The Role of Immigrants in the United States Labor Market and Chinese Import Competition*

Chan Yu†

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Abstract

Research has shown that there is a limited labor mobility response to trade shocks. However, studying aggregate mobility may miss important heterogeneity. This paper proposes a mechanism through which local labor markets adjust to trade shocks: immigrants' mobility. Immigrants are more responsive than natives to trade shocks. A $1000 increase in Chinese import exposure decreases the immigrant population by 2.6 percent but has little change in the native population. Additionally, immigrant mobility mitigates the effects of trade shocks on native labor outcomes. The study ultimately shows that natives in areas with more immigrants experience smaller declines in employment.

Keywords: Trade, Immigrants, Geographic Mobility, Manufacturing

JEL Codes: F14, F16, J15, J23, J31, J61, R12, R23

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†Chan Yu: PhD, Department of Economics, The University of Texas at Austin, 2225 Speedway, BRB 1.116, C3100, Austin, Texas 78712. (email: chanyu@utexas.edu); Phone: 518-428-6667. Please do not cite or distribute without permission of the author.

1 Introduction

Research has shown that trade shocks can increase the inequality in labor market outcomes across local labor markets, with local labor markets that are more specialized in tradable sectors being more impacted by trade shocks (Goldberg and Pavcnik, 2016; Dix-Carneiro and Kovak, 2017; Autor, 2018). Theoretically, a perfect labor mobility would facilitate the adjustment of the local labor supply and therefore dissipate the economic effects of trade shocks (Topel, 1986; Blanchard et al., 1992; Saks and Wozniak, 2011). In the absence of geographic mobility, the impacts of trade shocks tend to be localized and last over a long period of time. A series of empirical studies find weak or no evidence of trade shocks on the migration within developed countries such as the United States (Autor et al., 2013; Autor et al., 2014; Hakobyan and McLaren, 2016).[1] These studies seem to confirm the decline in internal migration rates in developed countries since the 1980s (Molloy et al., 2011; Ottaviano and Peri, 2012).

However, finding limited evidence of overall labor mobility does not necessarily mean that there are no labor mobility responses by particular groups of workers (Bound, Holzer, et al., 2000). As the most mobile workforce, immigrants could increase labor flows to the United States (Borjas, 2001; Cadena, 2013). The mobility of immigrants further adjusts the local labor supply and thereby reduces regional employment and wage inequalities arising from trade shocks. So far, there is scant empirical evidence regarding how immigrants respond to trade shocks. In this paper, I provide the first evidence on whether the mobility of immigrants helps to adjust local labor markets to trade shocks.[2] By focusing on the China trade shock and the United States local labor market, I attempt to answer the following two questions: First, do immigrants leave areas that are heavily impacted by the China trade

[1] Mclaren and Hakobyan (2012) find weak evidence in favor of the migration story by showing that a wage increase in locations that were expected to lose protection due to the trade policy change.

[2] As far as I know, most empirical works look at aggregate labor mobility. See David (2018) and Greenland, Lopresti, and McHenry (2019). Facchini, Liu, Mayda, and Zhou (2019) finds a mobility effect of the migrant workers to the trade policy change between China and the US. Different than their work, this paper explores how the mobility of immigrants to trade shocks will impact natives in a developed country.

shock? Second, does immigrant mobility mitigate the negative impacts of trade shocks on the employment and wages of native workers?

Understanding immigrant mobility responses is important as it may uncover a mechanism of geographic labor mobility through which regional divergences in employment and wages driven by trade shocks can be reduced. This study might also be informative of how to design future immigration policy to achieve better labor market outcomes for those natives who are less mobile (Clemens et al., 2018). In the event of an economic downturn, local labor markets may have limited capacity to absorb the supply of immigrants. If immigrants are generally immobile, then immigration may result in more negative impacts on natives, who would have been less hurt when there were fewer immigrants (Bonin et al., 2008). However, if immigrants play an effective role in adjusting the local labor market considering their high mobility, certain policies restricting immigration might not be optimal because immigrants could mitigate the adverse impacts of trade shocks on native outcomes.

I first analyze the effects of trade shocks on the native and immigrant populations. This paper uses the same methodology as the one used by Autor, Dorn, and Hanson (2013) to identify the impacts of Chinese import growth on population changes. The unexpected growth of China's manufacturing sector from 1990 to 2007 generated enormous import competition for manufacturers in the United States, which negatively impacted the local labor market (Autor et al., 2016).[3] To measure local import exposure, two sources of variation are exploited: the local (commuting zone) industry specialization and import growth by industry.[4] To address the concern of unobservable industry demand changes, the actual growth of United States imports from China is further instrumented by Chinese import growth in other developed countries excluding the United States. Because the growth of Chinese imports in other countries is less correlated with changes of the United States local labor market, this instrument could alleviate the endogeneity issue of using Chinese import growth in the

[3]From 1990 to 2007, the share of US manufacturing imports from China grew from 7% to 25%.

[4]Following Autor, Dorn and Hanson (2013), the model only includes import growth in the manufacturing sector.

United States (Bartik, 1991; Goldsmith-Pinkham et al., 2018).

My results for population changes reveal that immigrants are nearly five times more mobile than natives. In areas with greater exposure to Chinese import growth, the immigrant population decreases more. With a \$1000 increase in import exposure per worker, the immigrant population is significantly reduced by 2.6 percent.[5] In contrast, I find insignificant change in the native population. The native population is reduced by only 0.5 percent if import exposure increases by the same amount.[6] By extending the analysis to the inflow and outflow changes using the Census migration sample, I find that rising Chinese import competition significantly reduces the inflows and increases the outflows of immigrants, while there is insignificant change in the flow of natives.[7]

One possible explanation why immigrants are mobile is that they are not strongly tied to their local commuting zones and are flexible to move (Borjas, 2001). A further examination of the heterogeneous effects of trade shocks on immigrants with different lengths of stay, I find that the mobility effect is mainly driven by relatively new immigrants who have resided in the United States for fewer than ten years. A \$1000 increase in import exposure per worker reduces the population of immigrants with fewer than five years and with five to ten years in the United States by 7.6 percent and 4.4 percent, respectively. If immigrants have spent more than ten years in the United States, they become less responsive to trade shocks and are as immobile as natives.

To assess the role of immigrants in mitigating the effects of trade shocks on natives, I examine the estimated impacts of trade shocks on labor market outcomes for natives who live in areas with different fractions of immigrants. Considering that areas with a higher initial share of immigrants would lose more of those immigrants and thereby adjust the local

[5] An \$1000 increase in import exposure per worker is approximately a 27 percent increase in the mean of import exposure from 1990 to 2007 (\$3770).

[6] My estimate for the native population is consistent with what Autor, Dorn, and Hanson (2013) find. They find approximately a 0.355 decline in the aggregate population with a \$1000 increase in Chinese import exposure per worker. Also, the population effect is statistically insignificant.

[7] \$1000 increase in the import exposure per worker reduces immigrant inflow by 1281 (number of workers) and increases the outflow by 1017.

labor supply to a greater extent, one may expect that natives in these areas would be less adversely impacted by trade shocks. To investigate this hypothesis, I modify the model by adding an interaction between the initial immigrant share and the import exposure measure in the main specification.

One identification challenge is that high-immigration areas might experience different local economic condition change. I resolve the issue by adopting a past-settlement instrument for the actual immigrant population share (Card, 2009). The instrument is obtained by assigning the national immigrant population to each local labor market based on the geographic distribution of established immigrants.[8] Because new immigrants tend to live in the same areas as established immigrants who come from the same country, the geographic distribution of established immigrants can well predict the allocation of current immigrants. Meanwhile, national immigrant flows are less correlated with local economic condition change, therefore, the predicted immigrant population could avoid the above issue resulting from using the actual initial immigrant share.

I find that natives experience smaller declines in the employment if they reside in areas with more immigrants. A ten percentage point increase in the immigrant population share significantly raises the employment of natives by approximately 0.1 percentage points for college-educated natives and by 0.4 percentage points for non-college-educated natives. Based on a back-of-envelope calculation, immigrants could have reduced the negative impact of the China trade shock on the employment of natives without a college degree by approximately 36 percent. My results are robust when accounting for the dynamic growth of commuting zone and the sluggish labor market adjustment to past immigrant inflows.

By performing an analysis which distinguishes shocks to immigrant-intensive from native-intensive industries, I find that a higher concentration of immigrants in import-vulnerable industries may strengthen the mitigating effects on natives. Since the China trade shock hits high-immigrant-share industries the most, it is likely that natives in industries with a

[8] I choose 1970 as the baseline period when calculating the historical immigrant composition.

higher concentration of immigrants might be more insulated to trade shocks.[9] By multiplying overall import exposure with the immigrant employment share, I am able to compare the mitigating effects across industries with different immigrant employment intensity. Holding the immigrant population constant, rising import exposure in immigrant-intensive industries significantly reduces the employment losses for natives, while the mitigating effect is close to zero if trade shocks are in native-intensive industries. Therefore, a high share of immigrants in import-vulnerable industries additionally reduces the impacts of trade shocks on natives by adjusting the labor supply more in trade-impacted industries.

This paper has several contributions to the trade and immigration literature. First, as mentioned previously, existing trade studies suggest that the response of labor supply is incomplete and slow by showing a weak or no mobility effect of trade policy change (Topalova, 2010; Artuç et al., 2010; Autor et al., 2013; Hakobyan and McLaren, 2016; Goldberg and Pavcnik, 2016). The literature review shows that Greenland, Lopresti, and McHenry (2019) is the only paper that finds a population response to trade shocks in the developed countries by studying the elimination of trade uncertainty when China joined the WTO in 2001. They find that the mobility effect only appears at a lag of seven or more years. However, these studies may miss the important heterogeneity by only looking at the overall labor mobility. By distinguishing immigrants from natives, my paper first shows that immigrants are highly responsive to trade shocks while natives are not. More importantly, immigrants play a vital role in facilitating the adjustment of local labor supply when trade shocks occur. My results highlight the contribution of immigrants to the local labor market by mitigating the negative impacts of the China trade shock on labor outcomes of natives.

Second, prior studies documenting the relationship between the immigrant population and cross-section (state- or MSA-level) unemployment and wage growth find mixed empirical evidence (Bartel, 1989; Borjas, 2001; Bauer et al., 2005; Jaeger et al., 2007).[10] There is

[9] According to Altonji and Card (1991), immigrants are highly concentrated in low-wage manufacturing industries such as apparel (38.4%) and leather (27.3%) that are with highest Chinese import penetration (Autor et al., 2016).

[10] One limitation of these works studying the cross-sectional correlation is that immigrants might choose

limited work on the causal relationship between immigrant location choice to local economic condition change because finding an exogenous economic shock remains an empirical challenge (Cadena and Kovak, 2016).[11] This paper contributes to this literature by exploiting Chinese import growth which exogenously impacts the US local labor market.

This paper is most closely related to Cadena and Kovak (2016) which study the Great Recession at the city level.[12] My study complements their work by linking immigrant responses to trade policy changes. I improve their methodology by using a past-settlement instrument for the actual immigrant population. Moreover, this paper shows that a high concentration of immigrants in import-vulnerable industries additionally shields natives from trade shocks, emphasizing the importance of immigrant labor supply adjustment in industries where natives are employed. Rather than only looking at populations at the city level, I use the commuting zone as the location unit, which covers the entire United States and incorporates people's commuting and migration patterns in the local labor market.

Lastly, my findings shed light on the process of immigrant assimilation. Though numerous studies examine the convergence of labor market outcomes between immigrants and natives (Borjas, 1985; Borjas et al., 1992; Abramitzky et al., 2014), there are growing interests to examine other aspects of assimilation. Abramitzky, Boustan, and Eriksson (2016) find that the gap in name choice between immigrants and natives is reduced after immigrants have spent twenty years in the United States. Fouka, Mazumder, and Tabellini (2019) study the causal impact of the Great Migration on immigrants' assimilation efforts on naturalization, name choice, and intermarriage rates. My paper is in line with this stream of literature by providing new evidence on the convergence of mobility: immigrants become more similar to natives in terms of mobility with more years spent in the United States.

The rest of the paper proceeds as follows: the next section describes the data sets. Section

to live in high-wage locations due to unknown factors.

[11]A more recent work by Basso, D'Amuri, and Peri (2019) also study the Great Recession in Euro Area and show foreign-born workers are more mobile to the shocks than natives.

[12]They find a positive relationship between low-skilled Mexican population growth and employment growth. By dividing the sample into high- and low-immigration cities, they show that the employment of less-skilled native men decreases less in cities with more Mexican-borns.

3 discusses the main empirical strategy. Section 4 shows the main results of population changes in logs and migrant flows. Section 5 introduces the past-settlement model with and without distinguishing trade shocks in immigrant-intensive and native-intensive industries. Section 6 provides additional robustness analyses. Section 7 concludes.

2 Data

The main data I use is the U.S. Census decennial data set in the year 1970, 1980, 1990, 2000, and pooled American Community Survey (ACS) from 2005 to 2007 to indicate the year 2007.[13] The 1970 and 1980 data sets are used only for the pre-period analysis. My definition of workers are individuals between the ages of 16-64 who worked last year.[14] Immigrants are those individuals born outside the United States.[15] New immigrants are those who arrived in the United States within the last ten years and established immigrants are those who arrived more than ten years ago.

My outcomes of interests are the population, employment and wages of natives and immigrants. In the wage sample, I only include workers who are employed but are not self-employed. I exclude those workers from family owned business.[16] The hourly wage rate is calculated by dividing the annual wage rate by total annual working hours.[17] One issue with previous immigration studies using Metropolitan Statistical Area (MSA) level is that metropolitan area boundaries might change over time. In this study, the basic unit of

[13]I use the year before 2008 to avoid any contemporaneous effects of the Great Recession on the local labor market. The main analysis thus focuses on the period from 1990 to 2007 when China import growth increased the most.

[14]In this paper, I use workers to construct population samples not just working-age population. My estimates are unchanged when I use the 16-64 working-age population.

[15]The immigrant sample also includes people born in the United States territories because people from territories might behave similarly to immigrants considering their frequently traveling back and forth between territories and the United States. The five major U.S. territories are American Samoa, Guam, the Northern Mariana Islands, Puerto Rico, and the U.S. Virgin Islands.

[16]There are some individuals with zero wages because they work in family-owned business. I exclude these observations in the wage sample.

[17]According to the Census survey data, total annual working hours are the product of usually weekly working hours and total number of weeks worked during the last year.

analysis is at the commuting zone level.[18] Compared to the MSA level analysis, studying the labor mobility at the commuting zone level could improve the accuracy by covering the entire United States and incorporating daily commuting patterns of workers. When constructing populations and labor outcomes at the commuting zone level, I convert these outcomes at the Public Use Micro Area level (PUMA) to the commuting zone level.[19]

The import data comes from the United Nation Comtrade data and is available on and beyond 1991. The UN Comtrade dataset provides import and export volumes (in dollars) by country and product. The imports are recorded in a 6-digit Harmonized System. I aggregate the product-level imports to the four-digit SIC (Standard Industry Classification) industry level and obtain 397 manufacturing industries in all. For constructing the initial industry specialization, I also use the County Business Pattern (CBP) data for year 1980, 1990 and 2000. The CBP dataset records the number of employees at the establishment by county and industry. I aggregate the employment at the county-industry level to the commuting zone-industry level.

In Section 4.4 and Section 6.5, I use the 1980, 1990, and 2000 Census migration sample to study the effects of the China trade shock on migrant flows within the United States.[20] Since the Census migration sample provides geographic locations five years ago at the level of Public Use Microdata Area (MIGPUMA), I first convert the inflows and outflows at the MIGPUMA level to the commuting zone level.[21] Based on the information of the past and current residential commuting zone, I first exclude individuals whose residential locations are unchanged over the reference time. Among movers who have two different locations,

[18] Commuting zones are defined according to the USDA's definition. Though some commuting zones contain very few newly arrived immigrants, the robustness analysis shows that the results remain after excluding commuting zones with low immigration. See Section 6.2.

[19] David Dorn provides the crosswalk on his website, https://www.ddorn.net/data.htm.

[20] I did not use the 2007 ACS migration sample because ACS survey asks a different question regarding to the previous location. In the ACS survey, individuals are asked about the last year's locations not the location five years ago. To preserve the consistency of my estimates, I restrict the analysis to Census data sets and excludes the 2007 ACS data set.

[21] MIGPUMA is slightly different than PUMA in the way that MIGPUMA only shows the first three digits of the 5-digit PUMA code. This is not an issue for my analysis that is conducted at the commuting zone level because PUMAs with the first three digits the same are all from the same commuting zone.

the inflow is the total number of movers whose destinations are their current residential commuting zones, while the outflow is the number of movers whose originations are their residential locations five years ago. Migration rates are calculated by weighting inflows and outflows with the initial population for each group.

3 Empirical Strategy

One identification challenge is that trade liberalization might be endogenously determined (Goldberg and Pavcnik, 2016). For instance, Mexican and Central American import growth are driven by the United States demand changes. China's manufacturing growth has the advantage to avoid the above identification issue. The dramatic growth in China in the 1990s and 2000s was largely attributable to a series of reforms initiated by the Chinese government and were not anticipated by the western countries.[22] Between 1990-2007, the share of US imports of manufacturing goods from China grew from 7% to 25%. The intensified competition between the US and Chinese manufacturers hit the US manufacturing sector, where 20% immigrant workers and 17% native workers were employed.

3.1 Import Exposure Measure

To construct the commuting-zone import exposure measure, Autor, Dorn, and Hanson (2013) distributes the US import growth from China to each commuting zone based on each commuting zone's industry specialization. There are two reasons of using the US import growth to construct the local import exposure measure. First, trade volume data is unavailable at the commuting zone level. Second, unless manufactured goods are not tradable within the United States, actual import growth at the local level might be contaminated by local

[22]Before 1978, Chinese domestic production was not adjusted according to the market demand and was under the control of its government. This centralized economy generated a lot of inefficiencies and distortions. However, a series of new reforms led by the new chairman-Deng Xiao Ping, aiming to develop "socialism with Chinese characteristics", had transformed Chinese economy from highly centralized economy to market-oriented type and promoted the growth of China's productivity since then.

demand changes for manufacturing goods and correlated with unobserved factors. Autor, Dorn, and Hanson (2013) use a Bartik Shift-Share Instrument approach to overcome this problem.[23]

The degree of exposure to Chinese import growth is determined by two factors: the United States import growth from China in different industries and the commuting-zone industry specialization. First, each sector is exposed to a different level of Chinese import growth. Since China has its comparative advantage in producing labor intensive goods such as textiles and apparels, trade shocks generate much larger impacts on these sectors than other sectors. Second, there are sufficient geographic variations in the industry specialization. The effects of Chinese import growth in the US vary across local labor markets. Local labor markets that are highly specialized in competing sectors (with China) such as San Jose will be considerably more impacted than those less specialized ones.[24] US local import exposure to China's growth is thus a weighted Chinese imports, where the weight is the local industry specialization. Using the total import growth in the US captures the demand changes only driven by rising Chinese import competition.

$$\Delta IPW_{it}^{us} = \sum_{j} \frac{L_{ijt}}{L_{it}} \frac{\Delta Import_{jt}^{us}}{L_{jt}} \tag{1}$$

The industry specialization, $\frac{L_{ijt}}{L_{it}}$, is defined as the share of regional total employment in industry, j. L_{ijt} is the share workers that are employed in industry j in commuting zone i. Because removing the nonmanufacturing sector is not likely to affect the results, for simplicity, $\Delta Import_{jt}^{us}$ only includes the import growth in the manufacturing sector and is further rescaled by U.S. industrial employment, L_{jt}.[25] As one can see in Figure 1, there is a

[23]Import exposure measures are publicly available on the AEA website: https://www.aeaweb.org/articles?id=10.1257/aer.103.6.2121

[24]San Jose experienced the highest exposure to Chinese import growth. On average, there were approximately a \$3000 increase in Chinese import growth per worker from 1990-2000 and \$7000 increase from 2000-2007.

[25]The model used by removes nonmanufacturing sectors by assuming the price change in the nonmanufacturing sector is the same as the average price change in the manufacturing sector. To account for the price changes of nontraded sectors, it is important to rescale the weights in the above equation so that they

clear regional pattern of US import growth from China. The level of Chinese import exposure tends to be higher in certain areas such as the Atlantic, Northeastern, and Southeastern regions where manufacturing industries are concentrated. To account for regional growth that may lead to different population changes, I add twelve census division dummies in all specifications.

Table 1 shows the mean values of main variables from 1990 to 2007. 722 commuting zones are included in the study sample.[26] On average, there is approximately a 3.77 thousand dollar per worker growth of Chinese imports in the United States from 1990 to 2007. Some commuting zones have an extremely large or small immigrant population, such as San Francisco. Excluding these areas does not affect my estimates because very few commuting zones fall into this group.

The main measure in equation (1) does not include export growth from the United States to China. Trade liberalization with China may also induce an export growth in the United States, which might positively affect the United States local labor market. However, the size of Chinese import growth in the United States greatly exceeds the size of export growth from the United States to China so that the export channel should not generate as much significant impacts as the import channel.[27] For a robustness check, I will account for the export channel where net import growth is used to measure the US exposure to the China trade shock.

3.2 Model

Following Autor, Dorn, and Hanson (2013), the baseline model is a two-period stacked difference model (1990-2000, 2000-2007), where dependent and explanatory variables are all in changes of a decade.

sum to one. See Kovak (2013).

[26] Alaska, Hawaii, and District of Columbia are excluded because these states have very different economic conditions.

[27] Based on some facts, the trade balance for goods and service in US has shown a deficit since the 1980s.

$$\Delta LogN_{it} = \beta \Delta IPW_{it}^{us} + X_{it} + \gamma_t + e_{it} \tag{2}$$

For instance, I_{it} denotes the number of movers who move into commuting zone i between $t-1$ to t. Similarly, O_{it} is the number of movers who move out of commuting zone i during the same period.

The dependent variables, $\Delta LogN_{it}$, are changes in the natural logarithm of the native and immigrant populations throughout a decade. γ_t controls for decade fixed effects. X_{it} is a set of commuting-zone variables that might be correlated with the US import growth from China and affect the local population growth: the share of employment in manufacturing, foreign-borns, college-educated workers, routine employment, and an index of offshorability. All these control variables take the values at the initial period of a decade.

The share of manufacturing employment controls for underlying trends in the manufacturing sector (see also Section 4). Since most areas that are highly specialized in manufacturing are large cities which are attractive to immigrants and thus positively affect immigrant population growth, estimates for the immigrant population could be biased upward if omitting the concentration of employment in manufacturing. Also, previous immigration studies have shown that immigrants are more likely to move into the same areas where established immigrants went (Card and Lewis, 2007; Cadena and Kovak, 2016). To account for the effect of ethnic enclaves, I add the share of foreign-born population to the specification.

The skill composition is another important labor market characteristic that is associated with industry specialization. I control for the percentage of population with at a college degree to absorb the composition variation. Finally, the share of employment in routine-related occupations and offshorability variables are taken from Autor, Dorn, and Hanson (2013). These two variables absorb the impacts of automation and offshoring activities on low-skilled workers.[28]

[28]Routine-related occupations are jobs whose tasks involve routine information processing. They also include those blue collar production occupations involving repetitive motion and monitoring tasks. The offshorability index measures how likely the occupations require neither proximity to a specific work-site nor

3.3 Instrumental Variable

One concern about the model of equation (2) is that the Chinese import growth in the United States (ΔIPW_{it}^{us}) might be correlated with unobserved productivity shocks that also affect people's mobility (Kearney and Wilson, 2018). A decline in productivity of apparel and textile manufacturers in the United States may increase the US import demand. If so, the estimated population changes could be alternatively explained by the negative productivity shock rather than the increasing Chinese import competition.[29] Suppose the model previously predicts a negative relationship between Chinese import growth and the population growth of immigrants and natives, without isolating the productivity shocks, these estimates can be underestimated.

To address this concern, Autor, Dorn, and Hanson (2013) adopts a Bartik instrumental variable approach where the instrument is constructed using Chinese import growth in eight high-income countries.[30] Since Chinese manufacturers export products to both the United States and other high-income countries, import growth from China is highly correlated in the United States and these countries.[31] Using this instrument could overcome the above issue because Chinese import growth in other countries are less correlated with the US local demand changes. Instead of using the US import growth in equation (2), the instrument uses other countries' import growth to predict US local import exposure to the China trade shock.

$$\Delta IPW_{it}^{oth} = \sum_j \frac{L_{ijt-1}}{L_{it-1}} \frac{\Delta Import_{jt}^{oth}}{L_{jt-1}} \tag{3}$$

To avoid the reverse causality resulting from the impacts of Chinese import growth on manufacturing employment, the commuting-zone industry specialization in the US local

face-to-face contact with US workers.

[29]China has the highest comparative advantage in producing apparel goods.

[30]These eight high-income countries have similar trading environments as the United States. They are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[31]The correlation between import growth in the United States and import growth in other eight high-income countries from 1990 to 2007 is approximately 0.93.

labor market is the previous decade's industry share $(\frac{L_{ijt-1}}{L_{it-1}})$.[32]

The assumption for this IV approach is that Chinese import growth in the United States and other highly developed countries are only determined by internal factors in China (falling trade costs or rising comparative advantage), rather than any industry-specific shock that could occur worldwide. For instance, the computer bubble in early 2000s increased the global demand towards computer equipment and accessories. Therefore, the predicted import exposure measure might be contaminated by the technology shock in the computer sector. In Section 6.3, I address the concern by using a gravity model which accounts for industry-specific shocks. Another common issue arising with Bartik style instrument is that industry shares used for constructing the import exposure measure might be picking up unobservable labor market characteristics and render the instrument variable invalid. To handle this issue, I perform a pre-period analysis in Section 6.1 to examine whether industry shares are correlated with local economic condition (Goldsmith-Pinkham et al., 2018).

4 Results

4.1 Graphical Analysis

Before showing the estimated results, I used the raw data set to show the relationship between Chinese import growth and the population changes. In particular, the population changes are the residual parts once controlling for the concentration of employment in manufacturing.[33] According to Figure 2, the immigrant population decreases more in commuting zones that are more exposed to Chinese import growth. In contrast, the native population is almost unaffected. Additionally, the bottom graph in Figure 2 plots the relationship between the manufacturing concentration and the population changes. Unsurprisingly, a higher immi-

[32]In other words, $\frac{L_{ijt-1}}{L_{it-1}}$ is the local industry specialization of workers in the manufacturing sector at the initial period of the *previous* decade t-1 (1980 and 1990).

[33]Areas highly-exposed to trade shocks are likewise specialized in manufacturing and also attract immigrants. See Section 3.

grant population growth is found in these areas that are more specialized in manufacturing. Therefore, a positive trend in the immigrant population in areas that are highly concentrated in manufacturing might exist. Without adding the manufacturing concentration variable, the population changes may be underestimated. For this reason, I control for the share of employment in manufacturing in all specifications.

4.2 Main Results

Table 2 shows the impacts of the US import growth from China on native and immigrant populations by estimating the 2SLS model. Overall, I find a much larger decline in the immigrant population compared to the native population. As the odd columns of Table 2 display, with a \$1000 increase in import exposure per worker, the immigrant population decreases significantly by 2.504 percent while the native population decreases by only 0.636 percent.[34]

My main results are insensitive to the add-ins of control variables.[35] The even columns of Table 2 show the estimates with full controls of commuting-zone characteristics. A \$1000 increase in import exposure per worker decreases the immigrant population significantly by 2.643 percent but generates little change in the native population (0.483 percent). An alternative way to interpret the estimates is that per interquartile range increase in import exposure per worker leads to a 5.44 percent decline in the immigrant population ((2.49-0.43)$\times$2.643) but only a 0.99 percent decline in the native population.[36]

The last four columns of Table 2 show how immigrants' population response may vary with the number of years in the United States. I find that new immigrants who have spent fewer than ten years in the United States respond more than established ones who have spent

[34]The first stage results are same as the ones by Autor, Dorn, and Hanson (2013). A \$1000 per worker increase in predicted import exposure leads to a \$632 increase in observed US import exposure.

[35]A stricter test of the robustness to control for commuting-zone trends in economic growth is by adding 722 dummies in the main specification. My results are robust to adding the 722 dummies. However, the preciseness of estimates decreases a lot. Meanwhile, this exercise might bring in the issue of perfect multicollinearity between the import exposure measure and commuting-zone fixed effects when there are only two time periods. Due to these concerns, I do not include it in the paper.

[36]The values of import exposure at 25th and 75th percentile are 0.43 and 2.49 (kUSD).

more than ten years. Columns (6) and (8) show that a $1000 increase in import exposure per worker decreases the new immigrant population by 5.30 percent. However, for established immigrants, the estimated decline is only 1.26 percent and statistically insignificant. It is plausible that newly arrived immigrants are more mobile due to a lack of local human capital. I will show more evidence on this hypothesis in the next subsection.

The remaining rows of Table 2 show coefficients of main controls in the regressions. The second row shows the estimated impact of concentration of employment in manufacturing on native and immigrant population changes. The positive and significant coefficients suggest an increasing immigrant population in areas that are highly concentrated in manufacturing. The negative and significant coefficients on the foreign-born population share imply that immigrants tend to respond more in areas with higher shares of immigrants. A percentage point increase in the share of foreign-born population will further decrease the immigrant population by an additional 0.841 percent.

Routine-related occupation and offshorability index respectively account for the effects of automation and offshoring activities which may change the demand for low-skilled immigrants.[37] Since offshored jobs are tasks with intermediate complexity, increasing offshored jobs could push labor demands toward manual tasks that immigrants are likely to perform (Ottaviano, 2015). Thus, areas with a higher offshorability index are associated with a higher growth of the immigrant population. Finally, the share of employment in routine-related occupations measures the vulnerability to automation, which might displace low-skilled immigrants.[38]

I also report the OLS estimates in Table 3. Both the 2SLS and OLS models generate consistent estimates and imply that immigrants, especially those newly arrived, are much more responsive to trade shocks than natives. Yet, magnitudes of the OLS estimates are

[37] Autor, Dorn, and Hanson (2013) use the share of employment in routine task occupation to measure the penetration of automation. The offshorability index is a standardized measure to describe how closely an occupation requires face-to-face communication.

[38] On average, automation could generate a negative impact on low-skilled immigrants. Source: https://www.iseapublish.com/index.php/2017/05/03/future-job-automation-to-hit-hardest-in-low-wage-metropolitan-areas-like-las-vegas-orlando-and-riverside-san-bernardino/

smaller than those of 2SLS estimates. As such, it demonstrates that negative productivity shocks are likely to occur, which generates a downward bias for the OLS estimates (see discussion in Section 3.3). Therefore, I will use the 2SLS model as the preferred identification strategy for the rest of my analyses.

4.3 Immigrant Mobility by Year of Immigration

One possible explanation why new immigrants are more mobile than natives and established immigrants is that more recently arrived immigrants are less attached to the local labor market (Borjas, 2001). Compared to natives and established immigrants who have stronger local affiliations and social networks within the current environment, new immigrants might have lower migration costs and therefore are more flexible to move. To test this hypothesis, I examine the heterogeneous effects of trade shocks on immigrants with different lengths of stay in the US.[39]

Suppose labor market attachment is the main factor driving immigrants to move when they are exposed to Chinese import growth, one may expect to see that immigrants with fewer years in the United States should have larger population responses. Table 2 shows the population changes of immigrants who had arrived within and beyond the past ten years. However, using a ten-year interval to divide the immigrant population might be problematic if immigrants are not evenly distributed by year of arrival. Hence, I reinforce the findings in Table 2 by shortening the time interval to five years and looking at immigrant responses within and beyond five years following the immigration.

Table 4 tells a striking story: immigrants' mobility attenuates as immigrants have spent more years in the United States. The point estimates in columns (4) and (6) indicate that the

[39] I use the YRIMMIG variable reported by the Census to tell the year that an immigrant came to the United States. If the person has entered the United States more than once, Census uses the most recent year to indicate when person came to stay. One may concern about those who have spent many years in the United States and have multiple entries might be identified as new immigrants in my sample. However, the fraction of this group is small. Another way to address the concern is excluding those foreign-borns who have less than one year arrival and have been naturalized (not born abroad of American parents). There is approximately 6% of immigrants falling into this group in 1990 sample. After dropping these questionable observations, I find all my estimates are not changed.

China trade shock induces the largest decline in the population of new immigrants who had arrived within the past five years. There is a 7.639 percent decline of these immigrants with a $1000 increase in import exposure per worker. In contrast, the same amount of increase in import exposure reduces the population of those immigrants with five to ten years by 4.425 percent.[40] After more than ten years in the United States, immigrants become immobile. Their estimates are indistinguishable from those of natives (0.483 percent). For the purpose of comparison, I also report the estimated aggregate population change to Chinese import growth in first column. My estimates are close to the estimates generated by Autor, Dorn, and, Hanson (2013). They find a 0.355 percent decline in the overall population with a $1000 per worker increase in Chinese import exposure.

The heterogeneity of immigrants' year of arrival remains within education groups. In panels B and C, I further repeat the analysis by breaking the populations into those with no college education and at least some college education. The pattern in immigration year is even more pronounced for non-college-educated immigrants. A $1000 increase in import exposure per worker leads to a 10.657 percent population decline in non-college-educated new immigrants with fewer than five years. However, the equivalent increase in Chinese import exposure leads to a decline of only 1.640 percent in the established ones with more than ten years in the US. Though the population effect is much weaker for those more educated immigrants within ten years following the immigration, I still find that the mobility attenuates after ten years among them.

Apart from the analysis above, I divide the immigrant sample on a two-year interval of the immigration year and show the results in Figure 3. One could see an even clearer pattern in the relationship between the immigrant mobility and year of immigration as suggested by Table 4. Each point in Figure 3 shows the estimated population changes of immigrants whose year of arrival falls under a given interval under the impact of Chinese import growth. The most recently arrived immigrants tend to have the largest population decline. Over time,

[40] A simple test of the difference between coefficients in column (4) and column (5) suggests that the difference is statistically distinguishable.

immigrants converge to natives in terms of mobility: after around eight years of immigration, immigrants have similar mobility responses to natives. The results in immigration year align with the study by Borjas (2001) that immigrants behave as arbitrageurs in the labor market. With lower migration costs, new immigrants are more likely to move than natives and even established immigrants. However, after spending more years in the United States, immigrants become more attached to the local labor market and are as immobile as natives.

In Section 6.4, I also explore the heterogeneous effects by age, gender, home-ownership, and marital status. Since recently arrived immigrants after 1990 are from certain source countries and are younger, more likely to be single and house renters compared to established immigrants and natives, it might be that new immigrants respond more because they possess different characteristics. However, I find weak evidence of heterogeneous mobility effects, implying that these observable characteristics might play less of a role here.[41]

4.4 Migration Flows

The population change studied in the previous section shows the change in migrant stocks. To further confirm the geographic mobility effect of immigrants in the context of spatial equilibrium, it is important to examine how migrant flows vary across areas with different import exposure as well. Here I provide additional evidence on the inflow and outflow changes using the Census migration sample (Section 2). The model used for estimating the inflow and outflow changes is the same as the one in equation (2) except that dependent outcomes are decadal changes in native and immigrant inflows and outflows.

The regression results are reported in Table 5 and suggest that Chinese import growth significantly impacts the inflows and outflows of immigrants. With an interquartile range increase in import exposure per worker, the inflow of new immigrants is reduced by approximately 948 (number of workers), while the outflow is increased by 753 (number of workers).[42]

[41] I also split the immigrant population by language skill and citizenship, but I find no heterogeneity in these characteristics either.

[42] An interquartile range in import exposure between 1980-2000 is around 0.74 kUSD. The estimated

Because my migration sample excludes individuals who are abroad five years ago, the results in columns (3) and (6) might be underestimated by failing to capture the migration flow changes of the most mobile immigrant group.[43] However, I still find that point estimates in columns (3) and (6) are marginally significant. In addition, the large magnitudes of these coefficients imply that the immigrant population decline is accomplished by a decreasing inflow and an increasing outflow in areas that are more exposed to Chinese import growth. Consistent with the main results, the inflows and outflows of natives are statistically insignificant. In Section 6.5, I weight the inflows and outflows of immigrants by the initial population and construct the in- and out-migration rates for different groups (Appendix Table A.8).[44] My results are robust to different measures of migrant flows.

This analysis suggests that the internal migration plays an important role in changing the population of immigrants when they are exposed to rising Chinese import competition. However, I cannot reject the hypothesis that return migration might be affected by trade shocks because the Census does not contain those migrants who move back to their country of origin. A future research with more detailed datasets will be useful for better understanding the relationship between trade shocks and return migration.

5 Immigrant Mobility and Native Labor Outcomes

Having established that immigrants, especially those who have spent fewer years in the United States, are more responsive, I turn to study the contribution of immigrant mobility to the local economy that is negatively impacted by Chinese import competition. Specifically,

inflow and outflow changes are: 0.74×1281=948; 0.74 ×1017=753.

[43]Individuals who are abroad five years ago do not have origination commuting zones. I am only able to see their one-time movement from abroad in this migration sample. It is likely that these individuals might reduce their settlements in areas with higher exposure to Chinese import competition if they obtain the information about the US local labor market overseas and choose to reside in places with less exposure. However, this will result in a selection issue. Therefore, I do not include them when I draw the analysis of migrant flows.

[44]Since the Census only surveys at ten year interval, I do not have accurate population counts in 1975, 1985, and 1995. I impute the population of these years by subtracting populations in 1980, 1990, and 2000, with the five-year net population flows. For this reason, the inflow and outflow changes (in numbers) are the preferred outcomes of interests.

does the mobility of immigrants somewhat absorb the adverse impact on natives? I begin the analysis by assuming that natives and immigrants have a similar industry distribution within a local labor market. In Section 5.2, I relax this assumption by discussing the scenario in which immigrants tend to be more concentrated in import-vulnerable industries.

Prior studies suggest that immigrants and natives are imperfect substitutes, but less-educated immigrants and natives are close to perfect (Card, 2009).[45] When immigrants move out or not to move into a local labor market, the declining immigrant population might absorb the negative impacts of trade shocks on natives by adjusting the local labor supply (Cadena and Kovak, 2016).

To test the hypothesis, I add an interaction between the immigrant population share and Chinese import exposure into the main specification. As equation (4) shows, the new model illustrates how the effects of the China trade shock on native labor outcomes would vary with the immigrant population share. Instead of using the estimated immigrant population change that is a function of trade shocks, I am using the immigrant population share prior to the China trade shock.[46]

$$\Delta L_{it} = \beta_1 \Delta IPW_{it}^{us} \times ImmiShare_{i,90} + \beta_2 \Delta IPW_{it}^{us} + \beta_3 ImmiShare_{i,90} + X_{it} + \gamma_t \qquad (4)$$

The initial immigrant population share, $ImmiShare_{i,90}$, is defined as the share of immigrants ($M_{i,90}$) as a percentage of the total population ($P_{i,90}$) in commuting zone i in 1990. The dependent outcomes, ΔL_{it}, are decadal changes in the native employment to population ratio and log hourly wage rates. As a further check, I add several other variables in equation (4) to control for the geographic variation in the industrial and occupational employment of

[45] David Card (2009) uses an IV approach to show the inverse elasticity of substitution between less-educated immigrants and natives at the state level is approximately 40 and implies that less-educated immigrants are close to perfect substitutes to natives.

[46] Ideally, the model to test the effect of immigrant mobility on native outcomes that are impacted by trade shocks should be: $\Delta L_{it} = \beta_1 \Delta IPW_{it} \times \Delta\widehat{\text{Immigrants}}_{it} + \beta_2 \Delta IPW_{it} + \beta_3 \Delta\widehat{\text{Immigrants}}_{it} + X_{it} + \gamma_t$, where $\Delta\widehat{\text{Immigrants}}_{it}$ is the estimated immigrant population changes under the impact of the China trade shock which has been shown in Section 4.2. However, the model is problematic because the immigrant population changes simultaneously with trade shocks.

natives and immigrants.[47] Since natives living in areas with a large number of immigrants may work in other sectors that are less affected by the China trade shock, I add the share of immigrant workers in manufacturing to the specification. Also, it is possible that natives from high-immigration areas tend to perform non-manual tasks that are less affected by the China trade shock. Therefore, I control for the share of immigrants and natives that are employed in manual occupations (Autor et al., 2015).[48] Finally, I add the share of immigrants and natives with at least some college education, and the population size (Peri, 2016).[49]

5.1 Past-Settlement Instrument

One potential concern with the specification in equation (4) is that local labor market conditions are correlated with immigrant locations: immigrants tend to live in areas with higher economic growth. If so, then estimates in equation (4) may pick up the effects of these unobservables on native labor outcomes. Here I use a shift-share instrument for the immigrant population share to address this concern (Card, 2009).

The instrument uses the settlement patterns of earlier immigrants from different sending countries to predict the local immigrant population. By assigning the national immigrant populations across commuting zones based on their past settlements, this approach overcomes the identification issue because the national immigrant population is weakly correlated with the local economic condition.

$$ImmiShare_{i,90}^{IV} = \sum_k \frac{M_{ik,70}}{M_{k,70}} \times \frac{M_{k,90}}{P_{i,90}} \tag{5}$$

As equation (5) demonstrates, the instrument is generated by allocating the national immigrant population from sending country k ($M_{k,90}$) to a commuting zone i based on their

[47] My results are all robust to adding or dropping these variables.

[48] Manual occupations are those jobs such as machine operators, transportation, construction and service jobs.

[49] Previous specifications use the share of overall population with college education and do not distinguish immigrants from natives. Here I separate immigrants from natives and allow the skill composition to be varied across nativity groups.

settlement patterns in 1970. 1970 is chosen be the baseline period to avoid any anticipatory effect that immigrant settlements in more recent years might have predicted future economic growth of the local labor market.

Figure 4 and Table 6 display the first stage results of using the past-settlement instrument.[50] It implies a strong correlation between $ImmiShare^{IV}_{i,90}$ and the actual immigrant population share. Holding Chinese import exposure to be unchanged, a rise of one percentage point in the predicted share, $ImmiShare^{IV}_{i,90}$, will lead to a 0.817 percentage point increase in the immigrant population share. Additionally, the presence of statistical significance in only diagonal cells suggests that the first stage is well-identified because variations in instrumental variables mainly come from variations in the endogenous variables.

Table 7 reports the estimated mitigating effects of immigrant mobility on the native employment and wages, with and without the past-settlement instrument. I find a strong evidence that immigrants could mitigate the adverse impacts of trade shocks on native outcomes. The significant and positive coefficients in the first rows of Table 7 imply that the effect of trade shocks on the employment of natives is less negative in areas with more immigrants. With a ten percentage point increase in the immigrant share, there is an 0.43 percentage point increase in the employment of low-skilled natives who have no college education (0.043 × 10). The same increase in the immigrant share raises the employment of natives with at least some college education by 0.14 percentage points. Alternatively, an interquartile range increase in the immigrant share raises the employment of non-college-educated native workers by 0.138 percentage points.[51] Though the estimated wage effects are much weaker, it still shows that the hourly wage effects of trade shocks on low-skilled natives are less negative in areas with more immigrants.[52] A back-of-envelope calculation suggests

[50] There are three equations in the first stage: $\Delta IPW^{us}_{it} \times ImmiShare_{i,90} = \beta_1 \Delta IPW^{oth}_{it} \times ImmiShare^{IV}_{i,90} + \Delta IPW^{oth}_{it} + ImmiShare^{IV}_{i,90} + X_{it} + \gamma_t$; $\Delta IPW_{us} = \Delta IPW^{oth}_{it} \times ImmiShare^{IV}_{i,90} + \beta_2 \Delta IPW^{oth}_{it} + ImmiShare^{IV}_{i,90} + X_{it} + \gamma_t$; $ImmiShare_{i,90} = \Delta IPW^{oth}_{it} \times ImmiShare^{IV}_{i,90} + \Delta IPW^{oth}_{it} + \beta_3 ImmiShare^{IV}_{i,90} + X_{it} + \gamma_t$.

[51] The difference between the 75th percentile and 25th percentile immigrant share is 3.21 percentage points. One could calculate the change in native employment: 3.21×0.043=0.138 ppts.

[52] The wage estimates are more problematic since they are estimated by a selected group of workers who are currently employed. If natives who stay are those have high abilities and are less substituted by

that immigrants could dampen the effect of the China trade shock on low-skilled native employment by approximately 36 percent.[53] The results of not using the past-settlement instrument are shown in columns (5)-(8). I find my estimates are consistent in both models.

Table 8 shows how the mitigating effect varies with the degree of substitution between natives and immigrants. Prior studies suggest that native women, especially black women, have the highest degree of competition with immigrants (Altonji and Card, 1991). If so, when immigrants leave the local labor markets, low-skilled black women should benefit the most. Thus, I compare the estimated native employment effects across gender-race-education group. Although standard errors of black women with no college education are large, the point estimates still suggest that the employment of less-educated black women has a smaller decline compared to other groups (column (3)). Holding Chinese import exposure per worker to be unchanged, a ten percentage point increase in the immigrant population share could raise the employment of low-skilled black women by 1.18 percentage points.

One concern about the identification strategy is that the settlements of immigrants might be correlated to Chinese import exposure. Figure 5 shows the geographic distribution of immigrants across the US local labor markets. Though it seems that immigrants are concentrated in Western regions that are less exposed to the China trade shock, the high-immigration areas are not fully overlapped with high-exposed areas. In fact, the average correlation between Chinese import growth and the share of immigrant population is only -0.1, which is crucial to the preceding analysis.[54]

Another issue with the past-settlement approach is that it may generate a bias when the

immigrants, then it is difficult to observe a significant positive effect on wages.

[53] On average, the immigrant share is 6.19 percent per commuting zone in those areas with the share above the median-level. Thus, moving from zero-immigrant areas to high-immigration areas would reduce the impacts of the China trade shock on low-skilled native employment by 0.266 percentage points (0.043×6.19). According to Table 7, the estimated impact of trade shocks on low-skilled native employment is -0.738 percentage points in areas with no immigrants. Thus, immigrants reduce the negative effects of trade shocks on low-skilled native employment in high-immigration areas by approximately 36%.

[54] The correlation could be problematic when there is a non-linear effect of trade shocks on native outcomes. One may concern that the interaction term in equation (4) merely captures the non-linear effect of the China trade shock on natives. In a separate exercise, I also examine the nonlinear effects by adding a square term of import exposure to the specification. I find little evidence of the non-linear effects: estimates in Table 7 remain statistically significant after controlling for the non-linear effect.

local labor market responds to previous immigrant supply shocks in a general equilibrium setting (Jaeger et al., 2018). These high-immigration areas might have experienced increasing immigrant inflows in previous decades. As such, it may be difficult to disentangle the mitigating effect of immigrants from the labor effect of previous immigration-induced supply shock.[55] To show whether my estimates are biased by this dynamic labor market adjustment, I add a lagged immigrant population share in 1980 to control for the past inflows of immigrants. The lagged immigrant share is also instrumented by the 1980's national immigrant population and the settlements of immigrants in 1970. Additionally, I test the sensitivity of the results by adding 722 commuting zone dummies to absorb the effect of dynamic labor market adjustment and report the results in columns (5)-(9) of Table A.1. Displayed by Table A.1, my estimates for native outcomes are robust to these changes.

5.2 Immigrant Intensity in Manufacturing

Immigrants consist a large share of workers in the textile, leather, and apparel industries that are highly exposed to the China trade shock.[56] The high concentration of immigrants in these industries might additionally mitigate the effects of trade shocks on natives. This is because immigrants being more exposed to trade shocks could adjust their labor supply more. In contrast, natives in other industries with few immigrants in the workplace might be less insulated from trade shocks.

The preceding analysis uses overall Chinese import exposure without distinguishing trade shocks in immigrant-intensive industries from those in native-intensive industries. To investigate whether immigrants additionally shield natives from employment losses when immigrants are highly concentrated in import-vulnerable industries, I modify the model in equation (4) by dividing overall Chinese import exposure into the immigrant- and native-specific one according to the share of immigrants ($r_{ij,90}$) in an industry (j) in the local labor market

[55] In a theoretical framework, show that the bias is determined by the degree of serial correlation in the past-settlement instrument.

[56] According to the Pew Research Center estimate, textile, apparel, and leather are top industries in which workers are most likely to be immigrants.

(i) (Autor et al., 2018; Dorn et al., 2016a).[57]

$$\Delta IPW_{it}^{us,I} = \sum_j \frac{L_{ijt} r_{ij,90}}{L_{it}} \frac{\Delta Import_{jt}^{us}}{L_{jt}} \tag{6}$$

$$\Delta IPW_{it}^{us,N} = \sum_j \frac{L_{ijt}(1 - r_{ij,90})}{L_{it}} \frac{\Delta Import_{jt}^{us}}{L_{jt}} \tag{7}$$

Then overall import exposure is broken into two components: the immigrant ($\Delta IPW_{it}^{us,I}$) and native component ($\Delta IPW_{it}^{us,N}$). This enables me to identify whether trade shocks are in immigrant-intensive industries or not. To investigate how the mitigating effect on natives varies by industries with different degrees of immigrant intensity, I interact respectively the immigrant- and native-specific import exposure measure with the initial immigrant population share ($ImmiShare$). Ideally, I would like to add pairs of group-specific import exposure into the specification. However, this will lead to a substantial bias by having weak instruments in the 2SLS model.[58] Therefore, I use overall import exposure to control for the impact of the China trade shock on natives.[59]

As equation (8) displays, the interactions of immigrant- and native-specific import exposure with the immigrant share are introduced to allow that the immigrant employment share differs by industry. The immigrant- and native-specific interactions are corresondingly instrumented by the interactions of $\Delta IPW_{it}^{oth,I}$ and $\Delta IPW_{it}^{oth,N}$ with the past-settlement

[57] Autor et al., (2018) generate gender-specific exposure by apportioning overall import exposure to male and female industry shocks based on male and female employment shares. Following their strategy, I use the immigrant employment share, $r_{ij,90}$, to construct immigrant- and native-specific import exposure. $r_{ij,90}$ equals to the immigrant employment share in industry j in commuting zone i in 1990.

[58] The variation in $\Delta IPW_{it}^{us,I} \times ImmiShare_{i,90}$ is absorbed by $\Delta IPW_{it}^{us,I}$ after adding pairs of group-specific import exposure.

[59] Because of the way I construct group-specific import exposure, overall import exposure equals to the sum of $\Delta IPW_{it}^{us,I}$ and $\Delta IPW_{it}^{us,N}$. Two models should produce consistent estimates for the interactions.

instrument.[60]

$$\Delta L_{it} = \beta_1 \Delta IPW^{us,I}_{it} \times ImmiShare_{i,90} + \beta_2 \Delta IPW^{us,N}_{it} \times ImmiShare_{i,90} + \beta_3 \Delta IPW^{us}_{it} + \beta_4 ImmiShare_{i,90} + X_{it} + \gamma_t \tag{8}$$

Table 9 shows the results of estimating the above equation. Both the 2SLS and OLS model produce consistent estimates. Compared to the estimates in Table 7, I find a statistically significant and positive effect of immigrants on native employment changes if trade shocks are in immigrant-intensive industries (row (1)). It implies that immigrants could additionally shield natives from the China trade shock if more immigrants are concentrated in import-vulnerable industries at the initial period. The results are robust to the inclusion of controls (columns (1)-(2)). An interquartile range increase in immigrant-specific import exposure (per worker) will raise native employment by approximately 0.011 percentage points holding the population of immigrants unchanged.[61] In contrast, I find close to zero coefficient of the native interaction term, suggesting a weak mitigating effect of immigrants on natives if trade shocks hit in native-intensive industries where fewer immigrant workers are around and the adjustment of immigrant labor supply is less.

By distinguishing trade shocks in immigrant- from native-intensive industries, this exercise sheds lights on how the mitigating effect may interact with industries which immigrants sort into at the initial period. Also, while most previous studies focus on the labor supply of immigrants at the regional level, the analysis examines the heterogeneous effect by allowing immigrants to be unevenly distributed across industries.

[60] When constructing the immigrant- and native-specific instrument, I use the immigrant employment share in 1980: $\Delta IPW^{oth,I}_{it} = \sum_j \frac{L_{ijt-1} r_{ij,80}}{L_{it-1}} \frac{\Delta Import^{oth}_{jt}}{L_{jt-1}}$.

[61] Immigrant-specific import exposure at the 75th and 25th percentile is 0.11 and 0.01 kUSD between 1990 and 2007. (0.11-0.01)$\times$0.114=0.0114 percentage points.

6 Additional Empirical Evidence

6.1 Pre-period Analysis

Recall that one important source of variation in the import exposure measure is the local industry specialization. Consequently, the validity of the Bartik instrument in my model depends on the exogeneity of the industry specialization. If the industry specialization is correlated with other factors that affect population growth in a commuting zone, then the import exposure measure would capture both the effects of these unobservable factors and trade shocks, therefore, contaminating my estimates for population changes. To reduce this concern, I conduct a pre-period exercise to see if there were population responses when the China trade shock had not occurred in the preperiod. To do so, I regress the past population changes in the 1970s and 1980s on future import growth between 1990-2007.[62] Figures 6 and 7 compare the reduced-form population changes in the post- and pre-period.[63] The flat slopes in Figure 7 indicate a weak relationship between the pre-period population change and future import exposure, suggesting that the population growth followed a similar trend in areas with different future exposure to import growth.

Table 10 shows the formal estimates by regressing past population changes on future import growth between 1990-2007. Although the number of immigrants with no college education was increased significantly between 1970-1980 (column (2)), in the immediate decade (1980-1990) prior to China's rise, the population growth was weak.

[62]Future import growth is calculated by averaging import growth between 1990-2007. Because Chinese import growth is not constant overtime, I use the average of import exposure between 1990 to 2007 to indicate future import exposure.

[63]The OLS reduced form plots in Figure 6 and 7 are crowded. In Appendix Figure A.1 and Figure A.2, I also show a binned scatter plot to visualize the relationship between change in log populations and change in the predicted import exposure using *binscatter* command in STATA.

6.2 Dropping Low-Immigration Commuting Zones

This paper focuses on the population changes in logs to study the mobility responses of natives and immigrants to trade shocks. One may notice that the size of the immigrant sample is slightly smaller than that of the native sample because some commuting zones have zero new immigrant in 1990 and are automatically dropped when I compute the log population changes (Table 2 and 4).[64] Also, commuting zones with an extremely small number of immigrants might increase the standard errors and bias the estimates.[65] To alleviate the concern over outliers, I exclude those commuting zones with a small number of new immigrants (fewer than 100) at the initial period in the sample.

Table A.2 shows the estimated population changes when limiting the sample to commuting zones with at least 100 newly arrived immigrants at the initial period. My main results remain the same after dropping low-immigration commuting zones. The mobility effect of Chinese import growth is still statistically significant and strongest among the most recently arrived immigrants. This analysis further confirms that the results established in the previous section are robust and insensitive to the sample size change.

6.3 Alternative Measures

This section uses a broad set of alternative measures created by Autor, Dorn, and Hanson (2013) to examine the sensitivity of the results when accounting for US export growth to China, international competition, intermediate goods, industry- and country-specific demand side factors, and a different degree of labor intensity by sector. Overall, the estimates in Table A.3 are robust to switching to these measures for trade shocks.

Panels B-F of Table A.3 show estimates using the alternative measures. For the purpose of comparison, I also report the main results in Table 4 in the first row. When China increases its supply to the world, it also impedes the global sales of the United States

[64] Three commuting zones do not have any immigrant who arrive in the last ten years in 1990.

[65] Around twenty five percent commuting zones have fewer than 100 newly arrived immigrants with fewer than ten years in 1990.

manufacturing products. Thus, there is additional international competition between China and the US. Panel B accounts for this competition in the international market by using global imports from China. Panel C excludes the US imports of intermediate products from China because the US-China trade liberalization also benefits the US manufacturers who purchase intermediate products from China when input prices are reduced by trade liberalization.[66]

Panel D includes the effect of the US export growth on local population changes by replacing import growth with net import growthl. Panel E shows the results in a gravity model which isolates industry- and country-specific demand-side factors from China's exogenous growth.[67] By taking the residual parts of Chinese import growth, the gravity-based model only measures China's export capacity due to its comparative advantage or falling trade costs. Panel F shows the results in a factor content model that allows for capital utilization variation by sector. Because the United States is more abundant in the capital factor than the labor factor, workers in capital-intensive sectors should be less impacted by the China trade shock. In the factor content model, the import exposure measure is adjusted by the degree of labor intensity at the industry level.[68]

6.4 Observable Characteristics of Immigrants

More recently arrived immigrants mainly come from Mexico and Central America with a lower level of education than immigrants who arrived in the United States in earlier decades. Additionally, these new immigrants tend to be young, single, and house-renters (Table A.4). Do these observable characteristics explain why new immigrants are more responsive than other groups to trade shocks? This section explores the heterogeneous effects in these characteristics. I break the immigrant population by the Mexican-born and other foreign-born population, the population between 16-39 and 40-64 years of age, and the population with different home-ownership and marital status. Overall, I find little evidence of heterogeneity

[66] In the baseline model, Chinese import exposure is measured using both final and intermediate goods.
[67] See Autor, Dorn, and Hanson (2013) for more details of the gravity model.
[68] The degree of labor intensity is calculated using employment per dollar value of gross shipments.

effects in these characteristics.

As seen in columns of Table A.5, the China trade shock generates a similar decline in the Mexican-born and other foreign-born population. Also, I did not find any differential impact of trade shocks on population changes across groups with different ages, home-ownership, and marital status (see Table A.6). Within each group, the immigrant population change is statistically greater than the native population change. This exercise rules out the possibility that new immigrants respond more than other groups to trade shocks because new immigrants have distinct observable characteristics.

6.5 In- and Out-Migration

Previous analysis in Section 4.4 shows that the China trade shock impacts the immigrant population by increasing immigrant inflows and decreasing their outflows in areas with higher import exposure. In this section, I study the migrant flow as a fraction of the initial population by looking at in- and out-migration rates. In- and out-migration rates are the share of inflows (I_{it}) and outflows (O_{it}) as a percentage of the total population, N_{it-1}, in commuting zone i at the initial period $t-1$.

$$\text{In Migration}_{it} = \frac{I_{it}}{N_{it-1}} \tag{9}$$

$$\text{Out Migration}_{it} = \frac{O_{it}}{N_{it-1}} \tag{10}$$

An issue with migration rate is that initial populations of the year 1975, 1985, and 1995 are not available because the Census conducts its survey on a ten-year basis. Therefore, I impute the population of these years by subtracting the Census population in the year of 1980, 1990, and 2000, with the five-year net population flows, with an assumption that return migration is changed little over the sample period.[69] A descriptive statistic for in-

[69]The net population flow is then obtained by subtracting the sum of immigrant inflows and number of immigrants from abroad with the outflows.

and out-migration rates over a five year period is presented in Table A.7.[70]

Since the immigrant population change in logs can be broken into in- and out-migration rates, studying migration rates will help to understand the driving force behind the population change.

$$\Delta log N_{it} \simeq \frac{I_{it}}{N_{it-1}} - \frac{O_{it}}{N_{it-1}} \tag{11}$$

By estimating a three period fixed effect model in which dependent outcomes are in- and out-migration rates in logs, the results are reported in Table A.8.[71] The results show strong evidence that the China trade shock significantly affects the fraction of migrant flows over the immigrant population. On average, the China trade shock reduces the in-migration rate for new immigrants by 4.36 percent (0.44×9.909) and increases their out-migration rate by 3.66 percent (0.44×8.321).[72] As such, I find similar but weaker in- and out-migration changes for established immigrants. Again, I did not see any significant change in native migration rates because natives are not responsive to trade shocks.

6.6 Alternative Identification Strategy

The 2SLS model relies on an assumption that import growth in the US and other high-income countries is only driven by China's rise. However, if certain industries are more vulnerable to trade shocks due to a lack of technology growth, then the assumption is rendered invalid because the common factor driving import growth in the US and other high-income countries is a worldwide phenomenon: industry's capacity to innovate (Dorn et al., 2016b; Jaravel and Sager, 2018.). For this reason, I am using the identification strategy provided by Pierce and Schott to examine the sensitivity of my results (Greenland et al., 2019; Pierce and Schott,

[70] Over time, there was a slight decline in both in- and out- migration rates for natives from 1980 to 2000. The in- and out- migration measures are following Molloy, Smith, and Wozniak (2011).

[71] The regression I run is a fixed effect model where the in- and out-migration rates are in logarithm because the migration rate is highly skewed. $Y_{it} = \beta IPW_{it} + Z_i + \gamma_t + e_{it}$.

[72] The mean value of Chinese import exposure in level is 0.44 kUSD from 1980-2000.

2016a; b).[73]

Pierce and Schott use the elimination of uncertainty in the status of Normal Trade Relation (NTR) to study trade policy changes. In October 2000, the United States Congress granted Permanent NTR to China, which removed China's uncertainty of being imposed with high tariff rates under the non-NTR trade status.[74] Because each industry has a different tariff rate change, Pierce and Schott (2016) use the gap between the NTR and non-NTR tariff rate to measure an industry's exposure to trade policy changes. The level of exposure to trade policy changes in a commuting zone is then a weighted average of tariff gaps, where the weight is the commuting-zone industry specialization in 1990.[75]

$$NTRGap_i = \sum_j \frac{L_{ij,1990}}{L_{i,1990}} NTRGap_j \tag{12}$$

$$\Delta LogN_{it} = \beta_g NTRGap_i \times Post_t + X_{it-1} + Z_i + \gamma_t + e_{it} \tag{13}$$

The results in Table A.9 suggest that immigrants, especially newly arrived immigrants, are more responsive to trade policy changes. An interquartile increase in the NTR tariff gap leads to a 7.7 percent decrease in the immigrant population.[76] These estimates in Table A.9 are comparable to my main results. Previously, the baseline model suggests that an interquartile increase in Chinese import exposure leads to an approximately 5.44 percent (2.643×3.58) decline in the immigrant population.

[73]Pierce and Schott (2016a) study the effects of PNTR at the industry level. I am using the modified specification by Pierce and Schott (2016b) and Greenland et al., (2019) that conduct the analysis at the commuting zone level.

[74]Before China was granted with the permanent normal trade relation (PNTR), China had to acquire an annual waiver to maintain the free trade status with the United States so that Chinese exports were subject to low NTR tariff rates. Without acquiring the normal trade relation status, China exporters were imposed with much higher non-NTR tariff rates. Because whether China could maintain the normal trade relation status or not was determined by the Congress, manufacturers were fully exposed to the uncertainty before 2001.

[75]$NTRGap_j = \text{Non NTR Tariff}_j - \text{NTR Tariff}_j$, where j indexes for an industry.

[76]The interquartile change in the NTR Gap is approximately 0.051. I multiply 151.4 with 0.051 and obtain 7.7 log points.

7 Conclusion

Geographic labor mobility is an important mechanism for absorbing asymmetric labor demand shocks and equilibrating the local labor market. With a lower geographic mobility, it takes a longer time for the local labor market to reach an equilibrium. This will result in more disparities in employment and wages. Prior trade studies find little evidence that geographic mobility is a possible channel whereby the local labor market adjusts to trade shocks. However, looking at aggregate mobility may miss important heterogeneity. This paper has demonstrated that the mobility provided by immigrants could work as an important mechanism for the adjustment of local labor markets when trade shocks occur.

By distinguishing immigrants from natives, I find robust evidence that immigrants are responsive to trade shocks while natives are not. The immigrant mobility is almost five times as large as the native mobility in response to trade shocks. Most of the mobility effects are concentrated among recently arrived immigrants because new immigrants have fewer local affiliations compared to natives and established ones. As immigrants have more years in the United States and develop stronger local affiliations, they become more attached to the local labor market and behave similarly to natives in terms of the mobility.

Moreover, the high mobility of immigrants works as an important buffer for natives who are generally immobile. By using a past-settlement instrument, I show that natives are less adversely impacted of trade shocks when they are surrounded by more immigrants. Finding that the mobility of immigrants could reduce the adverse impacts of trade shocks on native labor outcomes is important for future immigration policy. It emphasizes the role of immigrants in tackling the trade issues between the United States and China. Policymakers may need to consider the mitigating effects provided by immigrant mobility when evaluating the impacts of immigrants on the local labor market.

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Table 1: Summary Statistics

1990-2007:	Full Sample
ΔImports from China	3.77
to US/worker	(2.72)
Share of employment	18.47
in manufacturing at t-1 (%)	(8.45)
Share of foreign-born	12.41
population at t-1 (%)	(11.83)
Share of population	50.74
with college at t-1 (%)	(8.26)
Share of employment	32.05
in routine occupations at t-1	(2.63)
Offshorability index	0.05
at t-1	(0.49)
ΔLog native	5.29
population (log pts)	(8.12)
ΔLog immigrant	40.93
population (log pts)	(28.66)
ΔLog new immigrant	43.60
population (log pts)	(51.66)
Number of commuting zones	722
Obs	1444

Notes: This table shows mean values of main outcome and control variables of commuting zones in the 1990s and 2000s. ΔImports from China to US/worker is the Chinese import exposure measure specified in equation (1). Routine-related occupations are occupations whose tasks involve routine information processing. The offshorability index measures how likely an occupation requires neither proximity to a specific work-site nor face-to-face contact with US workers. The full sample includes 1444 observations (722 commuting zones $\times$ 2 periods). Values are weighted by the commuting zone share of national population at the initial period of each decade.

Table 2: Chinese Import Exposure and Population Changes: 2SLS Estimates

Dependent variable: change in log working-age pop (log pts)

	Natives	Natives	Immigrants	Immigrants	New Immigrants	New Immigrants	Established Immigrants	Established Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔImports from China	-0.636	-0.483	-2.504***	-2.643***	-6.034***	-5.299***	-0.583	-1.260
to US/worker	(0.631)	(0.507)	(0.853)	(1.008)	(1.512)	(1.215)	(0.799)	(1.081)
Percentage of employment	0.017	-0.095	0.790***	0.606**	1.878***	1.055***	0.266	0.389*
in manufacturing	(0.070)	(0.068)	(0.192)	(0.236)	(0.277)	(0.307)	(0.163)	(0.217)
Share of foreign-born		-0.149***		-0.841***		-1.762***		-0.373**
population		(0.049)		(0.158)		(0.238)		(0.150)
Share of population		-0.127		-0.412*		-1.191***		-0.103
with college		(0.126)		(0.226)		(0.301)		(0.221)
Percentage of employment		-0.330		-0.927		-2.329**		-0.606
in routine occupations		(0.280)		(0.667)		(0.984)		(0.675)
Offshorability		2.251		24.668***		39.792***		19.060***
index		(1.683)		(5.337)		(8.220)		(5.147)
Full Controls	No	Yes	No	Yes	No	Yes	No	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1444	1444	1444	1444	1441	1441	1444	1444

Note: N=1444 (2 periods × 722 commuting zones). Three commuting-zones are dropped for not having any new immigrant in 1990 (columns (5)-(6)). Immigrants include both new (fewer than ten years) and established (more than ten years) immigrants. Odd columns show the results of specification that only controls for the concentration of employment in manufacturing, census division fixed effects, and decade fixed effects. Even columns show the results with full controls by adding the share foreign-born population, college-educated population, employment in routine-related occupation, offshorability in the specification. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 3: Chinese Import Exposure and Population Changes: OLS and 2SLS Estimates

Dependent variable: change in log working-age pop (log pts)

	Natives		Immigrants		New Immigrants		Established Immigrants	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔImports from China	0.239	-0.483	-1.008**	-2.643***	-2.563***	-5.299***	-0.078	-1.260
to US/worker	(0.180)	(0.507)	(0.425)	(1.008)	(0.758)	(1.215)	(0.528)	(1.081)
Percentage of employment	-0.180*	-0.095	0.412*	0.606***	0.731**	1.055***	0.250	0.389*
in manufacturing	(0.095)	(0.068)	(0.234)	(0.236)	(0.316)	(0.307)	(0.204)	(0.217)
Full Controls	No	Yes	No	Yes	No	Yes	No	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1444	1444	1444	1444	1441	1441	1444	1444

Note: This table compares the estimated population changes in the OLS model to those in the 2SLS model. Odd columns report the OLS estimates and even columns report the 2SLS results. All regressions include full controls and census division dummies. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 4: Estimated Population Changes by Year of Immigration: 2SLS Estimates

Dependent variable: change in log working-age pop (log pts)

				Year of Immigration		
	All	Natives	Immigrants	< 5 Years	5-10 Years	>= 10 Years
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
ΔImports from China	-0.315	-0.483	-2.643***	-7.639***	-4.425***	-1.166
to US/worker	(0.546)	(0.507)	(1.008)	(1.805)	(1.419)	(1.149)
Panel B. High School and below						
ΔImports from China	-0.572	-0.978*	-3.335***	-10.657***	-4.534***	-1.640
to US/worker	(0.623)	(0.518)	(1.181)	(2.307)	(1.603)	(1.412)
Panel C.Some College and above						
ΔImports from China	-0.246	-0.358	-1.712	-4.634**	-3.574*	-0.615
to US/worker	(0.515)	(0.517)	(1.046)	(2.132)	(1.932)	(1.152)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The last three columns show changes in the immigrant population by breaking the immigrant population into groups with different years of immigration. Column (4) shows the estimated population change for immigrants with fewer than five years in the US prior to the survey; column (5) shows the results for those with five to ten years in the US. The last column shows for those having more than ten years in the US. Around 15 commuting zones are dropped because of not having any immigrants falling into <= 5 and 5-10 group. The results in other columns are robust to dropping those commuting zones. All regressions include full controls of manufacturing employment share, foreign-born population share, the share of population with college education, routine employment share, offshorability, census division dummies and decade fixed effects. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 5: Estimated Migrant Flows Changes: 2SLS Estimates

Dependent variable: change in inflows and outflows (number)

	ΔInflows			ΔOutflows		
	Native	Established Immigrants	New Immigrants	Native	Established Immigrants	New Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
ΔImports from China	-864.02	-1013.13**	-1280.97*	769.52	1623.43	1016.75*
to US/worker	(4062.18)	(444.17)	(740.50)	(3534.98)	(1050.39)	(518.78)
Mean Outcome	1866.83	689.81	411.69	1848.41	682.45	409.30
Panel B. High School and below						
ΔImports from China	-713.96	-509.12***	-688.50*	-91.42	989.51	675.62**
to US/worker	(1221.12)	(183.84)	(406.48)	(1501.86)	(730.94)	(339.59)
Mean Outcome	-890.05	240.51	196.15	-873.51	238.90	195.62
Panel C.Some College and above						
ΔImports from China	-150.05	-504.00*	-592.46*	860.93	633.92*	341.13*
to US/worker	(3029.85)	(305.48)	(344.35)	(2160.10)	(378.82)	(196.09)
Mean Outcome	2756.88	449.30	215.53	2721.92	443.55	213.68

Notes: N=1352. 46 commuting zones are dropped for not having complete migration data in all years. Results are obtained by estimating the first stacked difference model in the main specification. Dependent variables are decadal changes in inflows and outflows in absolute numbers. All regressions include full controls of manufacturing employment share, foreign-born population share, the share of population with college education, routine employment share, offshorability, census division dummies and decade fixed effects. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 6: First Stage of the Past-Settlement Instrument

	ΔImports from China to US/worker × ImmiShare	ΔImports from China to US/worker	ImmiShare
	(1)	(2)	(3)
Instrumented by:			
Δ Predicted imports from China	0.817***	-0.053	0.092
to US/worker × ImmiShare^{IV}	(0.267)	(2.153)	(0.251)
ΔPredicted imports from China	-0.004	0.674***	0.013
to US/worker	(0.004)	0.115)	(0.006)
ImmiShare^{IV}	0.020	0.255	0.669***
	(0.042)	(0.305)	(0.072)
R square	0.814	0.585	0.853
Obs	1444	1444	1444

Notes: This table shows the first stage results in the past-settlement model. ImmiShare is the share of immigrant population in 1990 and ImmiShare$_{IV}$ is the past-settlement IV specified in equation (5). Columns (1)-(3) show the first stage results by of the 2SLS model with past-settlement IV. Regressions control for the manufacturing employment share, census, decade fixed effects and census division fixed effects. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 7: The Mitigating Effect of Immigrant Mobility on Natives: 2SLS Estimates 1990-2007

Dependent variable: change in employment to population (%pts) and log hourly wage (log pts)

	Past-Settlment IV				No Past-Settlement IV			
	Employment		Hourly Wage		Employment		Hourly Wage	
	College	No College	College	No College	College	No College	College	No College
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔImports from China	0.014**	0.043***	-0.004	0.024	0.016***	0.034***	0.003	0.055***
to US/worker × ImmiShare	(0.006)	(0.012)	(0.032)	(0.033)	(0.003)	(0.009)	(0.022)	(0.013)
ΔImports from China	-0.314***	-0.738***	-0.499	-0.734**	-0.102***	-0.229***	-0.191*	-0.430***
to US/worker	(0.096)	(0.201)	(0.358)	(0.368)	(0.031)	(0.041)	(0.110)	(0.105)
ImmiShare	-0.052	0.021	0.178	-0.666**	-0.065**	-0.162***	-0.007	-0.383***
	(0.064)	(0.125)	(0.395)	(0.335)	(0.025)	(0.043)	(0.125)	(0.110)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Past-Settlement IV	Yes	Yes	Yes	Yes	No	No	No	No
Obs	1444	1444	1444	1444	1444	1444	1444	1444

Notes: Dependent variables are changes in native employment to population and log hourly wages. Odd columns show the estimated results for low-skilled natives with no college education. Even columns show the results for high-skilled natives with at least some college education. Apart from adding basic controls (Table 2), regressions in this table include the share of immigrant workers in manufacturing, the share of immigrants and natives employed in manual occupations, population size, and the share of immigrants and natives with a least college education. Columns (5)-(8) show the results in the baseline model which does not use the past-settlement IV. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 8: The Mitigating Effect of Immigrant Mobility on Natives by Gender and Race: 2SLS Estimates 1990-2007

Dependent variable: change in employment to population (%pts)

	No College				College			
	White Men	White Women	Black Men	Black Women	White Men	White Women	Black Men	Black Women
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔImports from China	0.056***	0.020**	-0.073	0.118**	0.006	0.010*	0.043	-0.011
to US/worker × ImmiShare	(0.019)	(0.008)	(0.075)	(0.050)	(0.006)	(0.005)	(0.045)	(0.033)
ΔImports from China	-0.540***	-0.520***	0.050	-1.339**	-0.275***	-0.161**	-0.937***	-0.231
to US/worker	(0.176)	(0.142)	(0.659)	(0.655)	(0.088)	(0.069)	(0.359)	(0.468)
ImmiShare	0.263*	-0.007	-1.009	0.475	0.009	-0.055	0.033	-0.250
	(0.158)	(0.065)	(0.725)	(0.649)	(0.059)	(0.097)	(0.213)	(0.305)
Observations	1444	1444	1305	1239	1444	1444	1313	1251
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns (1)-(8) show the estimated employment effects by education, gender, and race. I only consider white and black workers who are the major workforce in manufacturing. All regressions include full set of controls and eight census division dummies. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 9: Immigrant- and Native-Specific Trade Shocks and The Mitigating Effects on Natives: 2SLS Estimates 1990-2007

Dependent variable: change in employment to population (%pts)

	2SLS				OLS	
	No College		College		No College	College
	(1)	(2)	(3)	(4)	(5)	(6)
ΔImports from China (Immigrant)	0.114***	0.131***	0.094***	0.077**	0.065***	0.047***
to US/worker × ImmiShare	(0.042)	(0.045)	(0.021)	(0.031)	(0.011)	(0.004)
F-statistic	[30.73]	[20.05]	[30.73]	[20.05]	na	na
ΔImports from China (Native)	-0.010	-0.026	-0.048*	-0.028	-0.005	-0.017*
to US/worker × ImmiShare	(0.051)	(0.023)	(0.028)	(0.018)	(0.021)	(0.009)
F-statistic	[20.50]	[36.92]	[20.50]	[36.92]	na	na
ΔImports from China	-0.524**	-0.357***	-0.135	-0.147**	-0.094**	-0.018
to US/worker	(0.244)	(0.117)	(0.128)	(0.071)	(0.039)	(0.027)
F-statistic	[34.46]	[125.16]	[34.46]	[125.16]	na	na
ImmiShare	-0.031	-0.089***	-0.081	-0.056***	-0.427***	-0.190***
	(0.181)	(0.026)	(0.140)	(0.016)	(0.067)	(0.032)
F-statistic	[21.77]	[28.50]	[21.77]	[28.50]	na	na
Full Control	Yes	Yes	No	No	Yes	Yes
Obs	1444	1444	1444	1444	1444	1444

Notes: This table shows the results of the model distinguishing trade shocks in immigrant- and native-dominant industries (equation (8)). The first row shows the results for immigrant-specific trade shocks, while the second row shows those for native-specific trade shocks. Columns (1)-(4) show the 2SLS estimates, while columns (5)-(6) show the OLS results without using any instrument. All specifications include the interactions between immigrant- and native-specific import exposure and the initial immigrant share of population, overall import exposure, and the initial immigrant share. F-statistics for the first stage results for corresponding instruments are reported in square brackets. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

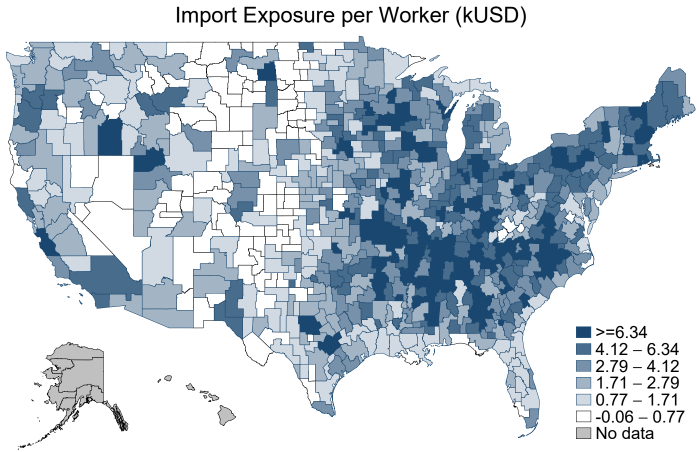
Table 10: Future Chinese Import Exposure and Preperiod Population Changes, 1970-1990: 2SLS Estimates

Dependent variable: change in log working-age pop (log pts)

	1970-1980			1980-1990		
	Natives	Immigrants	New Immigrants	Natives	Immigrants	New Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
Δ Future Imports from	0.976	2.390	-1.202	-0.428	-0.129	0.190
China to US per worker	(0.989)	(1.935)	(3.182)	(0.594)	(1.103)	(1.617)
Panel B. High School and below						
Δ Future Imports from	1.980	5.280***	-0.375	0.605	0.003	-1.875
China to US per worker	(1.247)	(2.045)	(3.557)	(0.748)	(1.303)	(2.140)
Panel C.Some College and above						
Δ Future Imports from	1.319	-0.952	-4.219	0.174	0.993	1.787
China to US per worker	(1.100)	(2.618)	(5.110)	(0.679)	(1.120)	(2.133)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	No	No	No	No	No	No
Obs	722	722	722	722	722	722

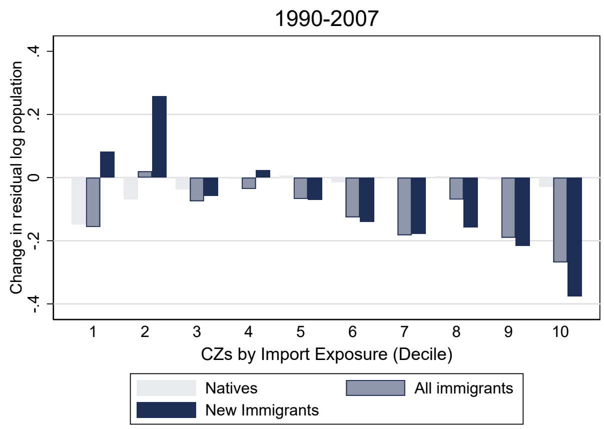
Notes: This table shows the effects of Chinese import growth between 1990-2007 on the past decadal changes in populations. Δ Future Imports from China to US per worker is the mean value of Δ Imports from China to US per worker between 1990-2007. Columns (1)-(3) show population changes from 1970 to 1980. Columns (4)-(6) show the population changes from 1980-1990. All regressions include the share of employment in manufacturing and eight census division dummies. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

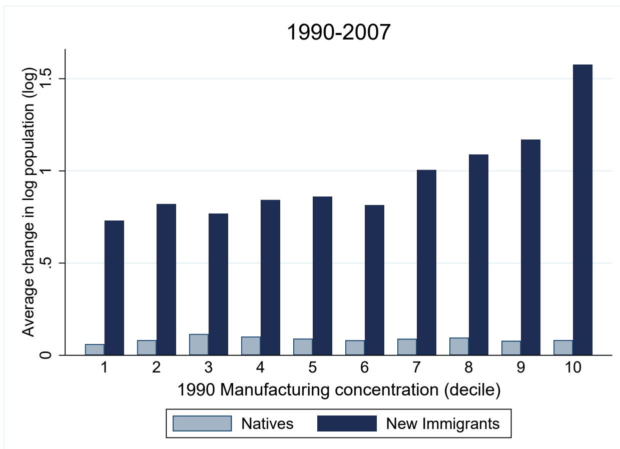
Figure 1: Geographic Variation in Chinese Import Exposure, 1990-2007



Note: N=722. The figure shows the geographic variation in Chinese import exposure (ΔIPW, kUSD).

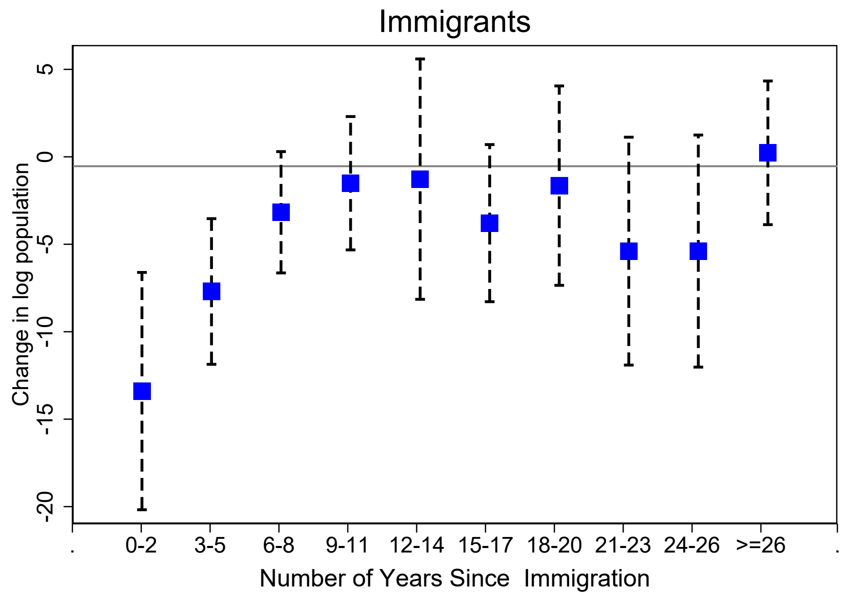
Figure 2: Change of log population and Chinese Import Exposure, 1990-2007





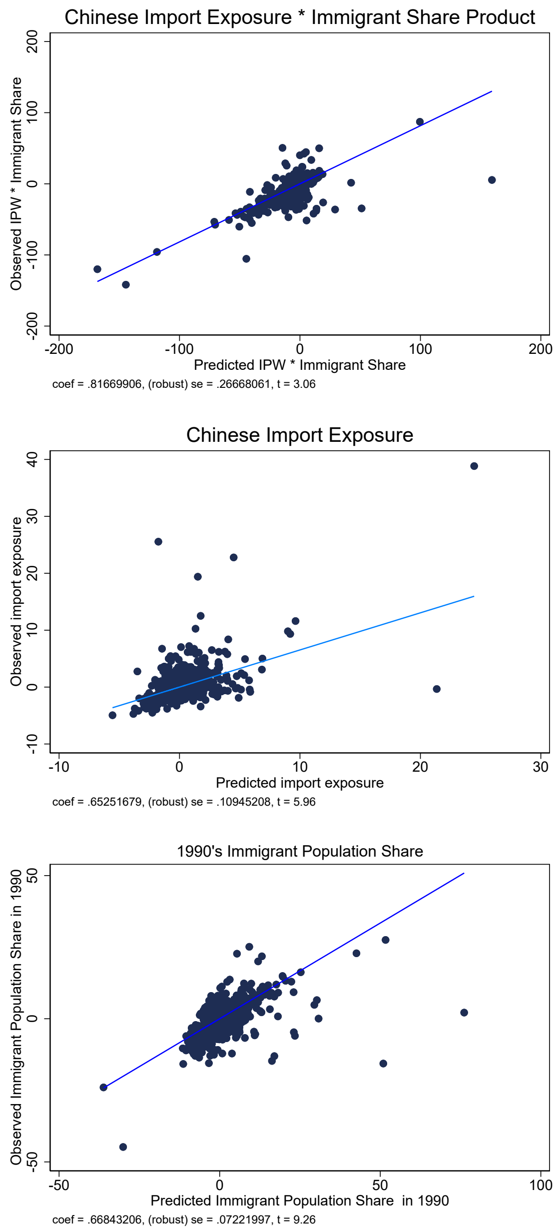
Note: N=722. In the top graph, the x-axis shows decile groups of commuting zones that are ranked by the US import growth from China between 1990-2007. 722 commuting zones are assigned to ten decile groups that are ranked by Chinese import exposure. For each decile group, I calculate the average native and immigrant population changes and show them in the Y-axis. The top graph shows how the population change varies by import exposure per worker between 1990 and 2007. The y-axis shows the residual parts of population changes obtained by regressing the population changes on the concentration of employment in manufacturing. The bottom graph shows the relationship between the concentration of employment in manufacturing and changes in populations. The x-axis shows decile groups that are ranked by the share of employment in manufacturing in 1990.

Figure 3: Estimated Change of Immigrant Population by Detailed Year of Immigration (log pts)



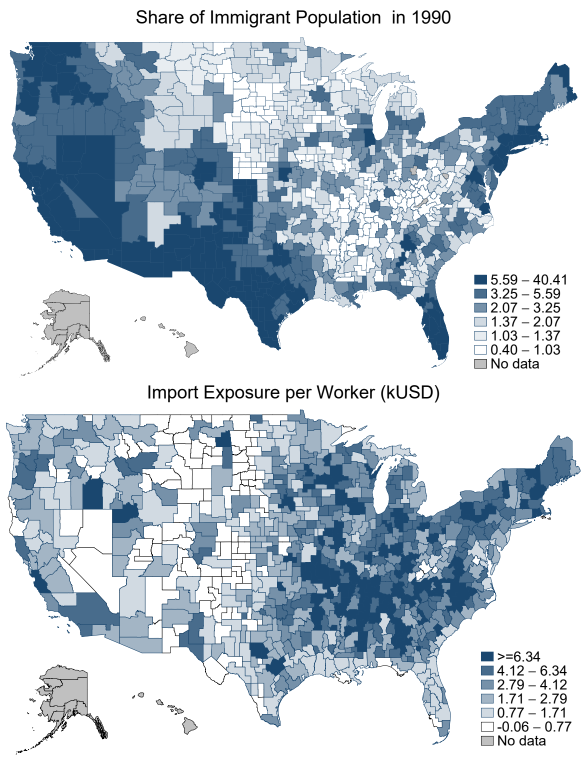
Note: N=722. Each dot represents the estimated population changes in immigrants whose year of arrival falls under a given two-year interval. The horizontal line is the point estimate of native population change when Chinese import exposure increases by $1000 per worker (-0.483). All regressions include full controls as ones in Table 2.

Figure 4: Mitigating Effects of Immigrants, First Stages



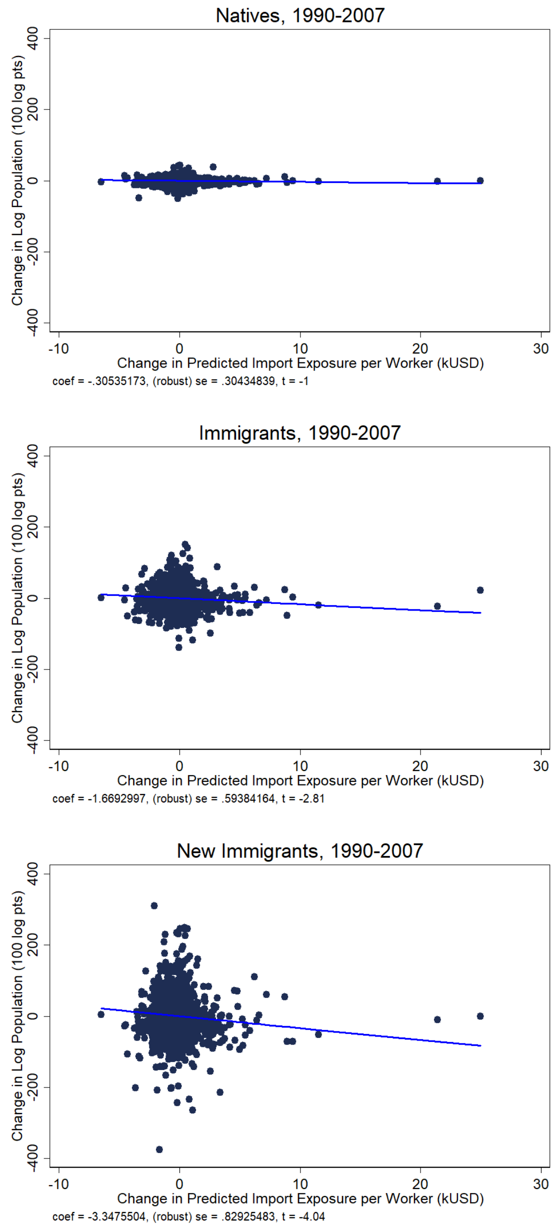
Note: N=1444. This figure shows the first stage results of using the past-settlement IV. The top graph shows for the interaction term between Chinese import exposure (ΔIPW) and 1990's foreign-born share. The middle graph shows the first stage for Chinese import exposure. The bottom one shows for the 1990's immigrant population share. All regressions include full controls and eight census division dummies. Models are weighted by commuting zone's initial share of national population.

Figure 5: Geographic Variation in the Immigrant Population Share (%), 1990



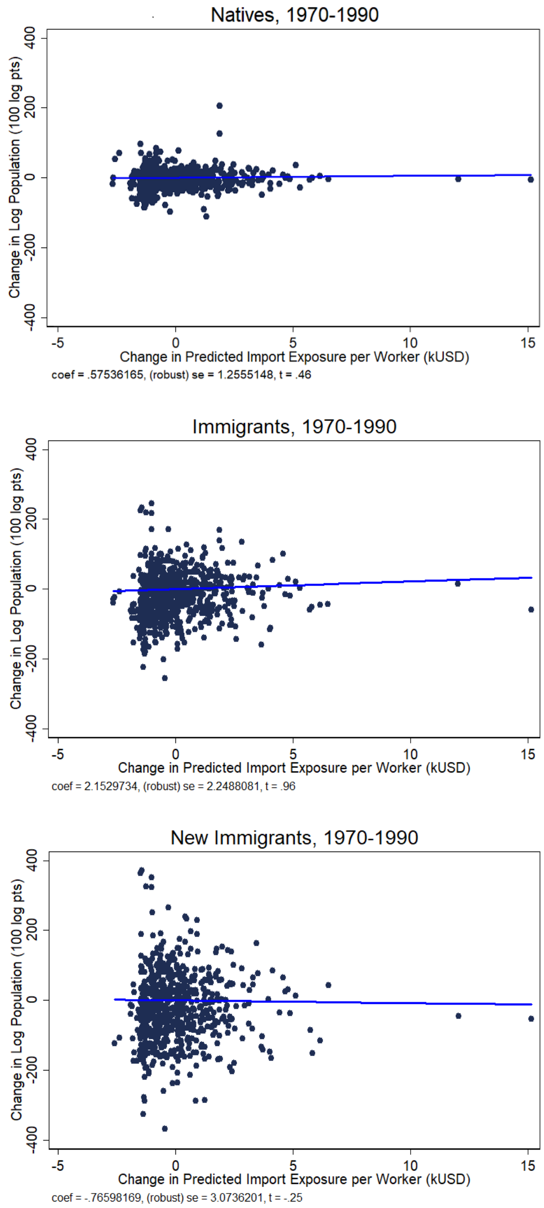
Note: The top graph and bottom graph show the geographic variations in 1990's immigrant population share and imports growth from China between 1990-2007.

Figure 6: Reduced Form Estimates of Population Changes by Nativity Group, 1990-2007 (log pts)



Note: N=1444. The X-axis shows the change in predicted import exposure per worker. The Y-axis shows the population change. Regressions in this figure are fully controlled for the concentration of employment in manufacturing, population share of college education, routine occupation index, offshorability, and share of foreign-born population. The corresponding binned scatterplots are shown in Appendix Figure A.1. Models are weighted using the initial share of national population at the commuting zone level in each decade.

Figure 7: Preperiod Estimates of Population Changes by Nativity Group, 1970-1990 (log pts)



Note: N=722. This figure shows the correlation between the population change in pre-period (1970-1990) and future Chinese import exposure (1990-2007). Future import exposure is obtained by averaging Chinese import exposure from 1990 to 2007. The binned scatterplots are also shown in Appendix Figure A.2. Regressions in this figure control for census division and decade fixed effects. Models are weighted by commuting zone's initial share of national population.

Table A.1: The Mitigating Effect of Immigrant Mobility on Natives: Robustness

Dependent variable: change in employment to population (%pts)

	Add Lagged Share				Add Czone Trends			
	Employment		Hourly Wages		Employment		Hourly Wages	
	College	No College	College	No College	College	No College	College	No College
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔImports from China	0.020*	0.045***	-0.002	0.093	0.059**	0.140***	-0.039	0.046
to US/worker × ImmiShare	(0.011)	(0.016)	(0.046)	(0.064)	(0.024)	(0.038)	(0.044)	(0.050)
ΔImports from China	-0.365***	-0.759***	-0.521	-1.346*	-1.140***	-2.175***	-0.928	-1.535**
to US/worker	(0.115)	(0.184)	(0.525)	(0.770)	(0.313)	(0.559)	(0.612)	(0.626)
ImmiShare	0.108	0.088	0.250	1.270	0.000	0.000	0.000	0.000
	(0.210)	(0.441)	(1.616)	(1.939)				
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ImmiShare$_{-1}$	Yes	Yes	Yes	Yes	No	No	No	No
Czone Dummies	No	No	No	No	Yes	Yes	Yes	Yes
Obs	1444	1444	1444	1444	1444	1444	1444	1444

Notes: This table examines the sensitivity of the results in Table 7. Columns (1)-(4) control for the local labor market's dynamic adjustment to past immigrant inflows by adding a lagged ImmiShare$_{-1}$. Columns (5)-(8) control for the general trend in economic growth across commuting zones by adding 722 commuting zone (Czone) dummies into the regression. ImmiShare is automatically omitted by adding the Czone dummies. All regressions include full controls and census division fixed effects. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.2: Estimated Population Changes: Dropping Czones with Low Immigration

Dependent variable: change in log working-age pop (log pts)

				Year of Immigration		
	All	Natives	Immigrants	< 5 Years	5-10 Years	>= 10 Years
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
ΔImports from China	-0.393	-0.549	-3.105***	-8.398***	-5.190***	-1.496
to US/worker	(0.636)	(0.571)	(1.112)	(2.230)	(1.690)	(1.332)
Panel B. High School and below						
ΔImports from China	-0.688	-1.094*	-3.670**	-10.772***	-5.147***	-1.729
to US/worker	(0.724)	(0.569)	(1.427)	(2.900)	(1.761)	(1.759)
Panel C.Some College and above						
ΔImports from China	-0.287	-0.392	-2.199**	-5.721**	-3.921*	-1.132
to US/worker	(0.595)	(0.588)	(1.085)	(2.272)	(2.294)	(1.201)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	944	944	944	944	944	944

Notes: This table shows the results of a robustness check for Table 4 by limiting the sample to commuting zones with at least 100 new immigrants in 1990. 472 commuting zones remain in the sample. All regressions include full controls of manufacturing employment share, foreign-born population share, the share of population with college education, routine employment share, offshorability, census division dummies and decade fixed effects. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.3: Alternative Import Exposure Measures and Population Changes, 1990-2007: 2SLS Estimates

Dependent variable: change in log working-age pop (log pts)

	Natives		Immigrants		New Immigrants		Established Immigrants	
	College	No college	College	No college	College	No college	College	No college
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Baseline Results:								
ΔImports from China	-0.358	-0.978**	-1.712	-3.335***	-3.657**	-6.762***	-0.698	-1.819
to US/worker	(0.518)	(0.518)	(1.046)	(1.181)	(1.379)	(1.449)	(1.107)	(1.303)
Panel B. Domestic plus international exposure:								
ΔGlobal imports from	-0.297	-0.717*	-1.493*	-2.935***	-2.908**	-5.406***	-0.733	-1.852*
China to US/worker	(0.440)	(0.429)	(0.876)	(0.923)	(1.162)	(1.240)	(0.954)	(1.061)
Panel C. Exposure to final goods only:								
ΔImports from China	0.034	-0.519	-1.696*	-2.100*	-2.974**	-3.959**	-1.051	-1.574
net intermediate to US/worker	(0.470)	(0.557)	(1.024)	(1.151)	(1.315)	(1.724)	(1.198)	(1.198)
Panel D. Net Chinese imports per worker:								
ΔNet imports from	-0.052	-0.517	-1.719**	-1.814*	-2.638**	-3.602**	-1.168	-1.160
China to US/worker	(0.361)	(0.467)	(0.840)	(1.047)	(1.165)	(1.528)	(0.958)	(1.045)
Panel E. Gravity residual:								
Net Import Exposure	-0.044	-0.307	-0.744*	-1.836***	-1.347**	-3.668***	-0.416	-0.770
from Chinese Productivity	(0.170)	(0.187)	(0.420)	(0.615)	(0.635)	(1.081)	(0.513)	(0.491)
Panel F. Factor content of net Chinese imports per worker:								
Δfactor content of net	-0.086	-0.945*	-1.878**	-1.703	-4.043***	-4.773***	-0.735	-0.359
imports/worker	(0.400)	(0.545)	(0.894)	(1.337)	(1.359)	(1.602)	(0.881)	(1.244)

Note: This table examines the sensitivity of the main results of population changes by using other import exposure measures following Autor, Dorn, and Hanson (2013). Panel A displays the baseline results in Table 4. Panel B shows the results when adding Chinese import growth in other countries to account for import competition in the international market. Panel C drops imported goods that are intermediate inputs. Panel D uses net export growth. Panel E uses the residual part of import exposure after controlling for country and industry fixed effects via a gravity approach. Panel F adds a factor content weight to account for labor intensity of a sector. All regressions include all controls and eight census division dummies. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.4: Characteristics of Natives and Immigrants in 1990

	Natives	Immigrants	New Immigrants
Mean Values	(1)	(2)	(3)
Age	38.3	38.1	32.8
Share of Female Population	32.5 %	33.5%	30.6 %
Percentage of Singles	20.1 %	17.2%	24.8 %
Share of Homeowners	73.97 %	63.48 %	42.32 %
Obs	1,408,687	121,328	45,053

Note: This table shows the mean values of observable characteristics in age, gender, marital status, and home ownership for natives, immigrants, and new immigrants in 1990.

Table A.5: Population Changes of Mexican and Other-Foreign Born: 2SLS Estimates

Dependent variable: change in log working-age pop (log pts)

	Men			Women		
New Immigrants	All	Mexican	Other Foreign-born	All	Mexican	Other Foreign-born
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
ΔImports from China	-5.502***	-6.931***	-5.679***	-4.783***	-4.993	-3.664***
to US/worker	(1.448)	(2.633)	(1.723)	(1.202)	(4.388)	(1.304)
Observations	1426	1147	1404	1432	967	1424
Panel B. High School and below						
ΔImports from China	-6.091***	-7.918***	-8.625***	-6.505***	-4.766	-6.905***
to US/worker	(1.879)	(2.763)	(2.195)	(1.751)	(4.494)	(2.557)
Observations	1384	1118	1295	1380	929	1294
Panel C.Some College and above						
ΔImports from China	-4.026**	2.400	-2.843	-3.615**	-7.347	-2.215
to US/worker	(1.879)	(6.272)	(2.107)	(1.771)	(5.896)	(1.731)
Observations	1365	752	1340	1355	542	1341
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimated immigrant population changes among newly arrived Mexican-borns and other foreign-borns. All regressions include full controls and eight census division dummies. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.6: The Heterogeneious Effects of Chinese Import Exposure on Population Changes across Groups: 2SLS Estimates

Dependent variable: change in log population (log pts)

	Age		Home-Ownership		Marriage	
	16-39	40-64	Owner	Renter	Married	Single
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Natives						
ΔImports from China	-0.550	-0.314	-0.514	-0.466	-0.455	-0.512
to US/worker	(0.711)	(0.379)	(0.616)	(0.524)	(0.491)	(0.680)
Panel B. Immigrants						
ΔImports from China	-3.151***	-1.789***	-2.146*	-3.828***	-2.188**	-4.429***
to US/worker	(1.002)	(1.106)	(1.301)	(1.214)	(1.048)	(1.343)
Panel C.New Immigrants						
ΔImports from China	-5.325***	-5.708**	-2.913***	-3.325**	-2.293**	-5.233***
to US/worker	(1.259)	(1.662)	(1.324)	(1.693)	(1.142)	(1.886)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Owners refer to workers who own a house and renters are those who rent an apartment or house. Married workers refer to individuals who have ever married (including those divorced and widowed), while single workers are those who have never married before. All regressions include full controls and eight census division dummies. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.7: Five Year In- and Out-Migration Rates,1980-2000

	1980		1990		2000	
Rate	In-Migration	Out-Migration	In-Migration	Out-Migration	In-Migration	Out-Migration
	(1)	(2)	(3)	(4)	(5)	(6)
Native	0.21	0.20	0.17	0.20	0.18	0.19
	(0.09)	(0.06)	(0.07)	(0.06)	(0.07)	(0.06)
Early Immigrant	0.28	0.24	0.22	0.26	0.27	0.25
	(0.16)	(0.10)	(0.12)	(0.09)	(0.12)	(0.10)
New Immigrant	0.24	0.25	0.30	0.23	0.24	0.23
	(0.15)	(0.21)	(0.14)	(0.19)	(0.12)	(0.12)
Obs	537	537	537	537	537	537

Note: The migration sample excludes those commuting zones with zero inflow or outflow of immigrants. 537 commuting zones are contained in the sample. All these migration rates are measured at the commuting zone level and weighted using the weight from the Census migration sample.

Table A.8: Chinese Import Exposure and In-Migration, Out-Migration, 1980-2000: 2SLS Estimates

Dependent variable: log Migration rates (log pts)

	No College			College		
	Natives	Established	New Immigrants	Natives	Established	New Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. In-Migration Rate						
Imports from China	0.535	-3.669	-9.909*	0.216	2.032	-0.568
China to US per worker	(1.260)	(3.147)	(5.360)	(1.126)	(2.481)	(3.636)
Panel B.Out-Migration Rate						
Imports from China	0.737	6.008**	8.321*	-1.097*	-1.632	-1.887
China to US per worker	(1.048)	(3.160)	(4.975)	(0.580)	(1.666)	(2.760)
Panel C. Net Migration Rate						
Imports from China	-0.202	-9.289**	-17.069**	1.313	-4.048	2.489
China to US per worker	(1.598)	(4.154)	(8.852)	(1.267)	(2.819)	(5.317)
State Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Czone FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1611	1611	1611	1611	1611	1611

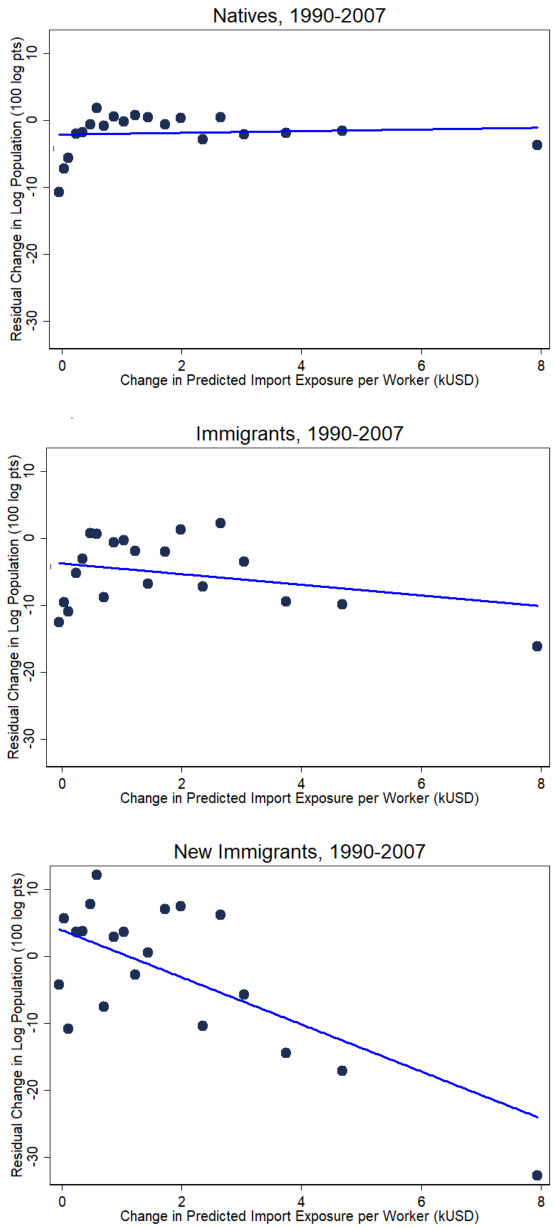
Note: N=1611. The net migration rate is the difference between the in-migration rate and out-migration rate in logs. Migration rates are constructed with the Census migration sample of the year 1980, 1990, and 2000. Estimates are obtained by regressing log migration rates on Chinese import exposure from 1980-2000. Chinese import growth is set to be zero from 1980 to 1990. I only control for the state linear trend, commuting zone and census fixed effects. I did not include those immigrants who were abroad five years ago. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table A.9: The Impact of Chinese Import Exposure on Population Changes: 2SLS Estimates

	Dependent variable: change in log working-age pop ($\frac{1}{100}$log pts)					
				Year of Immigration		
	All	Natives	Immigrants	< 5 Years	5-10 Years	>= 10 Years
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All						
$NTRGap \times Post$	-0.140	-0.332	-1.514**	-7.052***	-3.934***	0.523
	(0.164)	(0.208)	(0.647)	(1.707)	(0.896)	(0.467)
Panel B. High School and below						
$NTRGap \times Post$	-0.353*	-0.767***	-2.234**	-10.751***	-4.800***	0.716
	(0.178)	(0.257)	(0.916)	(1.857)	(1.077)	(0.672)
Panel C.Some College and above						
$NTRGap \times Post$	-0.231	-0.347	-0.557	-3.546**	-3.098***	0.389
	(0.188)	(0.225)	(0.394)	(1.389)	(1.139)	(0.451)
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Census Division FE	Yes	Yes	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes
Czone FE	Yes	Yes	Yes	Yes	Yes	Yes

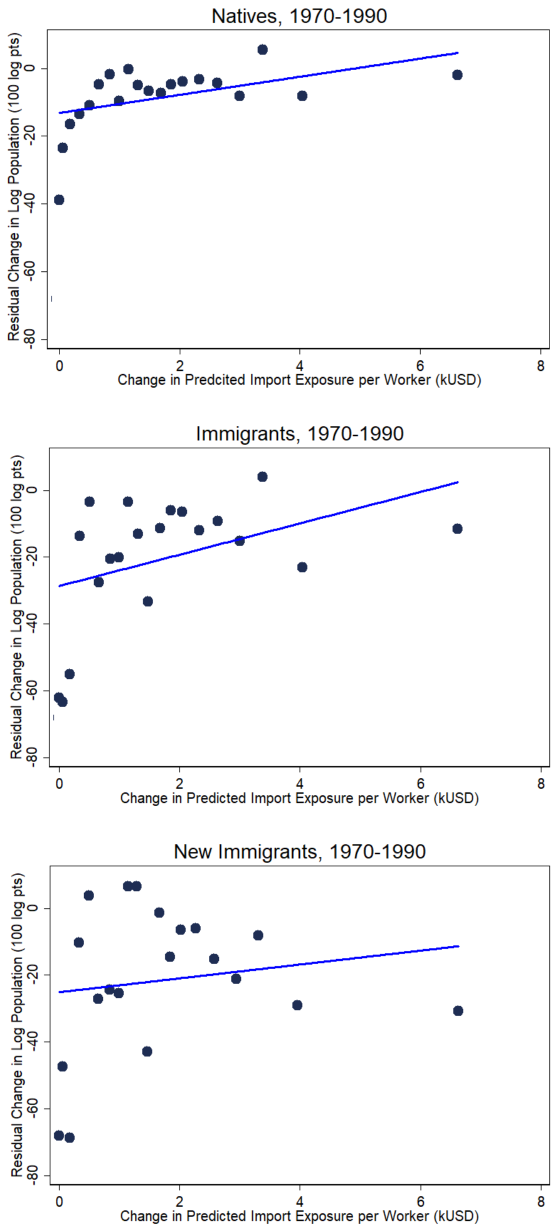
Notes: N=1444. The $NTRGap \times Post$ is set to be zero from 1990 to 2000 and equal the NTR Gap from 2000 to 2007. The mean value of NTR Gap is 0.087 (SD is 0.042) between 2000-2007. All regressions include all controls and eight census division dummies. Czone fixed effects are added to absorb the effects of time-invariant characteristics of commuting zones. Models are weighted by commuting zone's initial share of national population. Robust standard errors in parentheses are clustered to the state level. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure A.1: Binned Scatterplot: Reduced Form Estimates of Population Changes by Nativity Group, 1990-2007 (log pts)



Note: N=1444. This figure shows the binned scatter plot for Figure 6.

Figure A.2: Binned Scatterplot: Preperiod Estimates of Population Changes by Nativity Group, 1970-1990 (log pts)



Note: N=1444. This figure shows the binned scatter plot for Figure 7.