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

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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.

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1 Introduction

There is robust empirical evidence that the rise of developing countries, such as China, have lowered manufacturing employment for developed countries (Autor, Dorn, and Hanson 2013; Pierce and Schott 2016). Yet there is far less empirical evidence about how increases in trade between developing countries has affected local labor markets. This is surprising since the nature of trade between developing countries is much different than that of a developed country trading with a developing country. While developed countries often experience large trade deficits from trading with developing countries, trade is often more balanced between developing countries. This suggests that in the case of trade between developing countries, increased export demand may offset the negative labor demand shock coming from import competition. Further, in a developing country context, we have scant empirical evidence about what characteristics allow local labor markets to either mitigate the negative labor market effects of import competition or grow employment in the face of higher export demand. Understanding what characteristics allow local labor markets to grow employment when opening to trade is crucial for understanding how trade will affect employment and inequality. In a developing country context we also have a limited understanding of how changes in imports and exports affect the employment of the service sector, a sector that is less directly influenced by changes in manufactured goods trade.

To examine these questions, I use the experience of China's increased trading relationship with India after China's accession to the World Trade Organization (WTO) in 2001. Panel (a) of Figure 1 visualizes this, showing that the large increase in Chinese imports was matched by an equally large increase in exports from India to China. To examine the effect of this rise in imports and exports on the Indian labor market, I start by dividing India into 506 local labor markets based on 1998 district definitions. I then apportion imports from China and exports to China based on the 1998 distribution of workers across industries. 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 de-meaned growth rates of Chinese trade with all countries except India. 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. 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. My estimates indicate a marginal \$100 (2012 USD) in Chinese imports per worker from 1998-2005, grew a district's manufacturing employment by 9% from 1990-1998. When the Chinese imports were realized, the same district saw a decrease in manufacturing employment of approximately 2% from 1998-2005. This constitutes an 11% decline relative to the positive pre-trend.[1] For the average district, I find no effect of export demand on manufacturing employment. Further, I find no evidence that import or export exposure had an effect on the growth of services employment, suggesting that there are limited spillovers from manufacturing to other sectors. I also examine whether the China trade shock had an effect on district population. Consistent with other evidence on trade in developing countries, I find precisely estimated null effects. This suggests that individuals face substantial mobility frictions.

[Figure 1 about here.]

Finally, I explore heterogeneity in the effect based on districts' pre-existing characteristics. 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 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

[1] This is calculated as: -2% -9% = -11%

et al. 2016 find a positive (negative) effect of export demand (import competition) on wages and employment. My results provide new evidence in the Indian context and examine heterogeneity in the effect. Other studies isolate 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). 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. My results also address the topic of export demand and highlight that sufficiently educated, developed, or urban districts are most able to take advantage of increased export demand.

My results also contribute to a large literature examining the effects of trade liberalization on a myriad of non-labor market outcomes. Bastos 2020 examine how Chinese competition and export demand affects the exports of Belt & Road countries and find that Chinese demand (import competition) increased (lowered) exports. My results add a new perspective to the findings of Bastos 2020 by focusing on the local labor market effects. I find that the import competition effect outweighs the export demand effect, whereas Bastos 2020 find the opposite when exports are the dependent variable. Bastos 2020 also find that richer countries experience an attenuated effect of import competition on their own exports, whereas I find that import competition lowers manufacturing employment more in educated, developed, and urban districts. The effects of trade liberalization on crime (Dix-Carneiro, Soares, et al. 2018), education (Edmonds et al. 2010), and firm productivity (Topalova and Khandelwal 2011; Copestake 2021) have all been studied in the context of developing countries. My results contribute to these studies by providing evidence on the labor market effects of increased trade.

2 Data

2.1 Trade Data

The Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) houses data 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 digitize 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, I have bilateral trade flows at the NIC87 $\times$ country-pair $\times$ year level for the years 1998-2009.

2.2 Indian Labor Market Data

Following Imbert and Papp 2015, I use Indian districts as my measure of a local labor market. The average number of workers enumerated in the 1998 Economic Census (EC) per district is 108,011. The number of Indian districts has been growing over time. There were 593 districts recorded in the 2001 census, that number grew to 640 by the 2011 census and stood at 748 by 2021. In order to consistently measure districts, I use the Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG) database provided by Asher et al. 2021. The backbone of SHRUG are nearly 600,000 towns and villages that have been mapped into geographic areas called SHRIDs which are consistent across the 1990-2013 Indian Economic and Population Censuses. 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.[2] Since each SHRID uniquely matches to a district definition at any point in time, I aggregate SHRID level variables up to the district level.

District level labor market data comes from several sources. First, is the SHRUG database

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

itself, which is built on the 1990, 1998, and 2005 Indian economic censuses provided by the Ministry of Statistics and Programme Implementation (MOSPI). The economic censuses provide an enumeration of most Indian enterprises. Importantly, the EC does 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 the EC with significantly better coverage of manufacturing and services. This data provides a count of the total number of workers in the 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. 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. I use the 1998 EC to measure the distribution of workers across NIC87 industries in a given district. This distribution of workers is used to construct all trade shocks faced by the district.

2.3 Other Data

The SHRUG database also provides data on nightlights running from 1994 through 2013. I use nightlights as a proxy for economic activity and development (Henderson et al. 2011). In addition, the SHRUG database provides data from the 1991, 2001, and 2011 population censuses. This data is used to construct district characteristics, such as the share of persons who are illiterate. The data is also used to assess whether India-China trade had an effect on population growth and migration. This is important to assess since changes in a district's population could directly impact employment outcomes. As before, changes in 1991 to 2001 population are used to assess the potential existence of confounding pre-trends, while changes in 2001 to 2011 population are used to capture the effect of India-China trade on a district's population.

3 Empirical Strategy

To measure each district's exposure to Chinese imports and exports I use the following apportionment rule where 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 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. Exports_{dt} can be interpreted as the export value in hundred 2010 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 China-India trade.

3.1 Summary Statistics

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, these represent meaningful economic shocks.

[Table 1 about here.]

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 presents results 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 upward slope, there is significant variation between import and export exposure with the two measures having a correlation of 0.243.

[Figure 2 about here.]

3.2 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).

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

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

$\Delta \mathrm{Y}_{dt}$ is the change in a labor market variable of interest for district d over time period τ. $\Delta \mathrm{Exports}_{d,(98-05)}$ and $\Delta \mathrm{Imports}_{d,(98-05)}$ 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, 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 2021). $\mathbb{1}\{\mathrm{Post}\}$ 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. 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 are competitive, then the correlation between demand shocks and foreign supply shocks is likely to attenuate my estimates towards zero (Autor, Dorn, and Hanson 2013). In the case that imports are used as imported intermediates that don't compete with domestic producers then the bias would be positive. Given that imports likely consist of both intermediate inputs and final products, the direction of the bias is ambiguous.

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. By using Chinese imports of iron ore from other countries to instrument for Chinese imports from India, I am 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 following form 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. In a similar way, 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 analagous 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. 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.

[Figure 3 about here.]

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 (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 with differing distribution of their workforce across detailed NIC87 industries. I also include state × time period fixed effects in some specifications. While there are 571 1998 EC districts, there are only 35 states. The inclusion of state × 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. 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.

[Table 2 about here.]

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 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. 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. In column (2) when I add controls, the estimate on the change in imports interacted with a 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 35 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 large Kleibergen-Paap F-statistic. 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. Overall, the results suggest that the arrival of Chinese import competition caused a significant decline in Indian manufacturing employment 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 (exports) per worker leads to a 2 (.05) percentage point decline (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.[3] While changes in export demand had a positive impact on the manufacturing share, their impact is a quarter of the effect that imports had.

[Table 3 about here.]

Increased import competition should have a direct negative effect on manufacturing em-

[3] Weights are the district's 1990 population

ployment, 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 about here.]

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 from the decline in manufacturing labor demand where likely offset by movement into services occupations.

4.2 Population

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 geographies.

To examine this in my context, I use the 1991, 2001, and 2011 population censuses to measure changes in district population.[4] I employ a similar empirical strategy as in equation

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

(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 population 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 (decreases) in population greater than .08% (.22%). The first stage F statistics exceed 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. These results are in line from the literature's consensus that migration decisions are not affected by trade shocks. 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.

[Table 5 about here.]

5 Heterogeneity

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 opening to 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.[5] I also modify the controls slightly to include each district characteristic I am 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.

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 170.6. 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.

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

Is this effect stronger or weaker for more educated districts? The negative coefficient on ΔImports $\times$ $\mathbb{1}\{$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 7.8% reduction in manufacturing employment for every $100 in import penetration. Given the positive correlation between education and urban status, we would expect that 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 A1 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 ΔExports $\times$ $\mathbb{1}\{$Post$\}$ and ΔExports $\times$ $\mathbb{1}\{$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 $1.34 + 1.51 = 2.9\%$ (p=0.108) 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=0.002) [6.35% (p=0.065)] 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 6 about here.]

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 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 begins to reverse 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 about here.]

6 Conclusion

This paper contributes to our understanding of how opening to trade affects the labor market of developing countries. 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. Despite this small 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.

The results suggest that the negative effects of import competition on manufacturing employment are not simply a developed world phenomena, but are real and important even for a developing country such as India. My findings paint a more subtle picture regarding export demand. My results 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.

This research explores how simultaneous exposure to increased import penetration and export demand impacts labor markets. While this simultaneous increase in import and export exposure is one aspect of how the opening up of trade in developing countries differs from many developed countries, there are other important areas of research. First, not all imports are the same. Imports of intermediate inputs are likely to be much more relevant in the context of developing countries (Goldberg et al. 2010). While the imports of final goods results in import competition, greater variety and lower cost of foreign intermediate inputs may actually stimulate manufacturing employment for developing countries. Empirically distinguishing this and its effects on local labor markets would give us a richer understanding of the labor market effects of trade in a developing country context.

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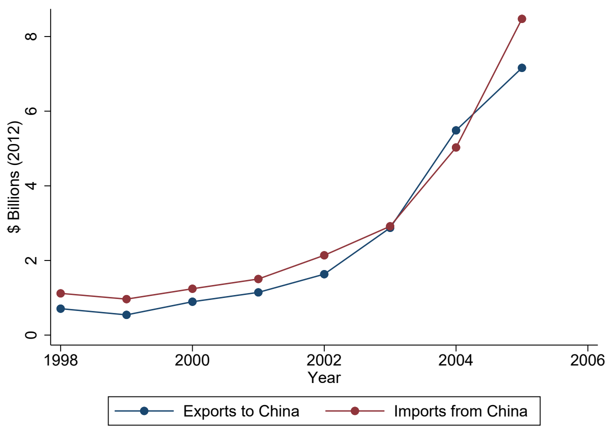
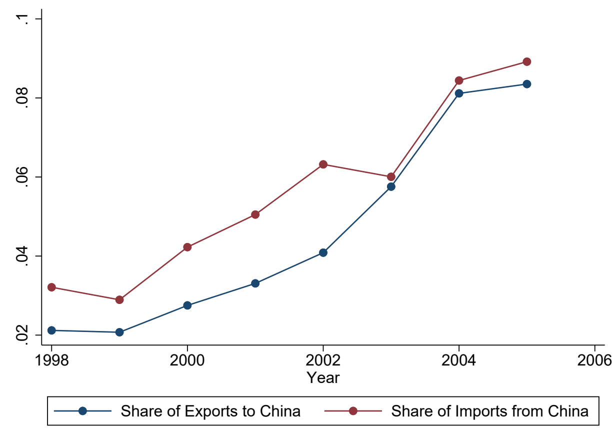
Figure 1: India-China Trade

(a) Imports/Exports

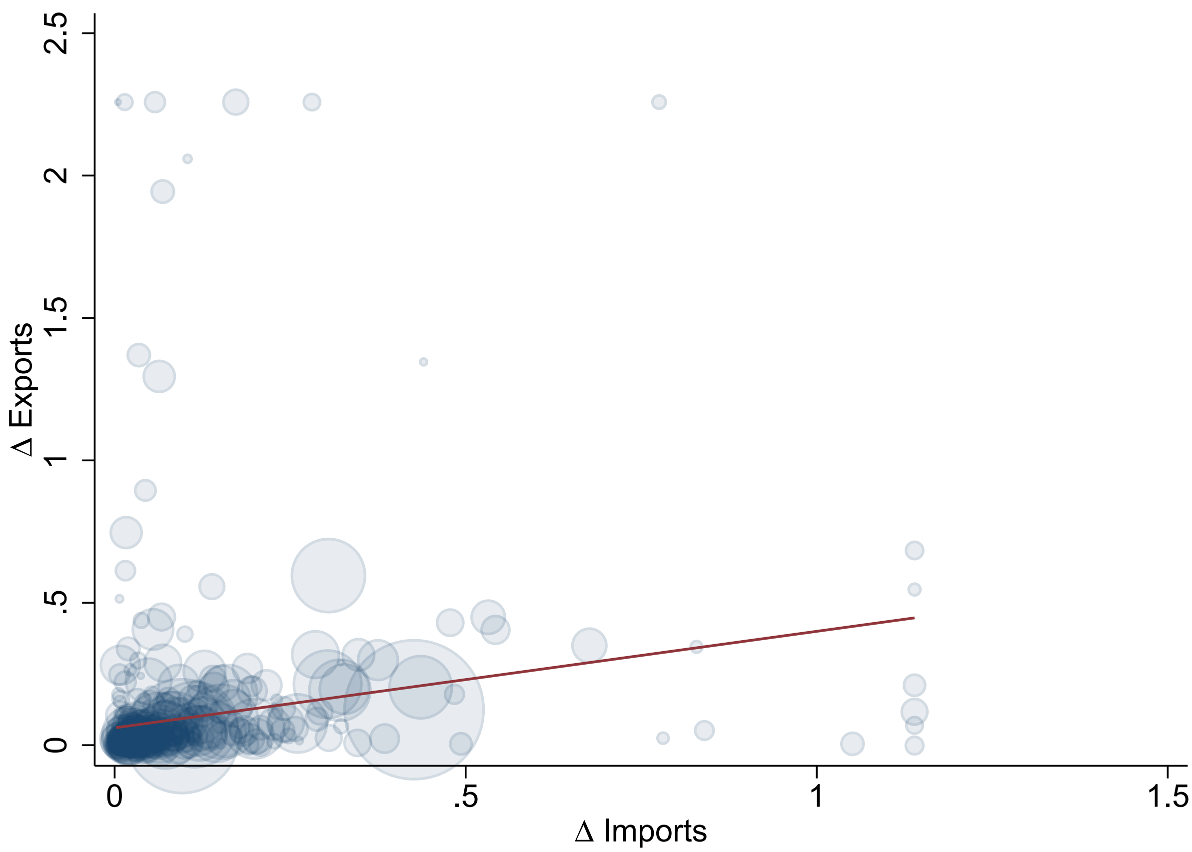


(b) Import/Export Share



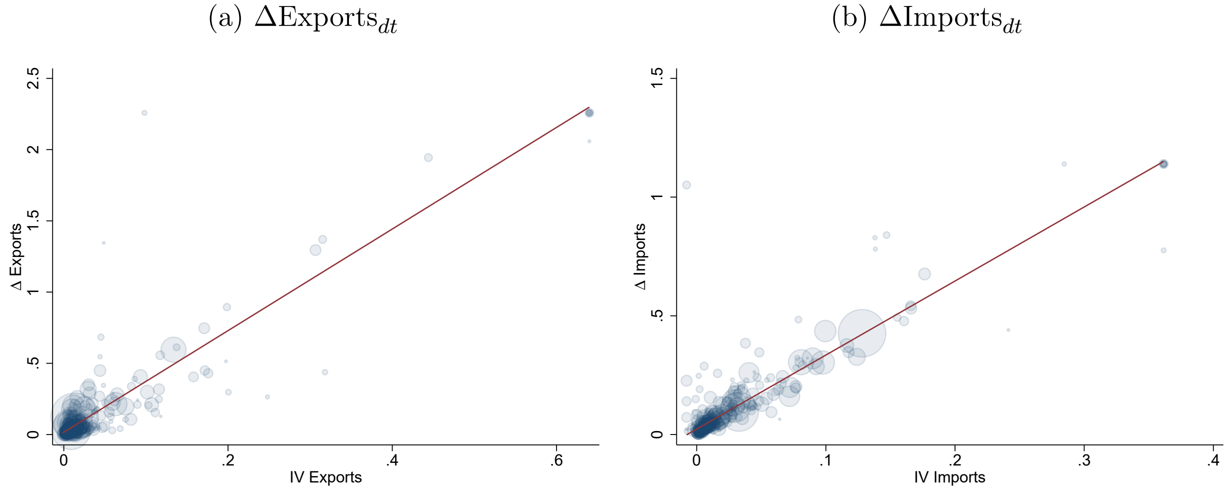
Notes: Panel (a) plots the aggregate Indian exports to China and imports from China while Panel (b) plots the share total imports and exports

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 1998 along with the line of best fit. The coefficient on $\Delta\text{Imports}_{dt}$ is .339 with a t-statistic of 3.72. R^2 is 0.06.

Figure 3: First Stage



Notes: Panels (a) and (b) plot the change in district exports (imports) per worker from 1998-2005 against the instrument value of exports (imports) along with the line of best fit.

Table 1: Summary Statistics

	Mean	St. Dev.	25%	50%	75%	95%
Δ Exports	0.96	2.17	0.09	0.32	0.76	4.06
Δ Imports	1.02	1.40	0.22	0.53	1.18	3.21
Rural Share_{98}	0.49	0.25	0.33	0.51	0.70	0.84
Mfn Share_{98}	0.29	0.11	0.21	0.27	0.34	0.53
Δ ln(Mfn Emp)	0.05	0.31	-0.13	0.08	0.24	0.51
Δ Mfn Share	-0.02	0.06	-0.06	-0.02	0.02	0.06
Observations	506					

Notes: This table presents results summary statistics for variables used in the analysis. All statistics are weighted where weights are the number of individuals recorded as employed in the 1990 EC. Districts are based on the 1998 EC definitions

Table 2: Manufacturing Employment

	Δ ln(Mfn Emp)					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Δ Imports	0.056**	0.090***	0.091***			
	(0.025)	(0.028)	(0.024)			
Δ Imports × $\mathbb{1}\{\text{Post}\}$	-0.075**	-0.111***	-0.106***	-0.067*	-0.118***	-0.105**
	(0.035)	(0.037)	(0.037)	(0.039)	(0.043)	(0.043)
Δ Exports	0.002	0.003	0.024			
	(0.011)	(0.010)	(0.017)			
Δ Exports × $\mathbb{1}\{\text{Post}\}$	0.012	0.012	-0.012	0.009	0.013	-0.013
	(0.013)	(0.013)	(0.018)	(0.012)	(0.012)	(0.016)
Mfn Share_{90} × $\mathbb{1}\{\text{Post}\}$		0.341	-0.065		0.353	-0.066
		(0.332)	(0.277)		(0.332)	(0.274)
$\ln(\text{Emp}_{90})$ × $\mathbb{1}\{\text{Post}\}$		0.186***	0.161***		0.186***	0.161***
		(0.039)	(0.042)		(0.040)	(0.041)
Rural Share_{90} × $\mathbb{1}\{\text{Post}\}$		-0.158	-0.340*		-0.165	-0.339*
		(0.146)	(0.200)		(0.148)	(0.202)
Mfn Share_{90}		-0.638**	-0.262		0.000	0.000
		(0.280)	(0.235)		(.)	(.)
$\ln(\text{Emp}_{90})$		-0.152***	-0.132***		0.000	0.000
		(0.026)	(0.029)		(.)	(.)
Rural Share_{90}		0.156	0.259		0.000	0.000
		(0.115)	(0.170)		(.)	(.)
Observations	1,012	1,012	1,012	1,012	1,012	1,012
KP F-Stat				194.4	186.0	119.8
District FE				✓	✓	✓
State × Year FE			✓			✓

Notes: This table presents results from estimating equation (2) where the dependent variable is the change in the log of manufacturing employment from 1990-1998. 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 (5)-(8), $\Delta\text{Exports}_{d\tau}$ 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 1998 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 3: Manufacturing Share of Employment

	Δ Mfn Share					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Δ Imports	0.006**	0.011***	0.010***			
	(0.003)	(0.003)	(0.003)			
Δ Imports × $\mathbb{1}\{$Post$\}$	-0.013***	-0.019***	-0.015***	-0.012**	-0.020***	-0.015**
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)
Δ Exports	-0.002	-0.002**	-0.001			
	(0.001)	(0.001)	(0.002)			
Δ Exports × $\mathbb{1}\{$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} × $\mathbb{1}\{$Post$\}$		0.183***	0.151*		0.185***	0.150*
		(0.066)	(0.078)		(0.068)	(0.079)
ln(Emp_{90}) × $\mathbb{1}\{$Post$\}$		0.008	0.007		0.008	0.007
		(0.012)	(0.014)		(0.012)	(0.014)
Rural Share_{90} × $\mathbb{1}\{$Post$\}$		-0.060*	-0.067		-0.061*	-0.067
		(0.033)	(0.040)		(0.033)	(0.041)
Mfn Share_{90}		-0.306***	-0.288***		0.000	0.000
		(0.054)	(0.057)		(.)	(.)
ln(Emp_{90})		-0.002	0.009		0.000	0.000
		(0.006)	(0.007)		(.)	(.)
Rural Share_{90}		0.038*	0.066**		0.000	0.000
		(0.021)	(0.027)		(.)	(.)
Observations	1,012	1,012	1,012	1,012	1,012	1,012
$\overline{\text{Mfn Share}_{98}}$	.29	.29	.29	.29	.29	.29
KP F-Stat				194.4	186.0	119.8
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 from 1990-1998. 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 (5)-(8), $\Delta\text{Exports}_{d\tau}$ 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 1998 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
Δ Imports	0.007	0.017	0.030**			
	(0.016)	(0.017)	(0.014)			
Δ Imports $\times$ $\mathbb{1}\{$Post$\}$	0.010	0.005	-0.013	0.012	0.003	-0.016
	(0.016)	(0.020)	(0.017)	(0.016)	(0.019)	(0.018)
Δ Exports	0.010	0.011	0.017*			
	(0.009)	(0.008)	(0.010)			
Δ Exports $\times$ $\mathbb{1}\{$Post$\}$	-0.011	-0.012	-0.013	-0.011	-0.013	-0.010
	(0.012)	(0.010)	(0.013)	(0.012)	(0.010)	(0.015)
Mfn Share$_{90}$ $\times$ $\mathbb{1}\{$Post$\}$		-0.409	-0.607**		-0.406	-0.604**
		(0.280)	(0.290)		(0.280)	(0.292)
ln(Emp$_{90}$) $\times$ $\mathbb{1}\{$Post$\}$		0.132***	0.112*		0.132***	0.111*
		(0.035)	(0.063)		(0.035)	(0.063)
Rural Share$_{90}$ $\times$ $\mathbb{1}\{$Post$\}$		0.181	0.051		0.180	0.050
		(0.128)	(0.178)		(0.126)	(0.176)
Mfn Share$_{90}$		0.588**	0.829***		0.000	0.000
		(0.264)	(0.252)		(.)	(.)
ln(Emp$_{90}$)		-0.127***	-0.167***		0.000	0.000
		(0.019)	(0.043)		(.)	(.)
Rural Share$_{90}$		-0.029	-0.109		0.000	0.000
		(0.088)	(0.177)		(.)	(.)
Observations	1,012	1,012	1,012	1,012	1,012	1,012
KP F-Stat				194.4	186.0	119.8
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 from 1990-1998. 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 (5)-(8), $\Delta\text{Exports}_{d\tau}$ 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 1998 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 5: Population

	Δ ln(Pop)					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
Δ Imports	0.002***	0.002***	0.003***			
	(0.001)	(0.001)	(0.001)			
Δ Imports $\times$ $\mathbb{1}\{$Post$\}$	-0.001	-0.001	-0.001	-0.001*	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Δ Exports	-0.000	-0.000	0.000			
	(0.000)	(0.000)	(0.001)			
Δ Exports $\times$ $\mathbb{1}\{$Post$\}$	0.000	-0.000	-0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mfn Share$_{90}$ $\times$ $\mathbb{1}\{$Post$\}$		-0.012	-0.021		-0.022	-0.060**
		(0.025)	(0.022)		(0.027)	(0.030)
ln(Pop$_{91}$) $\times$ $\mathbb{1}\{$Post$\}$		-0.007	0.005		0.011	0.014*
		(0.004)	(0.007)		(0.007)	(0.008)
Rural Share$_{91}$ $\times$ $\mathbb{1}\{$Post$\}$		-0.005	-0.042**		0.070**	0.075**
		(0.020)	(0.020)		(0.031)	(0.031)
Observations	1,034	1,034	1,034	1,034	1,034	1,034
KP F-Stat				13.7	14.6	8.8
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 district population from 2001-2011. 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 (5)-(8), $\Delta\text{Exports}_{d\tau}$ and $\Delta\text{Imports}_{d\tau}$ are instrumented for with the instruments constructed via equation (4). Regressions are weighted by 2001 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).

Table 6: Manufacturing Employment (Heterogeneity)

	Δ ln(Mfn Emp)		
	(1)	(2)	(3)
	Lit Share$_{91}$	Lights$_{98}$	Urban Share$_{98}$
Δ Imports $\times$ $\mathbb{1}\{\text{Post}\}$	-0.051	-0.026	-0.042
	(0.035)	(0.038)	(0.031)
Δ Exports $\times$ $\mathbb{1}\{\text{Post}\}$	0.013	-0.003	0.003
	(0.013)	(0.012)	(0.012)
Δ Imports $\times$ $\mathbb{1}\{\text{Post}\}\times$ Z	-0.078***	-0.061***	-0.083
	(0.025)	(0.008)	(0.054)
Δ Exports $\times$ $\mathbb{1}\{\text{Post}\}\times$ Z	0.015	0.040***	0.061*
	(0.009)	(0.010)	(0.034)
Mfn Share$_{98}$ $\times$ $\mathbb{1}\{\text{Post}\}$	-1.847***	-1.565***	-1.742***
	(0.496)	(0.373)	(0.449)
Urban Share$_{98}$ $\times$ $\mathbb{1}\{\text{Post}\}$	-0.062	-0.145	0.025
	(0.188)	(0.180)	(0.243)
Lit Share$_{91}$ $\times$ $\mathbb{1}\{\text{Post}\}$	-0.052	-0.818**	-0.578*
	(0.398)	(0.334)	(0.322)
Lights$_{98}$ $\times$ $\mathbb{1}\{\text{Post}\}$	0.009***	0.023***	0.011**
	(0.004)	(0.004)	(0.005)
Observations	1,020	1,020	1,020
KP F-Stat	170.6	94.9	80.7

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 (column (1) Z = Lit Share$_{91}$). The change in $\Delta\text{Exports}_{d\tau}$ is defined using equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{d\tau}$ 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).

Table 7: Services Employment (Heterogeneity)

	Δ ln(Services Emp)		
	(1)	(2)	(3)
	Lit Share_{91}	Lights_{98}	Urban Share_{98}
Δ Imports $\times$ $\mathbb{1}\{\text{Post}\}$	0.008	0.009	0.007
	(0.011)	(0.016)	(0.014)
Δ Exports $\times$ $\mathbb{1}\{\text{Post}\}$	-0.023**	-0.026***	-0.021**
	(0.009)	(0.010)	(0.009)
Δ Imports $\times$ $\mathbb{1}\{\text{Post}\}\times$ Z	0.016	-0.009	-0.004
	(0.013)	(0.006)	(0.019)
Δ Exports $\times$ $\mathbb{1}\{\text{Post}\}\times$ Z	0.017***	0.038***	0.047**
	(0.005)	(0.006)	(0.020)
Mfn Share_{98} $\times$ $\mathbb{1}\{\text{Post}\}$	0.154	0.239	0.173
	(0.241)	(0.233)	(0.246)
Urban Share_{98} $\times$ $\mathbb{1}\{\text{Post}\}$	-0.233	-0.251	-0.386**
	(0.147)	(0.154)	(0.175)
Lit Share_{91} $\times$ $\mathbb{1}\{\text{Post}\}$	-0.431	-0.331	-0.281
	(0.260)	(0.252)	(0.246)
Lights_{98} $\times$ $\mathbb{1}\{\text{Post}\}$	0.002	0.002	0.003
	(0.003)	(0.003)	(0.003)
Observations	1,020	1,020	1,020
KP F-Stat	170.6	94.9	80.7

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 (column (1) Z = Lit Share_{91}). The change in $\Delta\text{Exports}_{d\tau}$ is defined using equation (1) and measured as the change between 1998-2005. $\Delta\text{Imports}_{d\tau}$ 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).

A Appendix

A.1 Additional Specifications

[Table A1 about here.]

Table A1: Manufacturing Share (Heterogeneity)

	Δ Mfn Share		
	(1)	(2)	(3)
	Lit Share$_{91}$	Lights$_{98}$	Urban Share$_{98}$
Δ Imports $\times$ $\mathbb{1}\{$Post$\}$	-0.010	-0.003	-0.006
	(0.006)	(0.007)	(0.006)
Δ Exports $\times$ $\mathbb{1}\{$Post$\}$	0.007***	0.005***	0.005**
	(0.002)	(0.002)	(0.002)
Δ Imports $\times$ $\mathbb{1}\{$Post$\}\times$ Z	-0.020***	-0.012***	-0.019**
	(0.006)	(0.001)	(0.010)
Δ Exports $\times$ $\mathbb{1}\{$Post$\}\times$ Z	-0.000	0.001	0.002
	(0.002)	(0.001)	(0.005)
Mfn Share$_{98}$ $\times$ $\mathbb{1}\{$Post$\}$	-0.402***	-0.354***	-0.376***
	(0.073)	(0.052)	(0.069)
Urban Share$_{98}$ $\times$ $\mathbb{1}\{$Post$\}$	0.041	0.026	0.103**
	(0.036)	(0.033)	(0.046)
Lit Share$_{91}$ $\times$ $\mathbb{1}\{$Post$\}$	0.122	-0.066	-0.023
	(0.077)	(0.051)	(0.051)
Lights$_{98}$ $\times$ $\mathbb{1}\{$Post$\}$	0.001	0.004***	0.001
	(0.001)	(0.000)	(0.001)
Observations	1,020	1,020	1,020
KP F-Stat	170.6	94.9	80.7

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 (column (1) Z = Lit Share$_{91}$). The change in ΔExports$_{d\tau}$ is defined using equation (1) and measured as the change between 1998-2005. ΔImports$_{d\tau}$ 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).