal scraps	.05	.05	.048
366	TV, radio, receivers, sound devices	.044	.046	.047
368	electronic valves, tubes, and other n.e.c.	.044	.039	.039
331	iron and steel products	.036	.037	.034
337	casting of metals	.027	.024	.017
358	office and computing machinery	.026	.026	.024
100	mining of coal	.02	.024	.026
354	industrial machinery (excl. food & textile)	.013	.011	.011
339	non-ferrous metal	.01	.01	.011
Controls			✓	✓
State FE				✓

Notes: This table presents Rotemberg weights calculated according to Goldsmith-Pinkham et al. 2020 for the NIC-87 3-digit industries used to construct the district level export exposure instrument. All columns construct Rotemberg weights for regression models where the change in the log of manufacturing employment is the dependent variable and regressions are weighted by total 1990 employment in the district. Controls consist of the following variables calculated for each district in 1990: the share of employment in manufacturing, the natural log of total employment, and the share of the population living in rural areas. Only industries with Rotemberg weights greater than 1% are shown.

Table A.2: Rotemberg Weights for Export Exposure IV

NIC 87 Code	NIC 87 Description	(1)	(2)	(3)
120	mining of iron ore	.904	.905	.811
131	mining of chromite	.044	.044	.087
300	industrial organic/inorganic chemicals	.021	.02	.053
Controls			✓	✓
State FE				✓

Notes: This table presents Rotemberg weights calculated according to Goldsmith-Pinkham et al. 2020 for the NIC-87 3-digit industries used to construct the district level export exposure instrument. All columns construct Rotemberg weights for regression models where the change in the log of manufacturing employment is the dependent variable and regressions are weighted by total 1990 employment in the district. Controls consist of the following variables calculated for each district in 1990: the share of employment in manufacturing, the natural log of total employment, and the share of the population living in rural areas. Only industries with Rotemberg weights greater than 1% are shown.

Table A.3: Manufacturing Employment (Not Winsorized)

	Δ ln(Mfn Emp)		
	(1) IV	(2) IV	(3) IV
ΔImports $\times$ Post	-0.098**	-0.134**	-0.074**
	(0.049)	(0.056)	(0.036)
ΔExports $\times$ Post	0.005	0.008	-0.014
	(0.012)	(0.011)	(0.012)
Mfn Share_{90} $\times$ Post		0.335	-0.110
		(0.378)	(0.320)
ln(Emp_{90}) $\times$ Post		0.121*	0.161***
		(0.062)	(0.042)
Rural Share_{90} $\times$ Post		-0.028	-0.288
		(0.176)	(0.177)
Observations	1,020	1,020	1,012
District FE	✓	✓	
State $\times$ Year FE			✓
Controls		✓	✓

Notes: This table presents results from estimating Equation (2) where the dependent variable is the change in the log of manufacturing employment in period τ. The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{d\tau}$ is defined similarly. In all columns, $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Variables are not winsorized and regressions are weighted by the number of workers in the district according to the 1990 EC. Standard errors are clustered at the 1998 EC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table A.4: Manufacturing Employment (Inference Following Borusyak et al. 2022)

	Δ ln(Mfn Emp)		
	(1)	(2)	(3)
	IV	IV	IV
ΔImports $\times$ Post	-0.098***	-0.134***	-0.073**
	(0.028)	(0.049)	(0.033)
ΔExports $\times$ Post	0.005	0.008**	-0.014
	(0.003)	(0.004)	(0.009)
Observations	454	454	454
District FE	✓	✓	
State $\times$ Year FE			✓
Controls		✓	✓

Notes: This table presents results from estimating the shift-share IV specification outlined in Equation (2) via the procedure in Borusyak et al. 2022. The dependent variable is the change in the log of manufacturing employment in period τ. The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{d\tau}$ is defined similarly. In all columns, $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Variables are not winsorized and controls consist of the following variables calculated for each district in 1990 and interacted with a post indicator: the share of employment in manufacturing, the natural log of total employment, and the share of the population living in rural areas. Robust standard errors are calculated following Borusyak et al. 2022. *(p<0.1), **(p<0.05), ***(p<0.01).

Table A.5: Manufacturing Share (Not Winsorized)

	Δ Mfn Share		
	(1) IV	(2) IV	(3) IV
ΔImports $\times$ Post	-0.021**	-0.024**	-0.012*
	(0.010)	(0.010)	(0.006)
ΔExports $\times$ Post	0.003	0.003*	-0.000
	(0.002)	(0.002)	(0.003)
Mfn Share$_{90}$ $\times$ Post		0.219***	0.189**
		(0.079)	(0.084)
ln(Emp$_{90}$) $\times$ Post		-0.005	0.002
		(0.015)	(0.015)
Rural Share$_{90}$ $\times$ Post		-0.045	-0.084*
		(0.040)	(0.048)
Observations	1,020	1,020	1,012
District FE	✓	✓	
State $\times$ Year FE			✓
Controls		✓	✓

Notes: This table presents results from estimating Equation (2) where the dependent variable is the change in the manufacturing share in period τ. The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{d\tau}$ is defined similarly. In all columns, $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Variables are not winsorized and regressions are weighted by the number of workers in the district according to the 1990 EC. Standard errors are clustered at the 1998 EC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table A.6: Manufacturing Share (Inference Following Borusyak et al. 2022)

	Δ Mfn Share		
	(1)	(2)	(3)
	IV	IV	IV
ΔImports $\times$ Post	-0.021***	-0.024***	-0.012**
	(0.006)	(0.008)	(0.005)
ΔExports $\times$ Post	0.003***	0.003***	-0.000
	(0.001)	(0.001)	(0.002)
Observations	454	454	454
District FE	✓	✓	
State $\times$ Year FE			✓
Controls		✓	✓

Notes: This table presents results from estimating the shift-share IV specification outlined in Equation (2) via the procedure in Borusyak et al. 2022. The dependent variable is the change in the manufacturing share in period τ. The change in $\Delta \text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta \text{Imports}_{d\tau}$ is defined similarly. In all columns, $\Delta \text{Exports}_{d\tau}$ and $\Delta \text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Variables are not winsorized and controls consist of the following variables calculated for each district in 1990 and interacted with a post indicator: the share of employment in manufacturing, the natural log of total employment, and the share of the population living in rural areas. Robust standard errors are calculated following Borusyak et al. 2022. *(p<0.1), **(p<0.05), ***(p<0.01).

Table A.7: Services Employment (Not Winsorized)

	Δ ln(Services Emp)		
	(1) IV	(2) IV	(3) IV
ΔImports $\times$ Post	0.001	-0.015	-0.014
	(0.014)	(0.022)	(0.016)
ΔExports $\times$ Post	-0.010	-0.008	-0.016
	(0.007)	(0.006)	(0.013)
Mfn Share$_{90}$ $\times$ Post		-0.692*	-0.959**
		(0.420)	(0.441)
ln(Emp$_{90}$) $\times$ Post		0.134***	0.148*
		(0.042)	(0.083)
Rural Share$_{90}$ $\times$ Post		0.218	0.107
		(0.150)	(0.292)
Observations	1,020	1,020	1,012
District FE	✓	✓	
State $\times$ Year FE			✓
Controls		✓	✓

Notes: This table presents results from estimating Equation (2) where the dependent variable is the change in the log of services employment in period τ. The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{d\tau}$ is defined similarly. In all columns, $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Variables are not winsorized and regressions are weighted by the number of workers in the district according to the 1990 EC. Standard errors are clustered at the 1998 EC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table A.8: Services Employment (Inference Following Borusyak et al. 2022)

	Δ ln(Services Emp)		
	(1) IV	(2) IV	(3) IV
ΔImports $\times$ Post	0.001	-0.015	-0.014
	(0.006)	(0.012)	(0.010)
ΔExports $\times$ Post	-0.010***	-0.008***	-0.016***
	(0.003)	(0.003)	(0.004)
Observations	454	454	454
District FE	✓	✓	
State $\times$ Year FE			✓
Controls		✓	✓

Notes: This table presents results from estimating the shift-share IV specification outlined in Equation (2) via the procedure in Borusyak et al. 2022. The dependent variable is the change in the log of services employment in period τ. The change in $\Delta \text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta \text{Imports}_{d\tau}$ is defined similarly. In all columns, $\Delta \text{Exports}_{d\tau}$ and $\Delta \text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Variables are not winsorized and controls consist of the following variables calculated for each district in 1990 and interacted with a post indicator: the share of employment in manufacturing, the natural log of total employment, and the share of the population living in rural areas. Robust standard errors are calculated following Borusyak et al. 2022. *(p<0.1), **(p<0.05), ***(p<0.01).

Table A.9: Population (Not Winsorized)

	Δ ln(Pop)		
	(1) IV	(2) IV	(3) IV
ΔImports $\times$ Post	-0.003	-0.002	-0.002
	(0.002)	(0.002)	(0.002)
ΔExports $\times$ Post	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)
Mfn Share$_{90}$ $\times$ Post		-0.003	-0.048
		(0.035)	(0.032)
ln(Pop$_{91}$) $\times$ Post		0.008	0.014
		(0.008)	(0.009)
Rural Share$_{91}$ $\times$ Post		0.060	0.059
		(0.048)	(0.044)
Observations	1,142	1,044	1,034
District FE	✓	✓	
State $\times$ Year FE			✓
Controls		✓	✓

Notes: This table presents results from estimating Equation (2) where the dependent variable is the change in the log population in period τ. The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 2001-2011. $\Delta\text{Imports}_{d\tau}$ is defined similarly. In all columns, $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Variables are not winsorized and regressions are weighted by the number of workers in the district according to the 1991 PC. Standard errors are clustered at the 2001 PC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).

Table A.10: Population (Inference Following Borusyak et al. 2022)

	Δ ln(Population)		
	(1) IV	(2) IV	(3) IV
ΔImports × Post	-0.003*	-0.002	-0.002
	(0.002)	(0.002)	(0.002)
ΔExports × Post	0.001**	0.001***	0.000***
	(0.000)	(0.000)	(0.000)
Observations	462	462	462
District FE	✓	✓	
State × Year FE			✓
Controls		✓	✓

Notes: This table presents results from estimating the shift-share IV specification outlined in Equation (2) via the procedure in Borusyak et al. 2022. The dependent variable is the change in the log population in period τ. The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 2001-2011. $\Delta\text{Imports}_{d\tau}$ is defined similarly. In all columns, $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via Equation (4). Variables are not winsorized and controls consist of the following variables: the share of the district's 1990 population employed in manufacturing, the natural log of the district's 1991 population, and the share of the district's 1991 population living in rural areas. Robust standard errors are calculated following Borusyak et al. 2022. *(p<0.1), **(p<0.05), ***(p<0.01).

Table A.11: Manufacturing Share (Heterogeneity)

	Δ Mfn Share		
	(1)	(2)	(3)
	Lit Share_{91}	Lights_{98}	Urban Share_{98}
ΔImports $\times$ Post	-0.010	-0.004	-0.006
	(0.007)	(0.007)	(0.006)
ΔExports $\times$ Post	0.008***	0.005***	0.005**
	(0.002)	(0.002)	(0.002)
ΔImports $\times$ Post $\times$ Z	-0.021***	-0.012***	-0.020**
	(0.006)	(0.001)	(0.009)
ΔExports $\times$ Post $\times$ Z	-0.000	0.000	0.002
	(0.002)	(0.001)	(0.004)
Mfn Share_{98} $\times$ Post	-0.399***	-0.354***	-0.373***
	(0.085)	(0.080)	(0.085)
Urban Share_{98} $\times$ Post	0.042	0.027	0.105**
	(0.039)	(0.036)	(0.050)
Lit Share_{91} $\times$ Post	0.125	-0.066	-0.024
	(0.081)	(0.058)	(0.058)
Lights_{98} $\times$ Post	0.001	0.004***	0.001
	(0.001)	(0.001)	(0.001)
Observations	1,020	1,020	1,020
KP F-Stat	141.1	76.3	73.0

Notes: This table presents results from estimating augmented versions of Equation (2) via 2SLS where I include interactions with changes in imports/exports a post dummy and various characteristics. Z denotes the standardized version (mean zero, st. dev. one) of the column header (in column (1) Z is Lit Share_{91}). The change in $\Delta\text{Exports}_{d\tau}$ is defined using Equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{dBStau}$ is defined similarly. District fixed effects are included in all regressions and regressions are weighted by the number of workers in the 1990 EC. Standard errors are clustered at the 1998 EC district level and shown in parentheses. *(p<0.1), **(p<0.05), ***(p<0.01).