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# TRADING PLACES: MOBILITY RESPONSES OF NATIVE AND FOREIGN-BORN ADULTS TO THE CHINA TRADE SHOCK

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**ABSTRACT**

Previous research finds that the greater geographic mobility of foreign than native-born workers following economic shocks helps to facilitate local labor market adjustment to shifting regional economic conditions. We examine the role that immigration may have played in enabling U.S. commuting zones to respond to manufacturing job loss caused by import competition from China. Although population headcounts of the foreign-born fell by more than those of the native-born in regions exposed to the China trade shock, the overall contribution of immigration to labor market adjustment in this episode was small. Because most U.S. immigrants arrived in the country after manufacturing regions were already mature, few took up jobs in industries that would later see increased import penetration from China. The foreign-born share of the working-age population in regions with high trade exposure was only three-fifths that in regions with low exposure. Immigration thus appears more likely to aid adjustment to cyclical shocks, in which job loss occurs in regions that had recent booms in hiring, rather than facilitating adjustment to secular regional decline, in which hiring booms occurred in the more distant past.

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# 1 Introduction

Empirical analysis of migration provides abundant evidence that foreign-born and native-born workers differ in how they make location choices within national borders. As adults, the native-born tend to settle close to where they lived as children (Sprung-Keyser et al., 2022), which may contribute to why supplies of less-educated native-born labor are largely unresponsive to adverse changes in local labor demand (Topel, 1986; Bound and Holzer, 2000; Notowidigdo, 2020). For the foreign-born, mobility is often built into their working lives. Mexican immigrants long traveled back and forth across the U.S.-Mexico border, working in U.S. agriculture and construction during warmer months and returning to Mexico for the winter season (Durand et al., 2001; Woodruff and Zenteno, 2007). Since 1990, the expansion of U.S. temporary work visas has directed new immigrants into U.S. regions in which employment growth happens to be strong in their arrival year (Clemens and Lewis, 2022). For other migrants, mobility may serve to maximize short-run nominal income, so as to support family members back home or attain savings objectives (Dustmann and Görlach, 2016; Albert and Monras, 2022). Whatever the source of differential mobility patterns, if the foreign-born are indeed more footloose than the native-born, then, as Borjas (2001) hypothesized, immigration may ”grease the wheels of the labor market” by easing adjustment to shocks.

The literature documents instances in which immigration has helped smooth labor market adjustment. The original analysis in Borjas (2001) finds that over the 1960 to 1980 period, the supply of newly arrived immigrants (but not of older immigrants) was larger in U.S. states with higher initial earnings. During the same period, wage convergence across U.S. states was more rapid among skill groups that had a larger immigrant presence. More broadly, immigration helped accommodate changes in the U.S. economy that after 1960 induced the population to shift to the South and West and from cities to suburbs (Borjas et al., 1997).[1] Immigration also appears to aid in adjustment to cyclical fluctuations. During the Great Recession, the collapse of the U.S. housing market caused sudden job loss in regions that had been caught up in the subprime mortgage lending boom (Mian and Sufi, 2014). Cadena and Kovak (2016) show that over the 2006 to 2010 period, whereas net migration of less-educated native-born men was unresponsive to regional changes in labor demand, less-educated foreign-born men were substantially responsive to the same shocks.[2]

[1]Related work considers how immigration affects regional innovation and productivity (e.g., Kerr and Lincoln, 2010; Hunt and Gauthier-Loiselle, 2010; Peri, 2012; Stuen et al., 2012; Peri, 2016; and Burchardi et al., 2020).

[2]The findings in Monras (2020) suggest that immigration contributes to labor-market adjustment more through

This paper examines the role of immigration in adjustment to another well-studied labor market shock, the decline in manufacturing due to global import competition. A large literature has shown that increased Chinese manufacturing exports during the 1990s and 2000s caused widespread job loss in many countries (Autor et al., 2016; Redding, 2020; Dorn and Levell, 2021). U.S. commuting zones that were exposed to the China trade shock had larger reductions in manufacturing employment, earnings (especially for lower-wage workers), and employment-population ratios, while also suffering deteriorating outcomes across a wide range of other indicators (Autor et al., 2013a, 2014, 2019; Pierce and Schott, 2020). Although trade exposed regions did see larger net declines in working-age populations, these were small in the aggregate and concentrated among the young (Greenland and Lopresti, 2016; Greenland et al., 2019; Autor et al., 2022; Faber et al., 2022). Existing work has said little about the role of immigration in regional adjustment to manufacturing decline. We ask whether trade-exposed regions that had larger initial foreign-born populations had larger net outmigrations of labor, which may have eased adjustment to trade shocks.

As a persistent contractionary shift in labor demand, increased import competition from China represents a type of shock that the literature on immigration and labor market adjustment has yet to consider. In Borjas et al. (1997) and Borjas (2001), the shifts in motion were ones that increased the desirability of the Sunbelt. After 1960, the availability of automobiles and air conditioning, the construction of interstate highways, and growth-friendly regulations increased population flows into Southern and Western cities (Arkolakis et al., 2012; Baum-Snow, 2007; Glaeser and Tobio, 2008; Mangum and Coate, 2019). The mobility of the foreign-born, combined with rising immigration nationally, may have helped growing regions achieve steady state size more rapidly. The analysis in Cadena and Kovak (2016) considers the role of immigration in adjustment to a negative shock—the Great Recession—but one that was ostensibly cyclical in nature.[3] Because the early 2000s housing boom pulled workers into construction jobs in growing cities, adjustment to the ensuing housing bust may have been aided by the exodus of those recent arrivals. Indeed, Cadena and Kovak (2016) find that recession-induced reductions in supplies of foreign-born workers occurred in part by workers returning to their origin countries. We examine a case in which there is pressure for labor to leave regions that had been doing neither particularly well nor particularly poorly prior to the shock.

Further motivating our analysis is the unfortunate frequency with which large, persistent, neg-

the inmigration of labor than through the outmigration of labor.

[3] Yagan (2019) documents the Great Recession's deep and prolonged impacts.

ative, and localized labor demand shocks tend to occur. Import competition from China is one of several factors that have contributed to regional manufacturing job loss in recent decades (Charles et al., 2019). Another is the automation of manufacturing production fueled by the adoption of industrial robots (Acemoglu and Restrepo, 2020). Outside of manufacturing, the precipitous decline of coal mining after 1980 has triggered long-lasting and geographically concentrated employment declines (Black et al., 2005; Autor et al., 2022; Hanson, 2022; Krause, 2022). These episodes highlight the value of understanding the characteristics that make regions resilient to negative shocks, among which having larger supplies of foreign-born workers may be one.

We find that U.S. commuting zones (CZs) that were more exposed to the China trade shock had substantially larger net reductions in the population of foreign-born workers but not in the population of native-born workers. The small and insignificant native-born responses have narrow confidence intervals, which is suggestive of modest heterogeneity in native-born adjustment across places. For foreign-born workers, comparing CZs at the $75^{th}$ versus $25^{th}$ percentiles of exposure to the trade shock, the more exposed CZ would have seen 1.7 and 2.3 percentage-point larger decadal reductions, respectively, in the foreign-born population with a high school education or less and in the foreign-born population with some college education or more. Within trade-exposed CZs, foreign-born and native-born workers had comparably sized reductions in employment-population ratios. These trade-induced reductions in employment rates were larger in CZs whose initial foreign-born population shares were above (relative to below) the nation median.

The greater sensitivity of foreign-born workers relative to native-born workers to negative labor demand shocks is consistent with the findings in Cadena and Kovak (2016). Despite this differential sensitivity, immigration appears to have had a limited role in aggregate labor-market adjustment to the China trade shock. Simply put, at the time of the surge in import competition from China, foreign-born workers were in the wrong locations to contribute much to regional changes in labor supply. Although the foreign-born accounted for 18.8% of the working age population with a high school education or less in 2000—and 14.3% of all those of working age—immigrant labor was concentrated in regions with low China trade exposure. In CZs at the $75^{th}$ percentile of trade exposure, just 8.5% of high school and less working-age adults were foreign born, as compared to 14.1% of working-age adults in CZs at the $25^{th}$percentile of exposure. As a consequence, the implied differential change in labor supply associated with the presence of foreign-born workers between labor markets with high versus low trade exposure was effectively zero.

The minor role played by immigration in local labor market adjustment to the China trade shock underscores a fundamental albeit straightforward lesson for spatial equilibration in U.S. labor markets. It is insufficient that the foreign-born are relatively willing to move into places with more rapid job growth. For their mobility to buffer adverse shocks, they must initially be present in places subject to those negative shocks. The commuting zones that were exposed to import competition from China in the 1990s and 2000s were primarily specialized in mature manufacturing industries (Eriksson et al., 2019). After 1950, these industries had left larger, more expensive Northern cities for smaller, less expensive locations in the Midwest and Southeast. The relocation of manufacturing was largely complete by 1980, at which point the large U.S. immigration wave of less-educated labor from Latin America and the Caribbean was still building momentum. Most of the post-1980 immigrant arrivals from the Western Hemisphere followed earlier cohorts from their home countries by settling in U.S. states on the Mexican border, South Florida, and a handful of large cities. Few were attracted to traditional manufacturing regions.[4] These regions were not growing relative to the nation as a whole and lacked the established immigrant enclaves that tend to attract new arrivals from abroad (Borjas, 1995; Munshi, 2003).[5]

It thus appears that although immigration may grease the wheels of the labor market, it may do so largely by accident. The tendency for newly arrived immigrants to concentrate in regions with strong current job growth and (or) existing communities populated by their country people may indicate that immigration is better suited to ease adjustment to cyclical shocks, in which today's regionalized job growth may be followed by tomorrow's regionalized job loss, than to long-run structural shocks, in which the regions experiencing sagging labor demand may be decades past in the moment in which they were attracting footloose labor.

## 2 Empirical Setting: The Geography of Immigration and Trade

To motivate our analysis, we begin by comparing exposure to import competition from China with the allocation of foreign-born workers across U.S regions. Throughout our work, we use commuting

[4]One exception that we discuss below is the meatpacking industry (Champlin and Hake, 2006).

[5]Looking forward, efforts to decarbonize the U.S. economy may divert resources away from industries that extract, refine, and intensively use oil, gas, and coal (Chen et al., 2021). These sectors, which are concentrated in older industrial communities with few immigrants, may trigger a future round of spatially focused job loss (Hanson, 2022; Popp et al., 2022).

zones as our concept of local labor markets (Tolbert and Sizer, 1996; Dorn, 2009). Exposure to the China trade shock in the 2000s was greater in regions that previously had attracted relatively few foreign-born workers, either overall or among those with lower levels of educational attainment. The weak correlation between trade exposure and immigrant presence will be important for interpreting the empirical results that we present in Section 4.

Data for employment and population are from the 5% samples of 1990 and 2000 U.S. Census and the combined annual 1% samples of the American Communities Survey for 2006-2008 (which we use for 2007), 2009-2011 (which we use for 2010), 2011-2013 (which we use for 2012), and 2017-2019 (which we use for 2018), sourced from IPUMS USA (Ruggles et al., 2022). Trade data are from UN Comtrade and industry shipments data are from the NBER Manufacturing Database.

## 2.1 Import Competition from China

Over the last three decades, China has undergone a major expansion in its manufacturing exports. Key to this growth were reforms internal to China, which led the country to abandon decades of central planning (Naughton, 2007). These reforms permitted resources to reallocate from collectivized and state-owned enterprises to the private sector (Song et al., 2011; Khandelwal et al., 2013; Hsieh and Song, 2015), allowed labor to move from rural farms to industrial cities (Brandt et al., 2013), and reduced barriers to foreign trade and investment (Feenstra and Hanson, 2005; Yu, 2010; Bai et al., 2017; Brandt and Morrow, 2017).

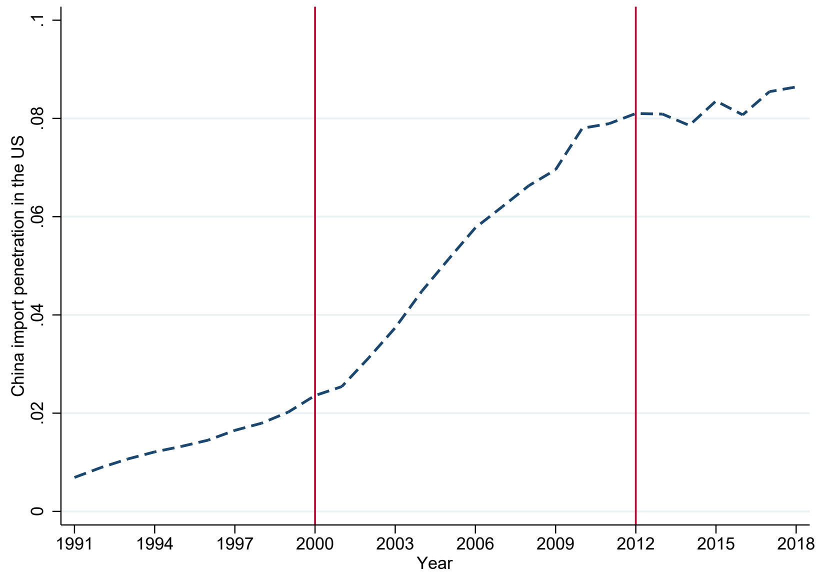
We define the growth of import penetration by China in U.S. industry $j$ and over time period $\tau$ as,

$$\boldsymbol{\Delta} IP^{cu}_{j\tau} = \frac{\Delta M^{cu}_{j\tau}}{Y_{jt} + M_{jt} - X_{jt}}, \tag{1}$$

where the numerator ($\Delta M^{cu}_{j\tau}$) in (1) is the increase of annual U.S. industry imports from China during $\tau$, and the denominator is U.S. industry domestic absorption (industry shipments, $Y_{jt}$, plus imports, $M_{jt}$, minus exports, $X_{jt}$) in a base year $t$ .[6] Autor et al. (2022) highlight three phases of China's recent manufacturing export growth: the gradual initiation of China's export boom in the early 1990s, the dramatic acceleration of China's export growth around the time of its accession to the World Trade Organization in 2001, and the plateauing of China's export expansion after 2012, which coincided with slowing national manufacturing productivity growth, diminished entry

[6] We measure imports using HS trade data from UN Comtrade, harmonized to 4-digit SIC industries, and industry shipments using the NBER manufacturing productivity database (Autor et al., 2014).

Figure 1: U.S. Manufacturing Imports from China




Note: Import penetration is the ratio of US imports of manufactured goods to U.S. domestic absorption (defined as manufacturing gross output plus imports minus exports). Values exclude oil and gas industries. Data are from UN Comtrade (for imports and exports) and the St. Louis Federal Reserve Bank (for gross output).

of private sector enterprises, and a return to heavy state intervention in the Chinese economy (Lardy, 2019; Brandt et al., 2020). These phases are clearly evident in Figure 2, which plots the value in (1) averaged across U.S. manufacturing industries, the share of China in U.S. domestic manufacturing absorption rose modestly from 0.7% in 1991 to 2.0% in 2000, then jumped to 8.1% in 2012 during the peak period of the China trade shock, and finally stabilized at close to this level over the ensuing decade. In our empirical analysis, we will use two measures of changes in industry trade exposure to China, a narrower measure that spans the primary shock period of 2000 to 2012, and which is our baseline, and a broader measure that encompasses the entire 1992 to 2012 period, which we use in extended analysis.

## 2.2 Regional Exposure to Import Competition

We first examine exposure to import competition from China across the 722 commuting zones in the continental United States. As in Acemoglu et al. (2016) and Autor et al. (2022), our measure of trade exposure is the sum of changes in Chinese import penetration across manufacturing industries, weighted by industry shares in initial CZ employment:

$$\Delta IP^{cu}_{i\tau} \quad = \quad 100 \times \sum_j s_{ijt} \Delta IP^{cu}_{j\tau}. \tag{2}$$

Here, $\Delta IP^{cu}_{j\tau}$ is the growth of Chinese import penetration for U.S. industry $j$ over time interval $\tau$ (2000 to 2012 in our baseline), $t$ is the initial period (2000 in our baseline), and $s_{ijt} \equiv L_{ijt}/L_{it}$ is the share of industry $j$ in CZ $i$'s total employment (including non-manufacturing) in the initial year. Differences in $\Delta IP^{cu}_{i\tau}$ across CZs stem from variation in local industry employment in the initial year, which arises from differential specialization in manufacturing, and in import-intensive industries specifically. The trade shock in (1) is taken from Autor et al. (2022) for the 1992-2012 and 2000-2012 time periods. For the 2000 to 2012 period, the decadalized mean value of (2) across CZs is 0.89 percentage points, with values of 1.2 percentage points at the $75^{th}$ percentile and 0.5 percentage points at the $25^{th}$ percentile (see Appendix Table A1).[7]

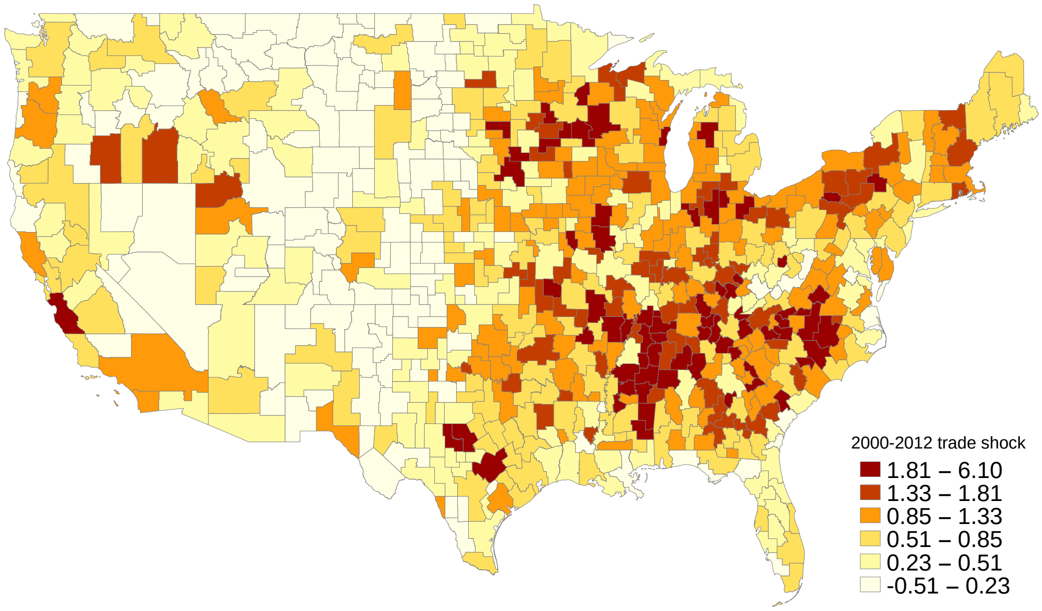
In Figure 2a, we map the China trade shock in equation (2) across commuting zones for the 2000 to 2012 time period. The most impacted CZs, shown in darker shades as those in the top two deciles of increased import penetration, are concentrated in the eastern half of the United States, and especially in the Southeast (north of the Deep South) and the Midwest, outside of large metropolitan areas. These CZs are where U.S. manufacturing relocated as it moved out of major cities in the Northeast and northern Midwest in the middle of the $20^{th}$century (Eriksson et al., 2019).[8] As U.S. manufacturing matured over the last century, the locus of innovation shifted from industry to services. The rise of advertising, finance, insurance, other business services, and later information technology, pushed manufacturing out of Northern cities and into smaller towns, some of which were located nearby in the Midwestern hinterland and others of which were located in the South and Southeast. Most of this relocation occurred between 1920 and 1980 (Kim and Margo, 2004), and therefore was largely complete before large-scale immigration of less-educated workers from Latin America and the Caribbean was in full swing (Hanson et al., 2022). Although the Latin American immigration wave was triggered by changes in U.S. immigration policy in the 1960s, it did not accelerate until the region underwent a series of economic crises in the 1980s and 1990s.

[7]This decadalized mean is smaller than the corresponding change that appears in Figure 1, owing to the fact that the expression in (2) takes the value in (1) and weights by industry shares in total CZ employment, including non-manufacturing.

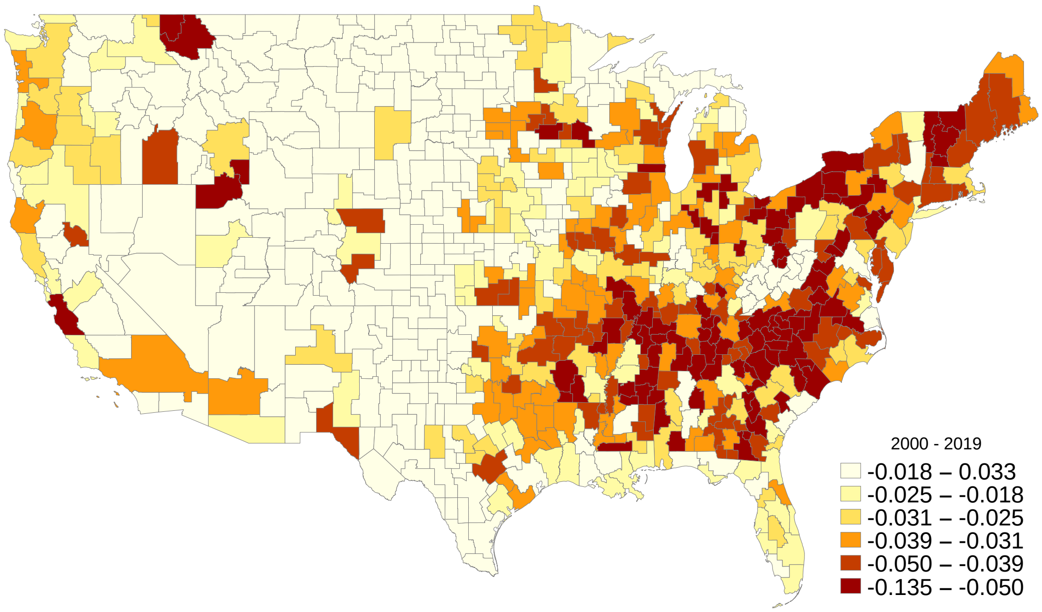
[8]Regarding regional exposure to other shocks, Autor et al. (2013b) show that there is little correlation between a CZ's exposure to Chinese import competition and exposure to routine task-replacing technological change.

Figure 2: Regional Exposure to Import Competition from China

(a) Δ import penetration, 2000-2012




(b) Δ manufacturing employment/working age population, 2000-2018




Note: Data are from UN Comtrade (for imports and exports), the NBER-CES Manufacturing Industry Database (for industry shipments), and the 2000 Census and 2017-2019 ACS samples (for employment and population).

Figure 2b reports the evolution of manufacturing employment as a share of the working-age population between 2000 and 2018. While the national manufacturing employment rate declined by 2.5 percentage points over this period (see Appendix Table A2), the map reveals considerable spatial variation in these changes, with deep employment contractions in parts of the South, Midwest and Northeast, and modest employment expansions in the Great Plains and some Southern and Western coastal areas. A visual comparison of Figures 2a and 2b reveals a strong correlation: many of the CZs that lost manufacturing employment overall (seen in panel b) were also more exposed to the China trade shock (seen in panel a). This visual evidence is supported by substantial causal analysis of the negative impacts of Chinese import competition on manufacturing employment across U.S. local labor markets (see, e.g., Autor et al., 2013a, 2016; Redding, 2020).

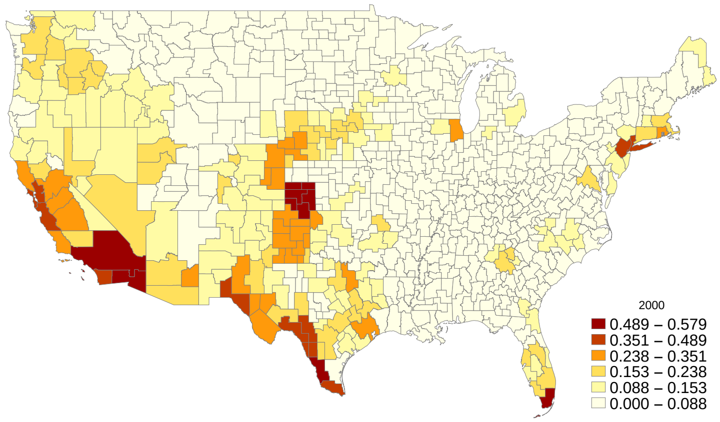
### 2.3 Regional Exposure to Immigration

We next examine the presence of foreign-born workers in manufacturing across U.S. commuting zones, before and after the intensification of the China trade shock in 2001. Figure 3 displays the foreign-born share of total manufacturing employment in 2000, 2012, and 2018, while Appendix Figure A1 does so limiting workers to those with a high school education or less. There is an apparent disconnect between the location of foreign-born manufacturing workers, shown in Figure 3a, and the geographic dispersion of the China trade shock, shown in Figure 2a: the regions that were most exposed to Chinese import competition after 2000 had few foreign-born manufacturing workers as of 2000. For CZs at the $75^{th}$ percentile of exposure to the trade shock, the foreign-born share of the working-age population in 2000 was just 8.5%, as compared to 14.1% for CZs at the $25^{th}$ percentile of trade exposure (see Appendix Table A3). This difference potentially limited the role of immigration in easing adjustment to trade-induced manufacturing job loss.

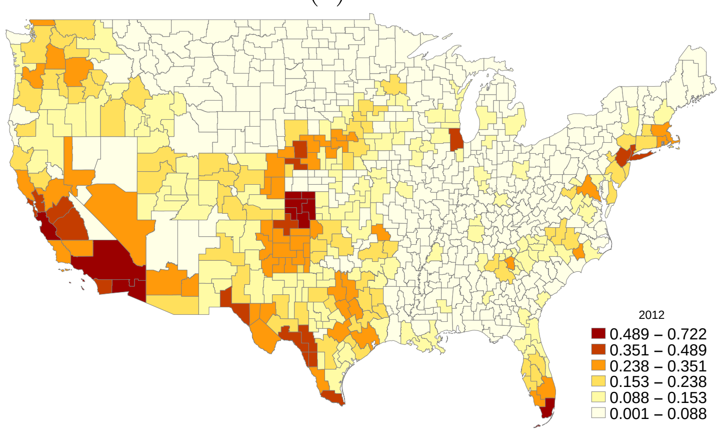
To explore the origins of this disconnect, note that in 2000 foreign-born manufacturing employment was concentrated on the West Coast, the Southwest, South Florida, and a handful of large cities. These locations were the gateway regions for immigration from Latin America and the Caribbean after 1970. In 2000, 51.7% of the working-age foreign born—and 69.7% of the working-age foreign with a high less education or less—were from these origin regions (Hanson et al., 2022). Just as previous generations of immigrants had tended to settle in enclaves comprised of their country people (Abramitzky and Boustan, 2017), so too did arrivals from the Western Hemisphere. Immigrants

Figure 3: Share of Foreign-Born Workers in Manufacturing Employment

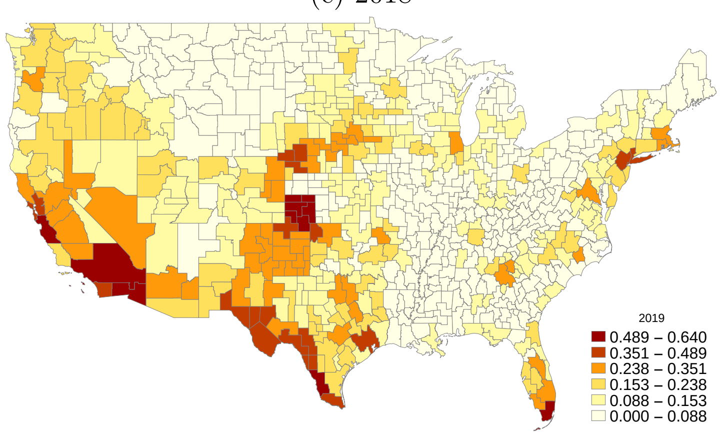
(a) 2000




(b) 2012




(c) 2018




Note: Data are from the 2000 Census and 2009-2011 and 2017-2019 combined one-year ACS samples. Employment is of those 18 to 64 years of age.

from Mexico located in states near to the U.S.-Mexico border, immigrants from Cuba and elsewhere in the Caribbean concentrated around Miami, and immigrants from South America clustered in the New York City area. As the Latin American immigration wave continued, immigrant clusters emerged in regions with strong job growth for less-educated workers, including farming communities in central California and the inland Northwest; the meatpacking belt of Colorado, Kansas, and Nebraska; and growing larger cities, such as Atlanta, Charlotte, Dallas-Ft. Worth, Denver, Houston, and Washington, D.C. (Durand et al., 2001; Champlin and Hake, 2006; Card and Lewis, 2007). The geographic pattern of foreign-born manufacturing employment in Figure 3a mirrors these settlement patterns. Comparing Figures 3a to 3c, we see that immigrant presence in manufacturing expanded around existing immigrant clusters over the 2000 to 2012 period and then showed little change after 2012, during which time U.S. immigration slowed sharply (Hanson et al., 2017).

When the China trade shock began to intensify after the year 2000, immigrant workers were modestly *overrepresented* in manufacturing. In 2000, foreign-born workers were 15.2% of manufacturing employment, as compared to 13.3% of total employment; among workers with a high school education or less, these shares were 18.0% and 16.8%, respectively (see Appendix Table A3). Yet, because foreign-born manufacturing workers were concentrated around existing immigrant population centers, the foreign-born were *underrepresented* in the regions exposed to the China trade shock, a fact that foreshadows the empirical results that we present in Section 4.

## 3 Empirical Specification

This section present our empirical specification, which builds on Autor et al. (2013a), Autor et al. (2022), and much previous work.[9] We aim to identify the causal impact of import competition from China on population headcounts for the native-born and foreign-born across U.S. commuting zones. Changes in headcounts are indicative of net migration and therefore of labor supply responses to changes in economic conditions.

[9]For discussion of previous literature, see Autor et al. (2016) and Redding (2020).

## 3.1 Baseline Specification

To quantify the impact of the China trade shock on labor supply, we estimate first-difference models for time differences of varying lengths. Our regressions have the form,

$$\Delta Y^{g}_{it+h} = \alpha_t + \beta_{1h} \Delta IP^{cu}_{i\tau} + \mathbf{X}'_{it} \beta_2 + \varepsilon_{it+h}, \tag{3}$$

where $\Delta Y^{g}_{it+h}$ is the change in log headcounts for group $g$ in CZ $i$ between the initial year $t$ and later year $t+h$. Our baseline specifications consider outcomes over three time periods: 2000 to 2007, which as seen in Figure 1 is the period of the most rapid increase in import penetration from China, overlapping with the period of analysis in Autor et al. (2013a); 2000 to 2012, which spans the period during which the China trade shock reached its full expression; and 2000 to 2019, which extends the time period up to just before the Covid-19 pandemic and the ensuing economic disruptions, and overlaps with the analysis in Autor et al. (2022) (see Appendix Table A4). Our baseline definition of the trade shock, $\Delta IP^{cu}_{i\tau}$, is for the period 2000 to 2012, whose first year is one year prior to China's WTO entry and whose final year post-dates both the plateauing of the trade shock in 2010 and the volatility in global trade that followed the 2008 to 2010 global financial crisis.[10] In later analysis, we study changes in outcomes over the expansive 1990 to 2018 period, for which we specify the trade shock as that which occurred over the 1992 to 2012 period.[11]

The impact of import competition on CZ population headcounts summarizes the net effect of trade shocks on the pool of both potential workers and non-working residents. Because our interest is in the impact of trade shocks on labor supply, we focus on individuals of working age, defined as those 18 to 64 years old. Native-born and foreign-born workers may differ in their migration responses to labor demand shocks, owing to the potentially stronger attachment of the former to their existing place of residence, which may arise from localized family connections, friend networks, or other bonds and which those born abroad may be less likely to possess. Labor supply responses to labor demand shocks may also differ by worker age and educational attainment. Younger workers

[10] Autor et al. (2022) show that across a wide range of labor market outcomes, one obtains nearly identical coefficient estimates when using trade shocks constructed for the 2000-2007, 2000-2010, 2000-2012, and 2000-2014 time periods. This similarity in results is a consequence of the trade shock being loaded on the 2000 to 2007 period. The CZ-level pairwise correlations of the 2000-2007, 2000-2010, 2000-2012, and 2000-2014 trade shocks range from 0.93 to 0.96.

[11] We focus on U.S. imports from China and not U.S exports to China because the former dwarf the latter and because our instrumentation strategy (see below) is less well-suited to isolating exogenous variation in U.S. export growth. The 2000-2012 increase in U.S. manufacturing imports from China ($292bn) was 4.1 times the increase in U.S. manufacturing exports to China ($71bn), for values in 2015 USD. Autor et al. (2013a) find similar results when replacing growth in U.S. imports with growth in U.S. net imports.

and more educated workers, for instance, appear to be relatively mobile geographically (Bound and Holzer, 2000). We therefore examine the responsiveness of population headcounts to greater import exposure separately for workers for workers with a high school education or less and with some college education or more, and for workers ages 18 to 39 and ages 40 to 64.

In equation (3), the control vector $\mathbf{X}'_{it}$ contains time trends for U.S. Census Divisions and a rich set of start-of-period CZ-level covariates: the manufacturing share of employment, which allows us to focus on variation in trade exposure arising from CZs' differential within-manufacturing industry mix; specialization in occupations according to their routine-task intensity and offshorability (based on Autor and Dorn, 2013), thus accounting for exposure to automation and non-China-specific globalization; the fractions of foreign-born, non-whites, and the college educated in the population, and the fraction of working-age women who are employed, which absorb variation in outcomes related to labor-force composition; and the population shares of residents ages 0 to 17, 18 to 39, and 40 to 64, which control for variation in migration incentives across age groups (see Appendix Table A1). We weight regressions by the CZ population in the initial year and cluster standard errors by state.

The analysis is complicated by the fact that there are strong secular trends in population growth across U.S. regions, which began well before the China trade shock (Blanchard and Katz, 1992). Greenland et al. (2019) suggest that results on the impact of trade shocks on population headcounts are sensitive to controlling for such trends.[12] Accordingly, we include the log change in CZ population over 1970 to 1990 as a control to absorb historical factors driving population growth.

## 3.2 Causal Identification

A challenge for identifying the causal impact of import exposure on population headcounts in equation (3) is that U.S. imports may change both because of shocks to U.S. product demand and because of shocks to foreign product supply, where the former may be correlated with the disturbance term, $\varepsilon_{it+h}$. To identify the foreign-supply-driven component of U.S. imports from China, we follow Autor et al. (2013a) and Acemoglu et al. (2016) in instrumenting U.S. China import exposure, $\Delta IP^{cu}_{i\tau}$, using non-U.S. China exposure, $\Delta IP^{co}_{i\tau}$, which we measure as the industry-level growth of Chinese

[12]Much of the analysis of the China trade shock focuses on outcomes expressed as ratios—e.g., the employment-population ratio, earnings per worker, income per capita. Taking ratios effectively differences out secular trends in regional employment or population growth, making impacts of trade exposure on these outcomes immune to the inclusion of controls for lagged population growth (see Autor et al., 2022).

exports to eight other high-income countries:[13]

$$\Delta IP^{co}_{i\tau} = \sum_j s_{ijt-10} \Delta IP^{co}_{j\tau}. \quad (4)$$

where $\Delta IP^{co}_{j\tau} = \Delta M^{co}_{j\tau}/(Y_{jt-3} + M_{jt-3} - X_{jt-3})$. This expression differs from that in (2) by using imports from China in other high-income markets ($\Delta M^{co}_{j\tau}$) in place of U.S. imports ($\Delta M^{cu}_{j\tau}$), the 3-year lag of industry absorption ($Y_{jt-3} + M_{jt-3} - X_{jt-3}$) in place of its base-year $t$ value, and the 10-year lag of CZ industry employment shares, $s_{ijt-10} \equiv L_{ijt-10}/L_{it-10}$, in place base-year $t$ values (see Appendix Table A1).[14]

Analyses of the China trade shock have used $\Delta IP^{co}_{i\tau}$ as a shift-share instrument in local labor market regressions (e.g., Autor et al., 2013a). Recent literature formalizes the basis for identification and inference in such shift-share settings. Borusyak et al. (2022b) treat identification as based on exogeneity of the shifts—i.e., the industry-levels changes in import penetration, while Adao et al. (2019b) present a related method for estimating standard errors. Conversely, Goldsmith-Pinkham et al. (2020) study a setting in which industry shifts (import penetration) are taken as given while initial industry employment shares are assumed to be exogenous.

Applying the framework in Borusyak et al. (2022b), for the instrument, $\Delta IP^{co}_{i\tau}$, to be orthogonal to the residual, $\varepsilon_{it+h}$, in (4), the following condition must hold: $\mathbb{E}\left[\sum_j s_j \Delta IP^{co}_{j\tau}\bar{\varepsilon}_j\right] = 0$, where $s_j$ is the national employment share of industry $j$ and $\bar{\varepsilon}_j \equiv \sum_i s_{ijt-10}\varepsilon_{it+h}/\sum_i s_{ijt-10}$ is the exposure-weighted average of unobserved shocks for industry $j$. This orthogonality condition is satisfied if either the large-sample covariance between the industry-level instrument $\Delta IP^{co}_{i\tau}$ and unobserved shocks $\bar{\varepsilon}_j$ is zero (exogeneity of the shifts), or if the employment shares $s_{ijt-10}$ are exogenous and uncorrelated with these shocks (exogeneity of the shares).[15] The substantial industry-level variation in the timing and intensity of the China trade shock documented by Autor et al. (2022) suggests that our approach is more consistent with assuming shift exogeneity than share exogeneity.[16] To check for orthogonality, Borusyak et al. (2022b) recommend regressing current shocks on past outcomes,

[13]The eight comparison countries (which are those for which comparable HS trade data are available for the full sample period) are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

[14]The use of lagged values helps reduce both the role of simultaneity and the influence of measurement error.

[15]Because of the shift-share structure—shocks originate in industries and are transmitted to regions via CZ industry employment shares—orthogonality is defined for the sample of industries, rather than the sample of regions.

[16]Formally, Borusyak et al. (2022b) show that orthogonality is satisfied if industry shocks are as-good-as-randomly assigned, conditional on industry-level unobservables and industry weights, ($\mathbb{E}\left[\Delta IP^{co}_{i\tau}|\bar{e}_j, s_j\right] = \mu$ for all $j$), where $\mu$ is a constant, and that there are many industry shocks ($\mathbb{E}[\sum_j s_j^2] \to 0$) which themselves are uncorrelated given unobservables and industry weights ($Cov\left[\Delta IP^{co}_{j\tau}, \Delta IP^{co}_{k\tau}|\bar{\varepsilon_j}, \bar{\varepsilon}_k, s_j, s_k\right] = 0$ for all industries $j$ and $k \neq j$).

which are likely correlated with current residuals. Autor et al. (2013a), Acemoglu et al. (2016), and Borusyak et al. (2022b) perform such validation exercises for CZs and industries and fail to reject orthogonality in the large majority of instances.[17]

# 4 Empirical Analysis

This section presents estimates of the impact of trade exposure on population headcounts across U.S. commuting zones. We use equation (3) to estimate how the 2000-2012 trade shock affected CZs over the period spanning 2000 to 2018, where we focus on three sets of outcomes: population headcounts for the working-age population, either in total or by education subgroup; population headcounts broken down by nativity (native-born versus foreign-born); and population headcounts broken down further by age (ages 18 to 39 versus ages 40 to 64). We then extend the analysis by (a) separating CZs by the initial size of their foreign-born population share, (b) considering the entire 1990 to 2018 time period, and (c) accounting for changes in the attractiveness of alternative domestic migration locations.

## 4.1 Baseline Results

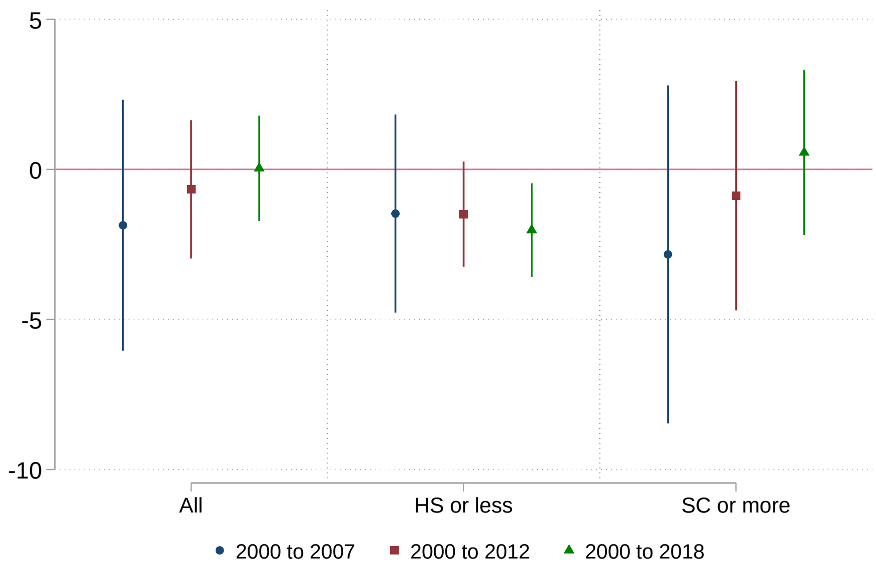
### 4.1.1 Population Headcounts by Educational Attainment

We begin with the impact of the China trade shock on population headcounts for all those of working age and this population separated by level of education. Figure 4 displays 2SLS point estimates (with vertical bars showing 95% confidence intervals) for the 2000-2012 trade shock, as defined in (1) and instrumented by (2). The top figure presents results for the regression in (3) with a sparse set of controls that include the initial manufacturing employment share and lagged population growth only; the bottom figure presents results with full controls included. Within each figure, we show

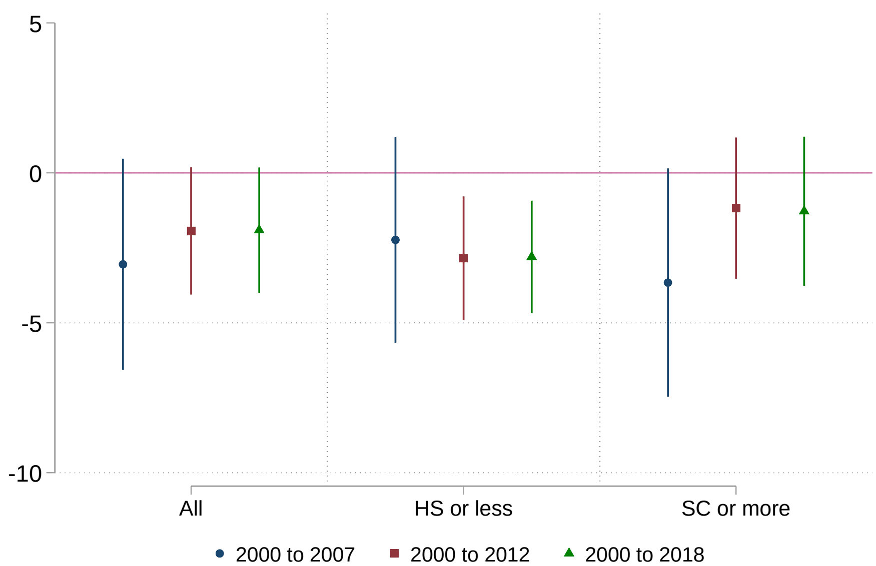
[17] Borusyak et al. (2022b) show that the impact coefficient in a regional shift-share regression is identified by regressing the industry level outcome on the industry level shift and using weights that are a function of regional industry employment shares. The corrected shift-share IV standard errors in Adao et al. (2019b), when applied to Autor et al. (2013a), widen confidence intervals asymmetrically to include more negative impacts of trade shocks on manufacturing employment (with no change in statistical significance). In finite samples, a question arises whether asymptotic approaches, such as Borusyak et al. (2022b) and Adao et al. (2019b), are more reliable than a simple cluster robust variance estimator, which is our preferred approach. Ferman (2019) use Monte Carlo simulations to assess this question, applying these methods to Autor et al. (2013a) and other cases. The results in Ferman (2019) suggest that in the context of the China trade shock, there is little gain to applying alternative methods for estimating standard errors. Our approach of clustering standard errors at the state level is consistent with Adao et al. (2019b), as long as common specialization patterns across CZs within states are the source of correlated errors.

Figure 4: Trade Shock Impact on Population Headcounts Ages 18 to 64 by Education, 2000-2018

(a) Sparse controls




(b) Full controls




Note: Panels (a) and (b) report 2SLS coefficient estimates for $\beta_{1h}$ in (3) and 95% confidence intervals for these estimates (shown using vertical bars). The dependent variable is the change in the log population over the indicated time period and for the indicated group (all those ages 18 to 64, those with a high school education or less, those with some college education or more). The trade shock is the decadalized 2000-2012 change in CZ import exposure, as defined in (2) and instrumented by (4). Sparse controls (panel a) are initial manufacturing employment shares and log population growth over 1970 to 1990; full controls (panel b) include initial-period CZ employment composition (shares of employment in manufacturing, routine-task-intensive occupations, and offshorable occupations, as well as the employment share among women), initial-period CZ demographic conditions (shares of the college educated, the foreign born, non-whites, and those ages 0-17, 18-39, and 40-64 in the population), Census region dummies, and the change in log population over 1970 to 1990. Regressions are weighted by the CZ working-age population in 2000; standard errors are clustered by state. See Appendix Table A5 for tabulated results.

results for changes in headcounts for three time periods (2000-2007, 2000-2012, 2000-2018) and three education groups (all, high school and less, some college and more).

Consider, first, results the full working-age population, shown in the left-hand panel of Figures 4a and 4b. Either with sparse or full controls, the impact of trade exposure on population headcounts is negative but imprecisely estimated, consistent with Autor et al. (2013a). Because existing research has shown that CZs exposed to greater import competition from China had larger reductions both in manufacturing employment and in total employment, we might expect a negative impact of greater import competition on local population, as workers migrated out of regions subject to adverse changes in labor demand. Yet, we see weak evidence of such shifts when looking across CZs for all workers. Although precision improves somewhat when we move from regressions with sparse controls in Figure 4a to full controls in Figure 4b, the trade-shock coefficient for the full working-age sample is statistically insignificant in both specifications in each of the three time periods.

Next, consider results for the working-age population with a high school education and less, shown in the middle panels of Figure 4a and 4b. Because manufacturing is intensive in the employment of less-educated workers, the high-school-and-less group were relatively highly-exposed to the China trade shock (see, e.g., Autor et al., 2013a). We might therefore expect their net migration responses to be larger than for more-educated workers. Alternatively, previous research has shown that less-educated workers are less geographically mobile in response to adverse labor demand shocks when compared to more-educated workers (see, e.g., Bound and Holzer, 2000; Notowidigdo, 2020), which could indicate that migration responsiveness to the China trade shock would be weaker for the less educated. Focusing on results with full controls in Figure 4b, the impact coefficient is $-2.24$ (t-value= $-1.27$) for the period 2000 to 2007, which is the end year of analysis in Autor et al. (2013a); reaches $-2.85$ (t-value= $-2.71$) for the 2000 to 2012 period, by which point the China trade shock had reached is maximum intensity; and remains close to this value at $-2.81$ (t-value= $-2.93$) for the full 2000 to 2018 period. The negative and imprecise results for 2000 to 2007 are consistent with Autor et al. (2013a), although the specifications in Figure 4 include lagged population growth as a control whereas the earlier work did not. The negative and statistically significant results for the later time periods are broadly consistent with the analysis in Autor et al. (2022), who examine trade-induced changes in the total population but do not in populations broken by education, nativity, and age, as we do here. With sufficient time, workers do begin on net to leave trade-exposed regions, although it takes a full decade for these results to materialize.

To interpret the magnitude of the point estimates, compare CZs at the $25^{th}$ and $75^{th}$ percentiles of trade exposure. Over 2000 to 2018, the latter would be predicted to have a decadalized reduction in its high-school-and-less working-age population that is 1.86 ($= -2.81 \times [1.17 - .51]$) percentage points larger than the former. This compares to the $25^{th}$–$75^{th}$ percentile differential change in log population headcounts of $-11.85$ ($= -9.31 - 2.54$) percentage points for the working-age population with no college education over the same period (see Appendix Table A4). The observed change in population headcounts for the less-educated over the first two decades of this century dwarfs that predicted by differential exposure to trade shocks, suggesting that any trade-shock induced net migration was small in the aggregate, an issue we examine further in Section 4.1.3.

When we turn our attention to the some-college-and-more population, shown in the third panels of Figures 4a and 4b, the impacts of trade exposure on log headcounts are smaller than for the high-school-and-less population and less precisely estimated. This is initial evidence that the greater trade exposure of the less-educated may have dominated the stronger migration responsiveness of the more-educated, when it comes to population impacts of the China trade shock. These results become clearer when we next dissagregate workers by education and nativity.

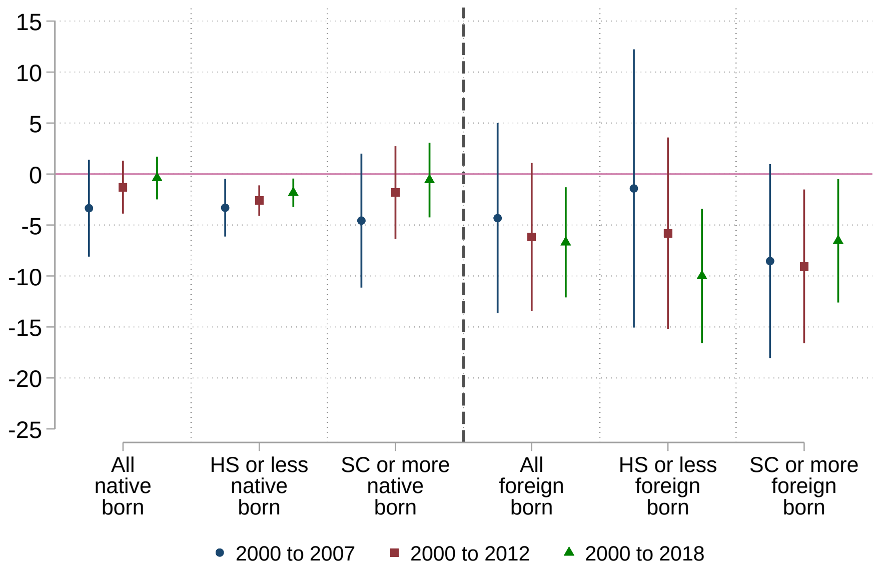
#### 4.1.2 Population Headcounts by Nativity

Figure 5 further disaggregates these results into effects on foreign and native-born adults. This figure retains the structure of Figure 4, reporting results in Figure 5a with sparse controls and in Figure 5b with full controls, with three panels in each figure for three education levels (all workers, high school or less, some college or more) with results for three time periods, 2000-2007, 2000-2012, 2000-2018.

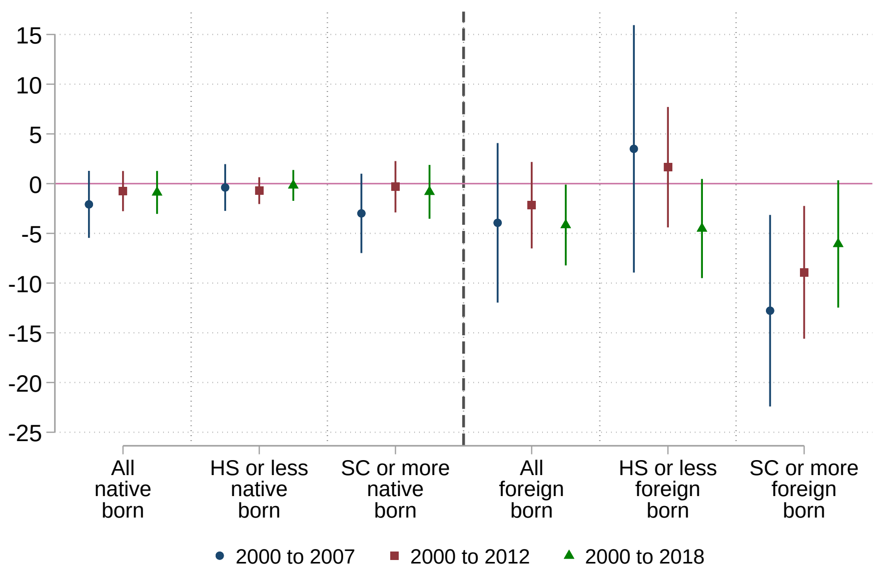
Focusing first on native-born adults in the specification with full controls in Figure 5b, we find small and imprecisely estimated impacts of trade exposure on native-born population headcounts across education groups and time periods. Over the 2000 to 2018 period, impact coefficients are $-0.88$ (t-value$= -0.80$) for all native-born, $-0.18$ (t-value$= -0.23$) for native-born with high school or less, and $-0.83$ (t-value$= -0.60$) for native-born with some college or more. Consistent with previous work, the more-educated have a stronger mobility response to adverse labor demand shocks than do the less-educated, though the difference is not statistically significant. When comparing

Figure 5: Trade Shock Impact on Population Headcounts by Nativity, 2000-2018

(a) Sparse controls




(b) Full controls




Note: Panels (a) and (b) report 2SLS coefficient estimates for $\beta_{1h}$ in (3) and 95% confidence intervals for these estimates (shown using vertical bars). The dependent variable is the change in the log population over the indicated time period and for the indicated group (all those ages 18 to 64, those with a high school education or less, those with some college education or more, either for the native-born or the foreign-born). The trade shock is the decadalized 2000-2012 change in CZ import exposure, as defined in (2) and instrumented by (4). Sparse controls (panel a) are initial manufacturing employment shares and log population growth over 1970 to 1990; full controls (panel b) include initial-period CZ employment composition (shares of employment in manufacturing, routine-task-intensive occupations, and offshorable occupations, as well as the employment share among women), initial-period CZ demographic conditions (shares of the college educated, the foreign born, non-whites, and those ages 0-17, 18-39, and 40-64 in the population), Census region dummies, and the change in log population over 1970 to 1990. Regressions are weighted by the CZ working-age population in 2000; standard errors are clustered by state. See Appendix Tables A6 and A7 for tabulated results.

CZs at the $25^{th}$ and $75^{th}$ percentiles of trade exposure, the latter would be predicted to have a decadalized reduction in its native-born working-age population that is just 0.58 ($= -0.88 \times [1.17 - .51]$) percentage points larger than the former, which compares to the $25^{th}$–$75^{th}$ percentile difference in CZ population changes for this group of $-10.31$ ($= 1.12 - 11.43$) percentage points (see Appendix Table A4). Overall, we see little impact of shocks to import competition on population headcounts for the native-born. The finding of weak net migration responses of the native born is similar in spirit to Cadena and Kovak (2016) for the Great Recession.

The impacts of trade exposure on population headcounts are quantitatively larger and statistically more precise for the foreign born, as shown in the right-hand trio of panels in Figure 5. Over the 2000 to 2018 period, the impact coefficient is $-4.16$ (t-value$= -2.01$) for all foreign-born workers. This value is 4.7 ($= 4.16/0.88$) times that of the corresponding impact coefficient for the native-born. When comparing CZs at the $25^{th}$ and $75^{th}$ percentiles of trade exposure, over the 2000 to 2018 period the latter would be predicted to have a decadalized reduction in its foreign-born working-age population that is 2.8 ($= -4.16 \times [1.17 - .51]$) percentage points larger than the former. This compares to the $25^{th}$–$75^{th}$ percentile differential change in log population headcounts of the working-age foreign born of $-23.3$ ($= 12.2 - 35.5$) percentage points over the same period. Turning to education subgroups, for those with high school or less, the impact coefficient is $-4.51$ (t-value$= -1.76$), and for those with some college or more, the impact coefficient is $-6.06$ (t-value$= -1.86$), each of which is marginally statistically significant. For the foreign-born, as for the native-born, the more educated appear to be more responsive to adverse labor demand shocks than the less educated (although, as in the earlier results, this difference is not statistically significant).

Appendix Figure A3 further divides the sample by age, reporting regressions for each nativity and education group separately for those ages 18 to 39 and those ages 40 to 64. Previous work suggests that younger workers have stronger migration responses than do older workers (e.g., Greenland et al., 2019). Similar to the results in Figure 5, we see larger responsiveness in population headcounts for the foreign-born when compared to the native-born across all education-by-age sub groups. These differences are more pronounced among workers 40 to 64 years of age. Perhaps surprisingly, it is the older foreign-born, and not the younger foreign-born, that have stronger net migration responses to trade shocks. This may be attributable to older workers predominating among those employed in manufacturing. Among the native-born, we see near zero responsiveness of population to trade exposure for each age cohort and education group combination.

#### 4.1.3 Interpreting the Results

Although the foreign-born have stronger net migration responses to trade shocks than the native-born, they were substantially under-represented in the most trade-exposed regions of the United States and hence played only a small role in spatial labor-market adjustments to trade-induced manufacturing job loss.

To characterize the contribution of the foreign-born to aggregate labor-suppy responses to the China trade shock, we again compare CZs at the $25^{th}$ and $75^{th}$ percentiles of exposure to imports from China to calculate the implied change in the aggregate labor supplies of these two CZs based on the initial presence of foreign-born workers in each. Given that the foreign-born were 8.5% of the working-age population in 2000 for CZs at the $75^{th}$ percentile of trade exposure, we can use the impact-coefficient estimate for all foreign born over 2000 to 2018 in Figure 5b to derive a trade-induced decadalized decrease in total working-age population of 0.41 ($= -4.16 \times 1.17 \times 0.085$) percentage points. When we perform a similar calculation for CZs at the $25^{th}$ percentile of trade exposure, for which the foreign-born were 14.1% of those of working age in 2000, we arrive a trade-induced decadalized decrease in total potential workers of 0.30 ($= -4.16 \times 0.51 \times 0.141$) percentage points. Because of the initial spatial allocation of foreign-born adults away from traditional manufacturing centers, they contributed only an extra 0.11 percentage-point reduction in potential labor supply in more-trade-exposed relative to less-trade-exposed local labor markets.

To put this quantity in perspective, Autor et al. (2022) estimate that for the 2000 to 2018 period, the impact coefficient for the China trade shock on the log total employment-population ratio was $-0.78$ (t-value $= -2.90$) percentage points, using an empirical specification very similar to that employed here. The implied differential reduction in the log employment-population ratio between more and less trade-exposed CZs would have been 0.52 ($= -0.78 \times [1.17 - .51]$) percentage points. More trade-exposed CZs would have effectively need to shed an extra half percentage point of the working-age population (while retaining the same number of jobs) to have maintained parity in their employment-population ratios with less trade-exposed CZs. Of this notional gap, net changes in the foreign-born population would have contributed just 17.5% ($0.11/[0.52 + 0.11]$)of the needed adjustment, assuming (somewhat heroically) that the departure of foreign-born adults would reduce population without reducing total jobs.

## 4.2 Extended Results

### 4.2.1 Separating Commuting Zones by Initial Foreign-Born Population

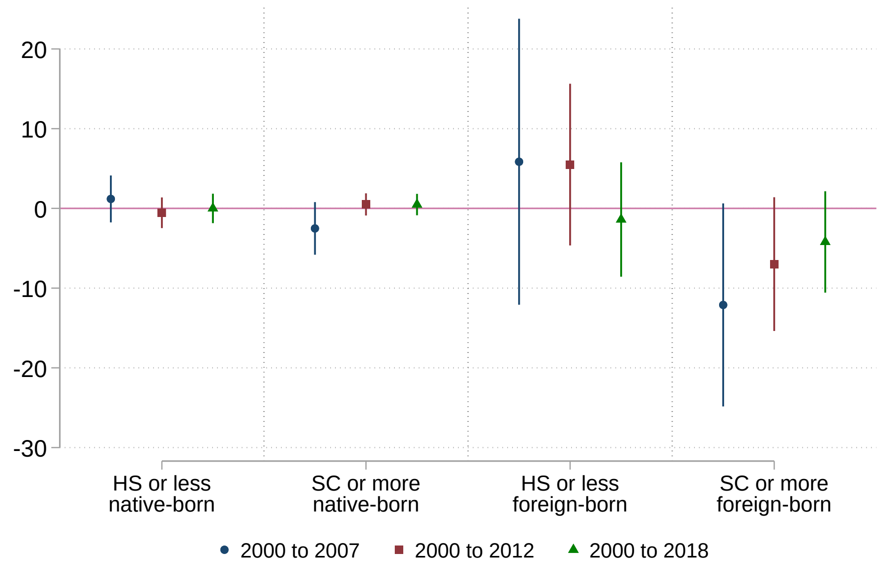
Literature on the location decisions of international migrants highlights the constructive role that migrant enclaves play in facilitating access to housing, community, and jobs for newly arrived co-ethnics (e.g., Borjas, 1995; Munshi, 2003). Because enclaves may tend to attract the most recent arrivals to a destination country, and because recent arrivals may not yet have formed strong locational ties to their new communities, they may be relatively responsive to economic shocks that change the relatively attractiveness of alternative locations. On the margin, we might therefore expect trade-shock-induced adjustments in the labor supply of the foreign born to be larger in migrant enclaves relative to other locations. To examine this possibility, Figure 6 presents regression results that separate commuting zones according to whether their share of the foreign-born in the local working-age population was above (panel a) or below (panel b) the national median in 2000.[18]

Examining results for the foreign-born, first, shown in the right two panels of Figure 6, we see much larger trade-induced adjustments in net populations for CZs with larger initial foreign-born populations. For the 2000 to 2018 period, the impact coefficient for foreign-born workers with a high school education and less of $-10.71$ (t-value $= -3.04$) in Figure 6b compares to that of $-1.40$ (t-value $= -0.38$) in Figure 6a. Turning to foreign-born workers with some college education and more, again for the 2000 to 2018 period, the impact coefficient of $-8.10$ (t-value $= -1.96$) in Figure 6b compares to that of $-4.21$ (t-value $= -1.30$) in Figure 6a. For the foreign-born, impacts are quantitatively larger and more precisely estimated in CZs with larger initial foreign-born populations. Among the native-born, differences in impact coefficients are much less pronounced between CZs with larger versus smaller foreign-born populations. For the native-born with some college education or more, impact coefficients are near zero in both sets of CZs; for the native-born with high school education or less, coefficients range from precisely estimated zeros in Figure 6a to small, positive, and noisily estimated values in Figure 6b.

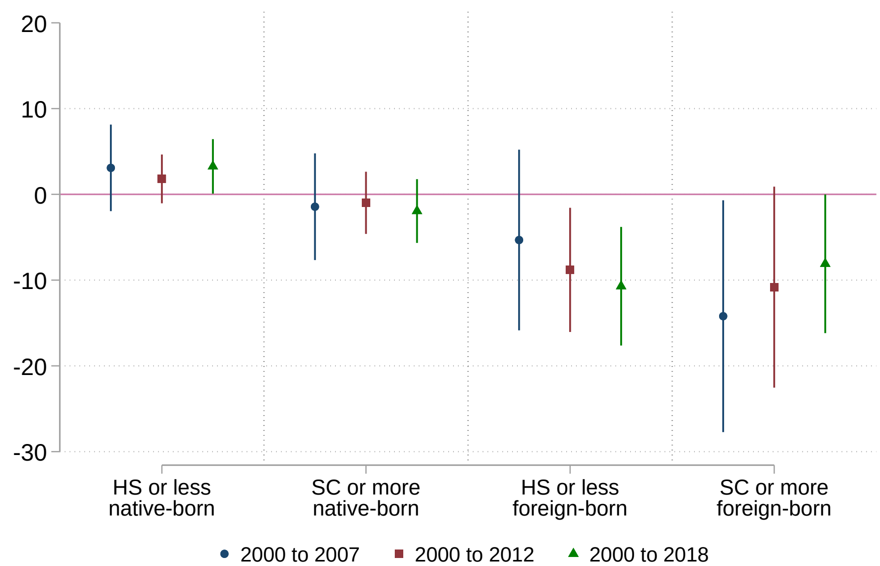
[18]Small sample sizes for immigrants from specific origin countries in many smaller commuting zones prevent us from imposing sample splits based on foreign-born population shares by origin country.

Figure 6: Trade Shock Impacts by Initial Foreign-Born Population, 2000-2018

(a) CZs with Below Median Initial Foreign-Born Population




(b) CZs with Above Median Initial Foreign-Born Population




Note: Panels (a) and (b) report 2SLS coefficient estimates for $\beta_{1h}$ in (3) and 95% confidence intervals for these estimates. The dependent variable is the change in the log population over the indicated time period and for the indicated group (those with a high school education or less, those with some college education or more, either for the native-born or the foreign-born); the trade shock is the decadalized 1991-2012 change in CZ import exposure, as defined in (2) and instrumented by (4). In panel (a), the sample is commuting zones with a below median share of the foreign-born in the working-age population in 2000; in panel (b), the sample is commuting zones with an above median share of the foreign-born in the working-age population in 2000. Control variables include initial-period CZ employment composition (shares of employment in manufacturing, routine-task-intensive occupations, and offshorable occupations, as well as the employment share among women), initial-period CZ demographic conditions (shares of the college educated, the foreign born, non-whites, and those ages 0-17, 18-39, and 40-64 in the population), Census region dummies, and the change in log population over 1970 to 1990. Regressions are weighted by the CZ working-age population in 2000; standard errors are clustered by state. See Appendix Tables A8 and A9 for complete results.

#### 4.2.2 Expanding the Sample Period to 1990 to 2018

We have focused on the post-2000 period, during which the China trade shock was at its most intense. Because the trade shock initiated in the early 1990s, we explore whether the main findings are affected by considering the entire 1990 to 2018 time period. We modify the specification in equation (3), such that the outcomes become the change in log population over 1990 to 2000 or 1990 to 2018, the initial period for control variables becomes 1990, and the trade shock in (2) and the instrument in (4) are now specified over the 1992 to 2018 period. Results, which are analogous in format to those in Figure A3, are presented in Figure 7.

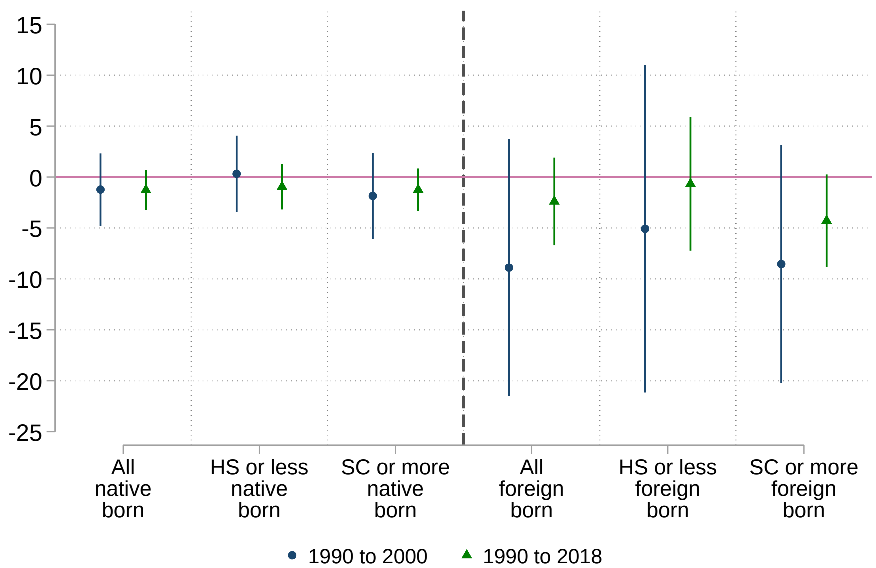
Coefficient estimates lose precision when expanding the analysis to the full 1990 to 2018 period, but they are qualitatively similar to those for 2000 to 2018. Impact coefficient estimates are again near zero and similar in magnitude to those for the 2000 to 2018 period for the native born, for all age and education groups, and for the foreign-born. One possible reason for the loss in statistical significance is that we have low precision for changes in log population headcounts over 1990 to 2000. This period was characterized by a smaller increase in import penetration by China, as seen in Figure 2, and more robust aggregate job growth in the United States. The post-2000 period, by contrast, saw the most intense period of the China trade shock and a jobless recovery to the 2000 recession, which may have concentrated localized impacts of import competition.

#### 4.2.3 Accounting for the Attractiveness of Alternative Destinations

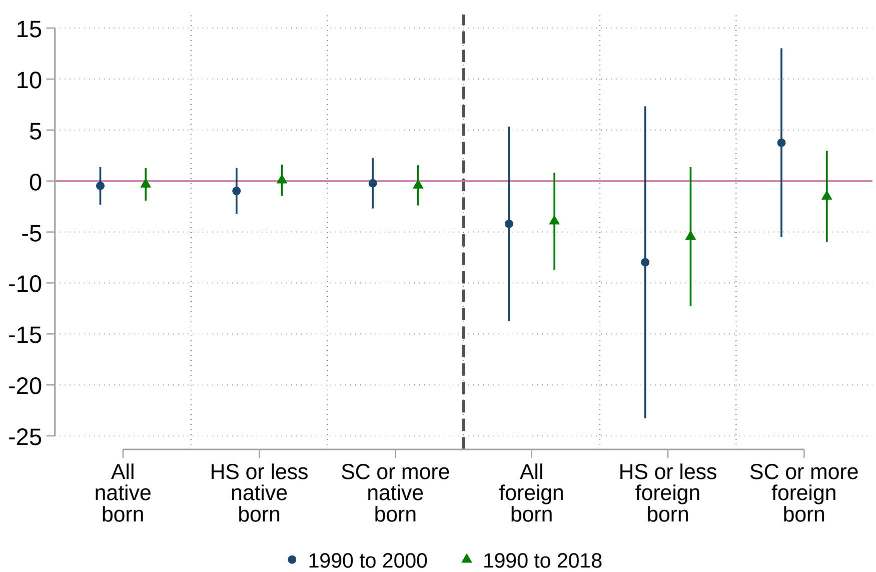
In recent work, Borusyak et al. (2022a) evaluate the literature on migration responses to local labor demand shocks. Standard spatial economic models (see, e.g., Redding 2020; Adao et al. 2019a) imply that labor supply responses to a localized shock will reflect, not just economic conditions in a given location, but also those in alternative destinations that local residents consider to be in their choice set. Failure to account for exposure to shocks in other regions may lead to biased coefficient estimates in specifications similar to ours. In the context of the China trade shock, we may estimate a low responsiveness of population headcounts to trade exposure, not because the elasticity of migration with respect to local economic conditions is low, but because the alternative destinations for residents in exposed local labor markets become unattractive simultaneously, perhaps because they are also directly exposed to the China trade shock or because they are exposed to other correlated negative labor demand shocks.

Figure 7: Trade Shock Impact on Population Headcounts, 1990-2018

(a) Younger Workers




(b) Older Workers




Note: Panels (a) and (b) report 2SLS coefficient estimates for $\beta_{1h}$ in (3) and 95% confidence intervals for these estimates. The dependent variable is the change in the log population over the indicated time period and for the indicated group (all those ages 18 to 64, those with a high school education or less, those with some college education or more, either for the native-born or the foreign-born); the trade shock is the decadalized 1992-2012 change in CZ import exposure, as defined in (2) and instrumented by (4). Control variables include initial-period CZ employment composition (shares of employment in manufacturing, routine-task-intensive occupations, and offshorable occupations, as well as the employment share among women), initial-period CZ demographic conditions (shares of the college educated, the foreign born, non-whites, and those ages 0-17, 18-39, and 40-64 in the population), Census region dummies, and the change in log population over 1970 to 1990. Regressions are weighted by the CZ working-age population in 2000; standard errors are clustered by state. See Appendix Tables A10 and A11 for complete results.

Inspired by the analysis in Borusyak et al. (2022a), we add the following control variable to equation (3):

$$\Delta IP^{co}_{-i\tau} = \sum_{k \neq i} \gamma_{ik} \Delta IP^{co}_{k\tau}. \tag{5}$$

where $\Delta IP^{co}_{k\tau}$ is the China trade shock facing CZ $k$ and $\gamma_{ik}$ is the importance of $CZ\ k$ as a migration location for residents of CZ $i$.[19] The quantity $\gamma_{ik}$ should capture the strength of migration flows between CZs $i$ and $k$. We take two approaches to proxying for this value. First, we assume that the attractiveness of other locations is driven entirely by geographic distance, as in simple gravity models of trade and migration, where we also assume that the importance of distance is the same for native-born and foreign-born workers. In this case, $\gamma_{ik}$ is the bilateral distance between $i$ and $k$. Second, we focus specifically on the migration propensities of foreign-born workers. Because their mobility appears to be substantially larger than the mobility of the native-born, and because they may evaluate other locations based on the presence of immigrant enclaves in those locations, we alternatively specify $\gamma_{ik}$ as the Euclidean distance between population shares for all non-U.S. national-origin groups as of 2000, for CZs $i$ and $k$. This second approach implicitly assumes that foreign-born workers in a given CZ evaluate other CZs based on the presence of their country people in those locations.

Estimation results when adding to the specification in (3) the value in equation (5), and instrumenting for this value using the analogous version of (4), appear in Appendix Tables A4 and A5. When adding the control in (5), we obtain nearly identical impact coefficients on the direct China trade shock, no matter whether we specify bilateral migration connections as depending on geographic distance (see Appendix Figure A4) or on initial similarity of foreign-born populations (see Appendix Figure A5). As for the control itself, coefficient estimates are positive, but imprecisely estimated, suggesting (weakly) that adverse shocks to likely destination locations reduce the propensity for outmigration from the origin location.

[19] This expression is motivated by equation (17) in Borusyak et al. (2022a). In their general formulation, they differentiate among CZs according to potential sources of migrants to CZ $i$ and potential migrant destinations for residents of CZ $i$. We implicitly assume that these sets are identical for each CZ.

# 5 Concluding Discussion

The United States has undergone major changes in regional labor demand and supply over the past four decades. The supply of foreign-born workers, and particularly of less-educated migrants from Latin America and the Caribbean, increased sharply after 1980, while adverse labor demand shifts hit regions that had been specialized in traditional manufacturing industries. As it turns out, the first shock appears to have contributed only modestly to adjustment to the second shock. Although, in line with previous research, supplies of foreign-born working-age adults appear to be have been much more responsive to localized labor demand shocks when compared to supplies of native-born adults, the concentration of Latin American and Caribbean immigrants in coastal and border regions, and away from inland manufacturing regions, meant that they were not positioned to facilitate local labor markets adjustment to trade-induced manufacturing job loss.

The experience of the China trade shock stands in contrast to that of the Great Recession, during which the greater migration elasticity of the foreign-born appears to have played a larger role in regional adjustment to the crash in the U.S. housing market and the severe localized disruptions that ensued. One lesson from this comparison is the role that history plays in determining where foreign-born workers currently reside and hence where they are positioned to grease the wheels of local labor market adjustment. Cyclical shocks that generate localized ups and downs in labor demand at relatively high temporal frequencies may both draw in and push out relatively geographically mobile adults, among whom the foreign-born are overrepresented. By contrast, specialization patterns that were established decades before the onset of mass immigration events may not benefit from immigrant mobility when structural changes eventually arise. For structural adjustment in the longer run, whether to globalization, technological change, or the incipient energy transition, the burden of labor market adjustment may be more likely to fall on less mobile native-born workers.

## References


Abramitzky, R. and L. Boustan (2017): "Immigration in American economic history," *Journal of economic literature*, 55, 1311–45.

Acemoglu, D., D. Autor, D. Dorn, G. H. Hanson, and B. Price (2016): "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, 34, S141–S198.

Acemoglu, D. and P. Restrepo (2020): "Robots and jobs: Evidence from US labor markets," *Journal of Political Economy*, 128, 2188–2244.

Adao, R., C. Arkolakis, and F. Esposito (2019a): "Spatial Linkages, Global Shocks, and Local Labor Markets: Theory and Evidence," Working paper, National Bureau of Economic Research.

Adao, R., M. Kolesár, and E. Morales (2019b): "Shift-share designs: Theory and inference," *The Quarterly Journal of Economics*, 134, 1949–2010.

Albert, C. and J. Monras (2022): "Immigration and spatial equilibrium: the role of expenditures in the country of origin," Tech. Rep. 11.

Arkolakis, C., A. Costinot, and A. Rodríguez-Clare (2012): "New trade models, same old gains?" *American Economic Review*, 102, 94–130.

Autor, D. H. and D. Dorn (2013): "The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market," *American Economic Review*, 103, 1553–1597.

Autor, D. H., D. Dorn, and G. H. Hanson (2013a): "The China Syndrome : Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103, 2121–2168.

——— (2013b): "The Geography of Trade and Technology Shocks in the United States," *American Economic Review*, 103, 220–225.

——— (2016): "The China Shock: Learning from Labor Market Adjustment to Large Changes in Trade," *Annual Review of Economics*, 8, 205–240.

——— (2019): "When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Nen," *American Economic Review: Insights*, 1, 161–78.

——— (2022): "On the Persistence of the China Shock," *Brookings Papers on Economic Activity*, 1, 381–437.

Autor, D. H., D. Dorn, G. H. Hanson, and J. Song (2014): "Trade Adjustment: Worker-Level Evidence," *Quarterly Journal of Economics*, 129, 1799–1860.

Bai, X., K. Krishna, and H. Ma (2017): "How you export matters: Export mode, learning and productivity in China," *Journal of International Economics*, 104, 122–137.

Baum-Snow, N. (2007): "Did highways cause suburbanization?" *Quarterly Journal of Economics*, 122, 775–805.

Black, D., T. McKinnish, and S. Sanders (2005): "The economic impact of the coal boom and bust," *The Economic Journal*, 115, 449–476.

Blanchard, O. J. and L. F. Katz (1992): "Regional evolutions," *Brookings Papers on Economic Activity*, 23, 1–75.

Borjas, G. J. (1995): "Ethnicity, Neighborhoods, and Human-Capital Externalities," *American Economic Review*, 85, 365–390.

——— (2001): "Does immigration grease the wheels of the labor market?" *Brookings Papers on Economic Activity*, 2001, 69–133.

Borjas, G. J., R. B. Freeman, L. F. Katz, J. DiNardo, and J. M. Abowd (1997): "How much do immigration and trade affect labor market outcomes?" *Brookings Papers on Economic Activity*, 1997, 1–90.

Borusyak, K., R. Dix-Carneiro, and B. Kovak (2022a): "Understanding Migration Responses to Local Shocks," Tech. rep., SSRN 4086847.

Borusyak, K., P. Hull, and X. Jaravel (2022b): "Quasi-experimental shift-share research designs," *The Review of Economic Studies*, 89, 181–213.

Bound, J. and H. J. Holzer (2000): "Demand shifts, population adjustments, and labor market outcomes during the 1980s," *Journal of labor Economics*, 18, 20–54.

Brandt, L., J. Litwack, E. Mileva, L. Wang, and L. Zhao (2020): "China's Productivity Slowdown and Future Growth Potential," Working paper, World Bank Policy Research Working Paper.

Brandt, L. and P. M. Morrow (2017): "Tariffs and the Organization of Trade in China," *Journal of International Economics*, 104, 85–103.

Brandt, L., T. Tombe, and X. Zhu (2013): "Factor market distortions across time, space and sectors in China," *Review of Economic Dynamics*, 16, 39–58.

Burchardi, K. B., T. Chaney, T. A. Hassan, L. Tarquinio, and S. J. Terry (2020): "Immigration, Innovation, and Growth," Working Paper 27075, National Bureau of Economic Research.

Cadena, B. C. and B. K. Kovak (2016): "Immigrants equilibrate local labor markets: Evidence from the Great Recession," *American Economic Journal: Applied Economics*, 8, 257–90.

Card, D. and E. G. Lewis (2007): "The diffusion of Mexican immigrants during the 1990s: Explanations and impacts," in *Mexican immigration to the United States*, University of Chicago Press, 193–228.

Champlin, D. and E. Hake (2006): "Immigration as industrial strategy in American meatpacking," *Review of Political Economy*, 18, 49–70.

Charles, K. K., E. Hurst, and M. Schwartz (2019): "The transformation of manufacturing and the decline in US employment," *NBER Macroeconomics Annual*, 33, 307–372.

Chen, Z., G. Marin, D. Popp, and F. Vona (2021): "The Employment Impact of a Green Fiscal Push: Evidence from the American Recovery and Reinvestment Act," *Brookings Papers on Economic Activity*, forthcoming.

Clemens, M. A. and E. G. Lewis (2022): "The effect of low-skill immigration restrictions on US firms and workers: Evidence from a randomized lottery," Tech. rep., National Bureau of Economic Research.

Dorn, D. (2009): "Essays on Inequality, Spatial Interaction, and the Demand for Skills," Dissertation University of St. Gallen No. 3613.

Dorn, D. and P. Levell (2021): "Trade and Inequality in Europe and the United States," Working paper, University of Zurich.

Durand, J., D. S. Massey, and R. M. Zenteno (2001): "Mexican immigration to the United States: Continuities and changes," *Latin American Research Review*, 107–127.

Dustmann, C. and J.-S. Görlach (2016): "The economics of temporary migrations," *Journal of Economic Literature*, 54, 98–136.

Eriksson, K., K. Russ, J. C. Shambaugh, and M. Xu (2019): "Trade Shocks and the Shifting Landscape of US Manufacturing," Working Paper 25646, National Bureau of Economic Research.

Faber, M., A. P. Sarto, and M. Tabellini (2022): "Local Shocks and Internal Migration: The Disparate Effects of Robots and Chinese Imports in the US," Working Paper 30048, National Bureau of Economic Research.

Feenstra, R. C. and G. H. Hanson (2005): "Ownership and control in outsourcing to China: Estimating the property-rights theory of the firm," *The Quarterly Journal of Economics*, 120, 729–761.

Ferman, B. (2019): "A simple way to assess inference methods," *arXiv preprint arXiv:1912.08772*.

Glaeser, E. L. and K. Tobio (2008): "The rise of the sunbelt," *Southern Economic Journal*, 74, 609–643.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020): "Bartik Instruments: What, When, Why, and How," *American Economic Review*, 110.

Greenland, A. and J. Lopresti (2016): "Import Exposure and Human Capital Adjustment: Evidence from the US," *Journal of International economics*, 100, 50–60.

Greenland, A., J. Lopresti, and P. McHenry (2019): "Import Competition and Internal Migration," *Review of Economics and Statistics*, 101, 44–59.

Hanson, G., C. Liu, and C. McIntosh (2017): "The rise and fall of US low-skilled immigration," Tech. rep., National Bureau of Economic Research.

Hanson, G. H. (2022): "Local Labor Market Impacts of the Energy Transition: Prospects and Policies," Working paper, Aspen Economic Study Group.

Hanson, G. H., P. Orrenius, and M. Zavodny (2022): "US Immigration from Latin America in Historical Perspective," Tech. rep., National Bureau of Economic Research.

Hsieh, C.-T. and Z. Song (2015): "Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China," *Brookings Papers on Economic Activity*, 1, 295–366.

Hunt, J. and M. Gauthier-Loiselle (2010): "How much does immigration boost innovation?" *American Economic Journal: Macroeconomics*, 2, 31–56.

Kerr, W. R. and W. F. Lincoln (2010): "The supply side of innovation: H-1B visa reforms and US ethnic invention," *Journal of Labor Economics*, 28, 473–508.

Khandelwal, A. K., P. K. Schott, and S.-J. Wei (2013): "Trade liberalization and embedded institutional reform: Evidence from Chinese exporters," *American Economic Review*, 103, 2169–95.

Kim, S. and R. A. Margo (2004): "Historical perspectives on US economic geography," in *Handbook of regional and urban economics*, Elsevier, vol. 4, 2981–3019.

Krause, E. (2022): "Job loss and selective migration in distressed communities: Evidence from Appalachia's coal country," Working paper, Harvard University.

Lardy, N. (2019): *The State Strikes Back: The End of Economic Reform in China?*, Peterson Institute for International Economics.

Mangum, K. and P. Coate (2019): "Fast locations and slowing labor mobility," .

Mian, A. and A. Sufi (2014): "What explains the 2007–2009 drop in employment?" *Econometrica*, 82, 2197–2223.

Monras, J. (2020): "Immigration and wage dynamics: Evidence from the mexican peso crisis," *Journal of Political Economy*, 128, 3017–3089.

Munshi, K. (2003): "Networks in the modern economy: Mexican migrants in the US labor market," *The Quarterly Journal of Economics*, 118, 549–599.

Naughton, B. (2007): *The Chinese Economy: Transitions and Growth*, MIT Press.

Notowidigdo, M. J. (2020): "The incidence of local labor demand shocks," *Journal of Labor Economics*, 38.

Peri, G. (2012): "The effect of immigration on productivity: Evidence from US states," *Review of Economics and Statistics*, 94, 348–358.

——— (2016): "Immigrants, productivity, and labor markets," *Journal of economic perspectives*, 30, 3–30.

Pierce, J. R. and P. K. Schott (2020): "Trade Liberalization and Mortality: Evidence from US Counties," *American Economic Review: Insights*, 2, 47–64.

Popp, D., F. Vona, G. Marin, and Z. Chen (2022): "The Employment Impact of Green Fiscal Push: Evidence from the American Recovery Act," *Brookings Papers on Economic Activity*, 1, 1–49.

Redding, S. J. (2020): "Trade and Geography," *National Bureau of Economic Research Working Paper Series*.

Ruggles, S., S. Flood, R. Goeken, M. Schouweiler, and S. Matthew (2022): "IPUMS USA: Version 12.0," *Minnesota Population Center, Minneapolis, MN.*

Song, Z., K. Storesletten, and F. Zilibotti (2011): "Growing like china," *American Economic Review*, 101, 196–233.

Sprung-Keyser, B., N. Hendren, S. Porter, et al. (2022): "The Radius of Economic Opportunity: Evidence from Migration and Local Labor Markets," Tech. rep.

Stuen, E. T., A. M. Mobarak, and K. E. Maskus (2012): "Skilled immigration and innovation: evidence from enrolment fluctuations in US doctoral programmes," *The Economic Journal*, 122, 1143–1176.

Tolbert, C. M. and M. Sizer (1996): "US Commuting Zones and Labor Market Areas: A 1990 Update," *U.S. Department of Agriculture*, Economic Research Service Staff Paper.

Topel, R. H. (1986): "Local labor markets," *Journal of Political economy*, 94, S111–S143.

Woodruff, C. and R. Zenteno (2007): "Migration networks and microenterprises in Mexico," *Journal of Development Economics*, 82, 509–528.

Yagan, D. (2019): "Employment hysteresis from the great recession," *Journal of Political Economy*, 127, 2505–2558.

Yu, M. (2010): "Trade Liberalization and Productivity: Evidence from Chinese Firms," *Economic Research Journal*, 12, 97–110.

# Appendix

## A.1 Summary Statistics and Additional Figures

Table A1: Summary Statistics for the China Trade Shock and Control Variables

| Variable | Mean | Standard deviation | $25^{th}$ percentile | $50^{th}$ percentile | $75^{th}$ percentile |
|---|---|---|---|---|---|
| **Trade shocks** | | | | | |
| 2000-2012 trade shock to US | 0.891 | 0.589 | 0.506 | 0.753 | 1.174 |
| 2000-2012 trade shock instrument | 1.223 | 0.693 | 0.799 | 1.169 | 1.441 |
| 1992-2012 trade shock to US | 1.117 | 0.669 | 0.767 | 1.032 | 1.282 |
| 1992-2012 trade shock instrument | 1.337 | 0.710 | 0.841 | 1.328 | 1.560 |
| **Controls** | | | | | |
| Manuf. share of employment | 16.19 | 7.47 | 11.28 | 15.33 | 19.62 |
| Share pop. college educated | 53.62 | 7.46 | 50.36 | 53.91 | 57.97 |
| Share pop. foreign born | 14.81 | 12.83 | 4.81 | 9.33 | 22.75 |
| Share empl. female | 64.41 | 5.50 | 60.49 | 64.74 | 68.17 |
| Share empl. routine jobs | 31.92 | 2.36 | 30.55 | 32.23 | 33.81 |
| Offshorability index | 0.00 | 0.51 | -0.37 | 0.13 | 0.35 |
| Share pop. age 65+ | 12.37 | 2.92 | 10.62 | 12.04 | 13.80 |
| Share pop. age 40-64 | 30.11 | 1.86 | 29.15 | 30.33 | 31.33 |
| Share pop. age 0-17 | 25.63 | 2.22 | 24.52 | 25.29 | 26.80 |
| Share pop. non-white | 18.15 | 10.93 | 9.41 | 17.66 | 24.98 |
| Change in log pop. 1970-1990 | 12.26 | 12.26 | 2.17 | 10.14 | 19.23 |

Note: Trade shock variables are from Autor et al. (2022). Control variables, except for population growth, are measured in 2000. Data are from Ipums.org for the 1970, 1990, and 2000 Census.

Table A2: Manufacturing Employment/Working-Age Population

| Variable | Mean | Standard deviation | $25^{th}$ percentile | $50^{th}$ percentile | $75^{th}$ percentile |
|---|---|---|---|---|---|
| **2000** | | | | | |
| All individuals | 11.16 | 5.65 | 6.65 | 10.63 | 15.15 |
| High school or less | 6.68 | 3.94 | 3.58 | 5.99 | 9.49 |
| Some college or more | 4.48 | 2.20 | 2.83 | 4.24 | 5.82 |
| **2012** | | | | | |
| All individuals | 8.36 | 4.02 | 5.11 | 7.86 | 10.97 |
| High school or less | 4.37 | 2.41 | 2.40 | 4.01 | 5.95 |
| Some college or more | 3.99 | 1.94 | 2.58 | 3.69 | 5.01 |
| **2018** | | | | | |
| All individuals | 8.64 | 4.19 | 5.62 | 8.06 | 11.30 |
| High school or less | 4.38 | 2.41 | 2.48 | 3.98 | 5.99 |
| Some college or more | 4.25 | 2.12 | 2.65 | 3.94 | 5.41 |

Note: Data are from Ipums.org for the 2000 Census, and the 2011-2013 and 2017-2019 ACS.

Table A3: Foreign Born Share of the Working-Age Population

| | 2000 | 2012 | 2018 |
|---|---|---|---|
| Population | | | |
| Share foreign-born | 14.28 | 16.82 | 17.52 |
| Share foreign-born, HS or less | 18.05 | 22.04 | 22.20 |
| Share foreign-born, SC or more | 11.18 | 13.45 | 14.73 |
| Employment | | | |
| Share foreign-born | 13.33 | 17.89 | 18.71 |
| Share foreign-born, HS or less | 16.77 | 24.84 | 24.88 |
| Share foreign-born, SC or more | 11.07 | 14.30 | 15.70 |
| Manufacturing employment | | | |
| Share foreign-born | 15.23 | 19.41 | 19.55 |
| Share foreign-born, HS or less | 17.98 | 24.04 | 23.33 |
| Share foreign-born, SC or more | 12.38 | 15.78 | 16.82 |
| Population in least exposed CZs ($1^{st}$ quartile) | | | |
| Share foreign-born | 14.29 | 17.17 | 17.72 |
| Share foreign-born, HS or less | 17.84 | 22.46 | 22.55 |
| Share foreign-born, SC or more | 11.43 | 13.81 | 14.87 |
| Population in most exposed CZs ($4^{th}$ quartile) | | | |
| Share foreign-born | 10.77 | 13.00 | 13.77 |
| Share foreign-born, HS or less | 13.02 | 16.66 | 16.65 |
| Share foreign-born, SC or more | 8.65 | 10.41 | 11.92 |

Note: Data are from Ipums.org for the 2000 Census, and the 2011-2013 and 2017-2019 ACS.

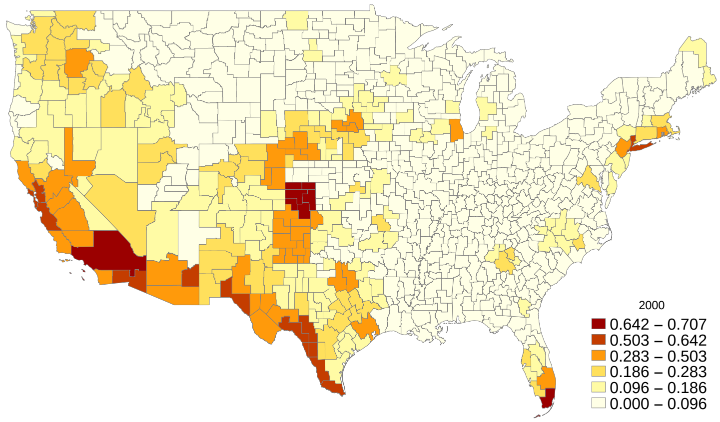
Table A4: Log Changes in the Working-Age Population

| Variable | Mean | Standard deviation | $25^{th}$ percentile | $50^{th}$ percentile | $75^{th}$ percentile |
|---|---|---|---|---|---|
| **2000-2007** | | | | | |
| All | 11.71 | 9.13 | 6.11 | 10.49 | 15.27 |
| HS or less | 2.66 | 11.35 | -5.35 | -0.22 | 8.79 |
| SC or more | 19.14 | 8.77 | 14.79 | 17.94 | 24.20 |
| Native-born | 8.74 | 8.43 | 3.23 | 8.02 | 15.04 |
| HS or less | -1.72 | 10.57 | -9.58 | -3.96 | 6.64 |
| SC or more | 16.45 | 8.60 | 11.26 | 16.43 | 21.60 |
| Foreign-born | 35.68 | 22.89 | 16.99 | 36.26 | 51.40 |
| HS or less | 30.11 | 32.77 | 7.93 | 31.25 | 51.54 |
| SC or more | 41.44 | 24.44 | 26.32 | 41.25 | 56.42 |
| **2000-2012** | | | | | |
| All | 10.03 | 7.24 | 5.39 | 8.50 | 14.25 |
| HS or less | -1.42 | 8.61 | -7.09 | -3.27 | 4.05 |
| SC or more | 18.75 | 6.98 | 13.97 | 17.80 | 22.54 |
| Native-born | 7.81 | 6.99 | 2.66 | 6.58 | 12.92 |
| HS or less | -5.13 | 8.77 | -11.44 | -7.46 | 1.76 |
| SC or more | 16.60 | 6.84 | 12.48 | 15.90 | 20.33 |
| Foreign-born | 30.65 | 17.85 | 15.62 | 30.48 | 43.42 |
| HS or less | 24.62 | 23.96 | 6.11 | 24.54 | 36.91 |
| SC or more | 38.18 | 17.88 | 24.33 | 38.69 | 51.48 |
| **2000-2018** | | | | | |
| All | 7.63 | 7.30 | 3.02 | 6.11 | 12.27 |
| HS or less | -2.81 | 8.31 | -9.31 | -4.06 | 2.54 |
| SC or more | 15.16 | 6.95 | 10.65 | 13.68 | 19.42 |
| Native-born | 5.87 | 7.14 | 1.12 | 4.52 | 11.43 |
| HS or less | -5.13 | 8.82 | -12.19 | -7.47 | 1.62 |
| SC or more | 13.04 | 6.60 | 7.97 | 11.89 | 17.16 |
| Foreign-born | 24.70 | 15.39 | 12.23 | 25.36 | 35.49 |
| HS or less | 16.68 | 18.95 | 3.97 | 16.13 | 28.44 |
| SC or more | 33.89 | 15.77 | 21.46 | 33.74 | 46.31 |

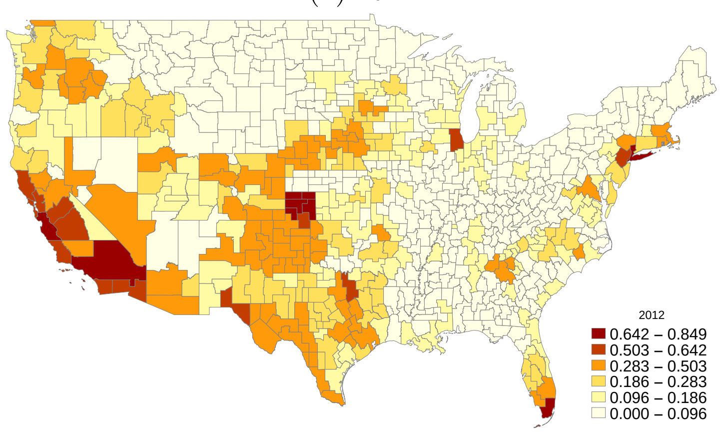
Note: Data are from Ipums.org for the 2000 Census, and the 2006-2008, 2011-2013, and 2017-2019 ACS.

Figure A1: Share of Foreign-Born in Manufacturing Employment, Workers Ages 18 to 64 with a High School Education or Less

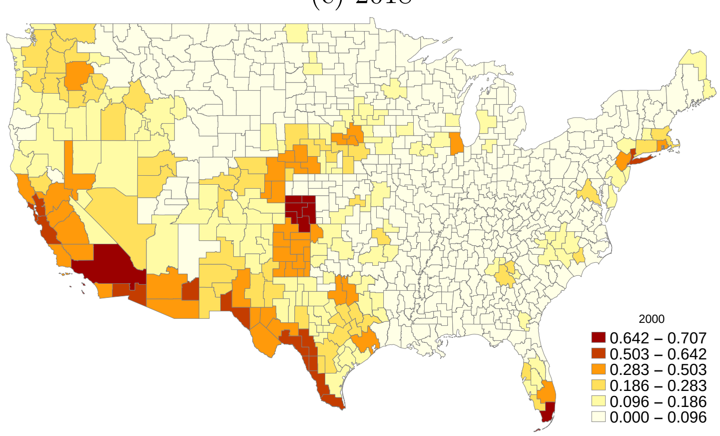
(a) 2000




(b) 2012



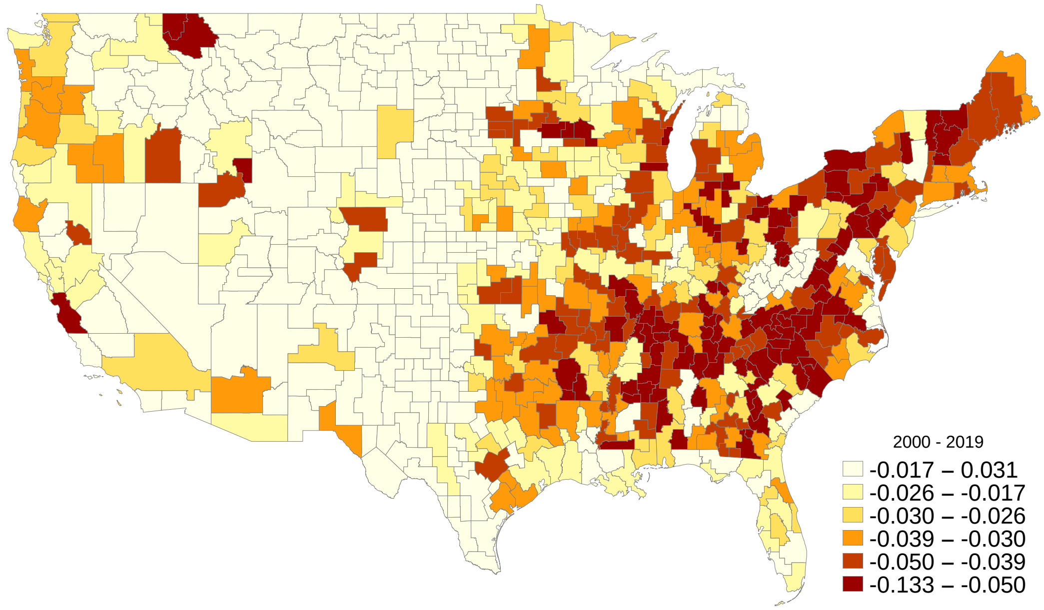

(c) 2018



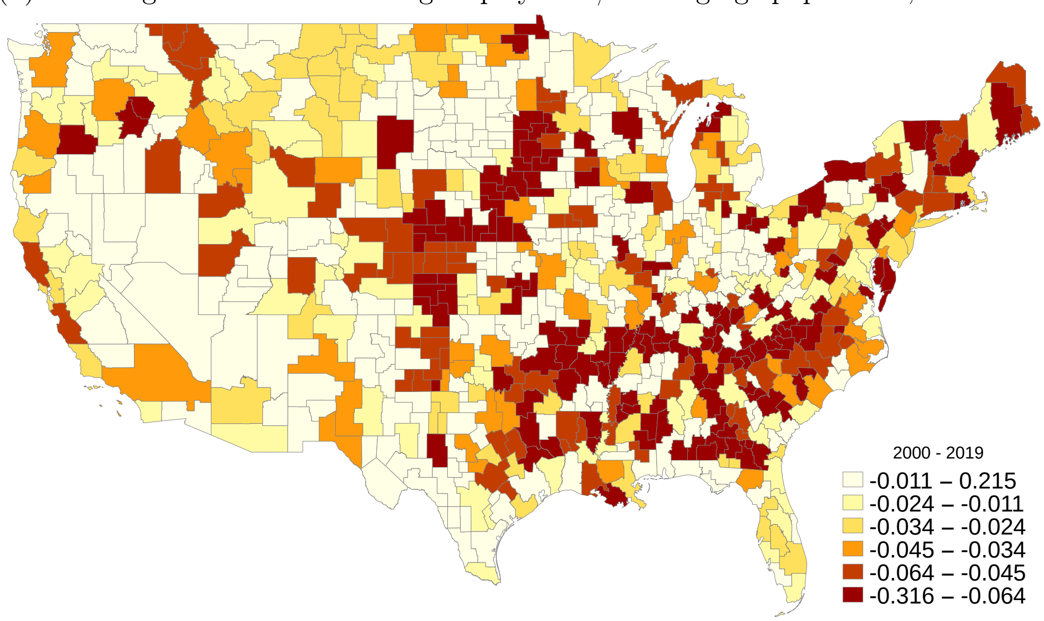

Note: Data are from 2000 Census and the 2010-2013 and 2017-2019 ACS.

Figure A2: Change in Manufacturing Employment by Worker Nativity, 2000-2018

(a) $\Delta$ Native-born manufacturing employment/working age population, 2000-2018




(b) $\Delta$ Foreign-born manufacturing employment/working age population, 2000-2018

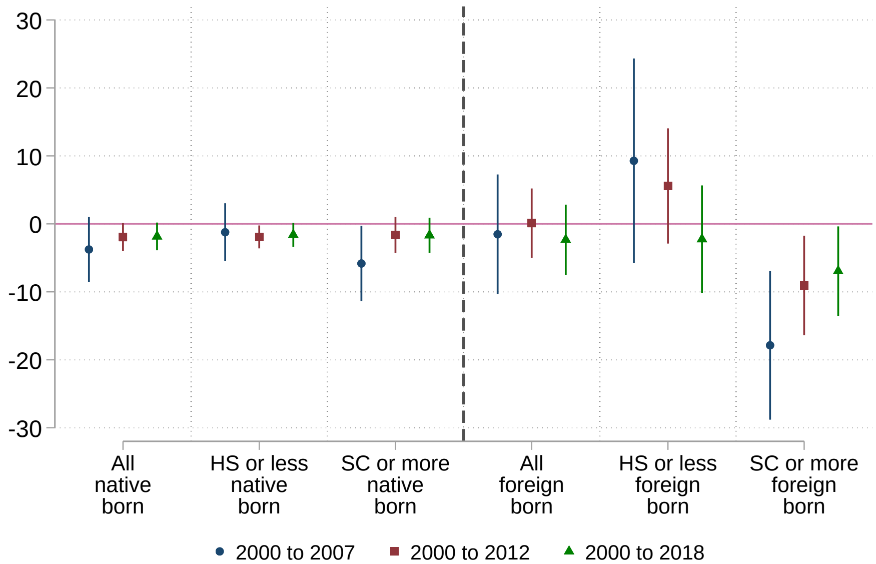



Note: Data are from 2000 Census and the 2009-2011 and 2017-2019 ACS.

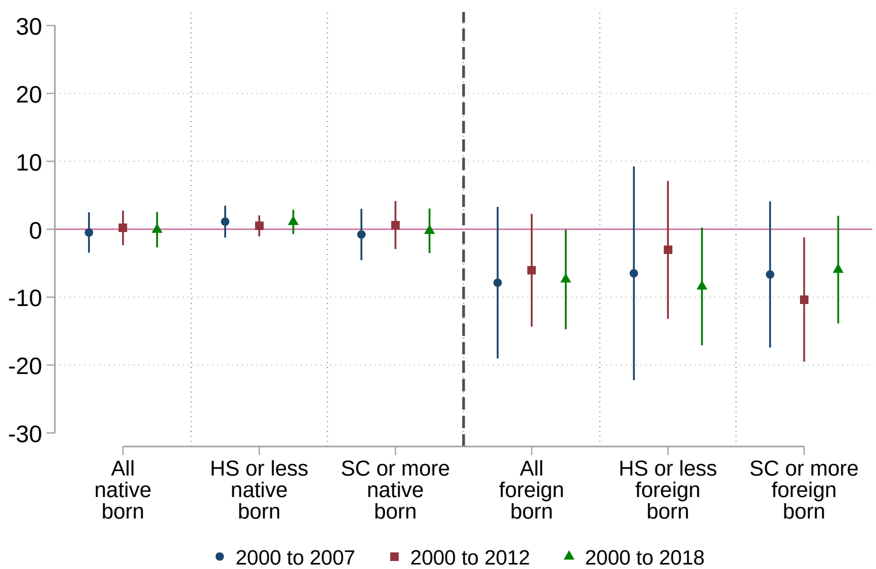
## A.2 Regressions Separating Workers by Age

Figure A3: Trade Shock Impact on Population Headcounts by Age, 2000-2018

(a) Individuals Ages 18 to 39




(b) Individuals Ages 40 to 64

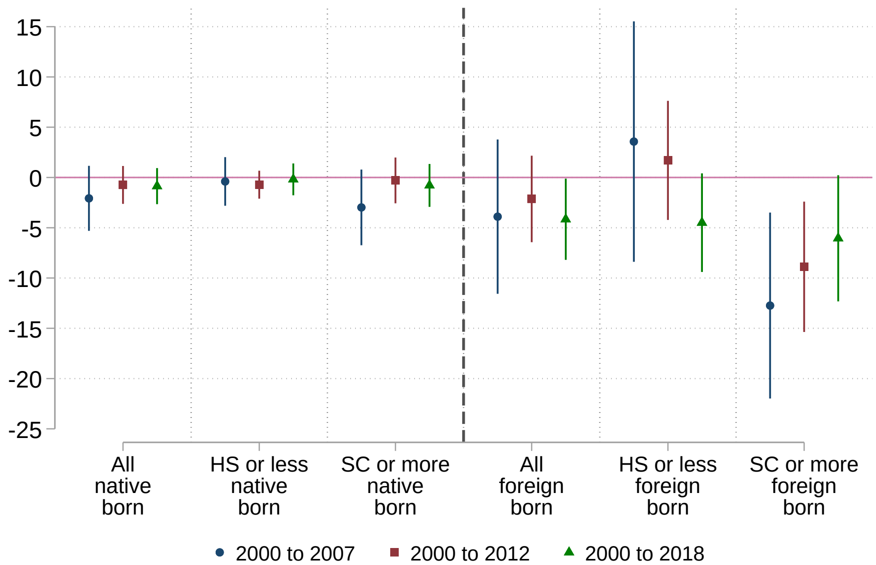



Note: Panels (a) and (b) report 2SLS coefficient estimates for $\beta_{1h}$ in (3) and 95% confidence intervals for these estimates. The dependent variable is the change in the log population over the indicated time period and for the indicated group; the trade shock is the decadalized 2000-2012 change in CZ import exposure, as defined in (2) and instrumented by (4). Control variables include initial-period CZ employment composition (shares of employment in manufacturing, routine-task-intensive occupations, and offshorable occupations, as well as the employment share among women), initial-period CZ demographic conditions (shares of the college educated, the foreign born, non-whites, and those ages 0-17, 18-39, and 40-64 in the population), Census region dummies, and the change in log population over 1970 to 1990. Regressions are weighted by the CZ working-age population in 2000; standard errors are clustered by state.

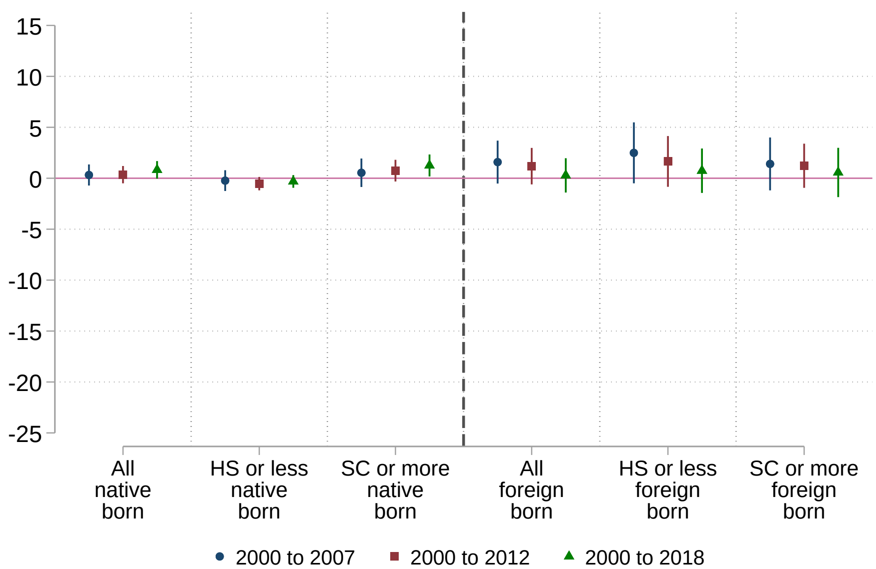
## A.3 Regressions Controlling for Trade Shocks in Nearby Regions

Figure A4: Trade Shock Impact on Population Headcounts, 2000-2018

(a) Impact of Local Trade Shock



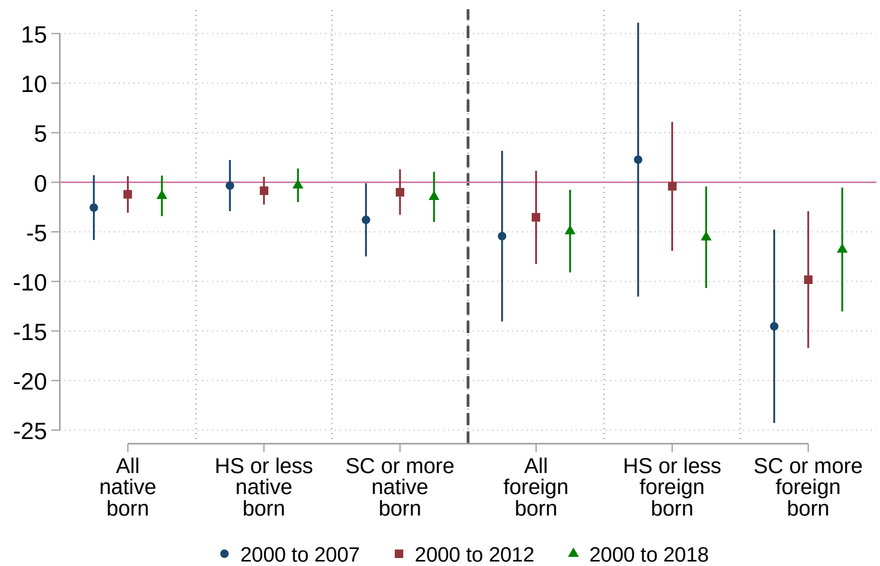

(b) Impact of Trade Shock in Surrounding Regions, Weighted by Geographic Distance



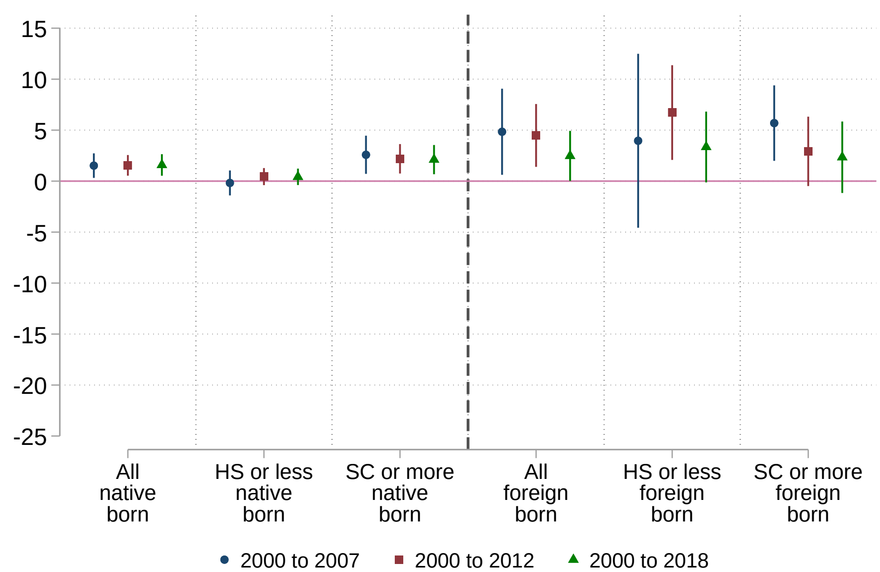

Note: Panels (a) replicates the results in Figure 5, adding in the control shown in equation (5), coefficient estimates for which are given in panel (b) (where 95% confidence intervals for estimates are given by vertical bars). The dependent variable is the change in the log population over the indicated time period and for the indicated group; the trade shock is the decadalized 1991-2012 change in CZ import exposure, as defined in (2) and instrumented by (4). Control variables include initial-period CZ employment composition (shares of employment in manufacturing, routine-task-intensive occupations, and offshorable occupations, as well as the employment share among women), initial-period CZ demographic conditions (shares of the college educated, the foreign born, non-whites, and those ages 0-17, 18-39, and 40-64 in the population), Census region dummies, and the change in log population over 1970 to 1990. Regressions are weighted by the CZ working-age population in 2000; standard errors are clustered by state.

Figure A5: Trade Shock Impact on Population Headcounts, 2000-2018

(a) Impact of Local Trade Shock




(b) Impact of Trade Shock in Surrounding Regions, Weighted by Euclidean Distance of Foreign-Born Populations




Note: Panels (a) replicates the results in Figure 5, adding in the control shown in equation (5), coefficient estimates for which are given in panel (b) (where 95% confidence intervals for estimates are given by vertical bars). The dependent variable is the change in the log population over the indicated time period and for the indicated group; the trade shock is the decadalized 1991-2012 change in CZ import exposure, as defined in (2) and instrumented by (4). Control variables include initial-period CZ employment composition (shares of employment in manufacturing, routine-task-intensive occupations, and offshorable occupations, as well as the employment share among women), initial-period CZ demographic conditions (shares of the college educated, the foreign born, non-whites, and those ages 0-17, 18-39, and 40-64 in the population), Census region dummies, and the change in log population over 1970 to 1990. Regressions are weighted by the CZ working-age population in 2000; standard errors are clustered by state.

## A.4 Complete Regression Results

Table A5: Regression Results for Figure 4

| | All individuals | | | HS or less | | | SC or more | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 |
| Trade shock 2000-2012 | -3.052 | -1.935 | -1.914 | -2.235 | -2.847 | -2.806 | -3.661 | -1.177 | -1.282 |
| | (1.797) | (1.084) | (1.068) | (1.752) | (1.052) | (0.957) | (1.944) | (1.202) | (1.268) |
| Manuf. share of employment | 0.091 | -0.043 | -0.000 | 0.119 | 0.009 | 0.022 | 0.100 | -0.057 | 0.008 |
| | (0.109) | (0.065) | (0.059) | (0.102) | (0.070) | (0.063) | (0.132) | (0.074) | (0.072) |
| Share pop. college educated | 0.011 | -0.014 | 0.022 | 0.115 | 0.043 | 0.081 | -0.414 | -0.439 | -0.332 |
| | (0.079) | (0.075) | (0.069) | (0.078) | (0.075) | (0.063) | (0.099) | (0.080) | (0.079) |
| Share pop. foreign born | -0.145 | -0.031 | -0.035 | -0.192 | -0.024 | -0.056 | -0.120 | -0.053 | -0.036 |
| | (0.116) | (0.052) | (0.048) | (0.143) | (0.053) | (0.049) | (0.102) | (0.054) | (0.051) |
| Share empl. female | 0.061 | 0.249 | 0.229 | -0.011 | 0.261 | 0.208 | 0.060 | 0.180 | 0.193 |
| | (0.117) | (0.095) | (0.079) | (0.163) | (0.104) | (0.095) | (0.123) | (0.115) | (0.095) |
| Share empl. routine jobs | -0.005 | -0.101 | -0.127 | -0.192 | -0.256 | -0.145 | -0.011 | -0.127 | -0.173 |
| | (0.225) | (0.125) | (0.098) | (0.265) | (0.154) | (0.140) | (0.230) | (0.141) | (0.121) |
| Offshorability index | 3.921 | 2.309 | 3.946 | 4.398 | 2.874 | 3.213 | 4.717 | 2.908 | 4.996 |
| | (2.170) | (1.164) | (1.140) | (2.658) | (1.301) | (1.137) | (1.929) | (1.246) | (1.279) |
| Share pop. age 65+ | -0.377 | -0.402 | -0.330 | -0.337 | -0.152 | -0.146 | -0.542 | -0.665 | -0.518 |
| | (0.166) | (0.123) | (0.127) | (0.204) | (0.123) | (0.137) | (0.192) | (0.131) | (0.130) |
| Share pop. age 40-64 | -0.772 | -0.823 | -0.831 | -0.789 | -0.934 | -0.901 | -0.730 | -0.712 | -0.759 |
| | (0.224) | (0.171) | (0.168) | (0.272) | (0.181) | (0.136) | (0.228) | (0.162) | (0.193) |
| Share pop. age 0-17 | 0.490 | 0.242 | 0.118 | 0.490 | 0.265 | 0.257 | 0.272 | 0.078 | -0.058 |
| | (0.276) | (0.169) | (0.157) | (0.355) | (0.159) | (0.190) | (0.279) | (0.188) | (0.182) |
| Share pop. non-white | -0.126 | -0.093 | -0.096 | -0.059 | -0.070 | -0.117 | -0.198 | -0.113 | -0.091 |
| | (0.060) | (0.036) | (0.035) | (0.066) | (0.035) | (0.036) | (0.059) | (0.043) | (0.038) |
| Change in log pop. 1970-1990 | 0.586 | 0.373 | 0.367 | 0.694 | 0.464 | 0.421 | 0.507 | 0.309 | 0.335 |
| | (0.041) | (0.031) | (0.028) | (0.052) | (0.035) | (0.027) | (0.041) | (0.033) | (0.034) |
| Constant | 20.921 | 19.654 | 19.270 | 13.529 | 7.360 | 4.923 | 60.207 | 61.569 | 53.578 |
| | (17.325) | (11.730) | (11.440) | (22.701) | (12.103) | (10.626) | (17.042) | (11.159) | (11.698) |
| Region FE | X | X | X | X | X | X | X | X | X |
| Observations | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 |
| Adj. $R^2$ | 0.723 | 0.800 | 0.811 | 0.762 | 0.827 | 0.832 | 0.585 | 0.697 | 0.713 |

Note: See notes to Figure 4 for regression details.

Table A6: Regression Results for Native-Born Workers in Figure 5

| | | | | Native-born | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | All individuals | | | HS or less | | | SC or more | | |
| | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 |
| Trade shock 2000-2012 | -2.084 | -0.751 | -0.884 | -0.389 | -0.704 | -0.178 | -2.991 | -0.313 | -0.825 |
| | (1.719) | (1.031) | (1.101) | (1.199) | (0.688) | (0.790) | (2.036) | (1.318) | (1.380) |
| Manuf. share of employment | 0.028 | -0.110 | -0.058 | 0.003 | -0.106 | -0.118 | 0.064 | -0.106 | -0.017 |
| | (0.106) | (0.063) | (0.063) | (0.088) | (0.055) | (0.067) | (0.136) | (0.077) | (0.077) |
| Share pop. college educated | -0.009 | -0.062 | -0.030 | 0.051 | -0.059 | -0.020 | -0.423 | -0.459 | -0.351 |
| | (0.071) | (0.071) | (0.070) | (0.088) | (0.078) | (0.071) | (0.094) | (0.075) | (0.077) |
| Share pop. foreign born | -0.141 | -0.026 | -0.024 | -0.177 | -0.074 | -0.084 | -0.190 | -0.091 | -0.071 |
| | (0.108) | (0.064) | (0.082) | (0.099) | (0.056) | (0.068) | (0.116) | (0.069) | (0.081) |
| Share empl. female | 0.032 | 0.178 | 0.113 | -0.050 | 0.152 | 0.025 | 0.066 | 0.154 | 0.127 |
| | (0.125) | (0.106) | (0.107) | (0.150) | (0.087) | (0.097) | (0.138) | (0.128) | (0.121) |
| Share empl. routine jobs | 0.525 | 0.409 | 0.352 | 0.616 | 0.594 | 0.523 | 0.381 | 0.227 | 0.225 |
| | (0.309) | (0.233) | (0.210) | (0.409) | (0.339) | (0.263) | (0.280) | (0.195) | (0.199) |
| Offshorability index | -0.662 | -0.720 | 1.240 | -2.387 | -1.313 | 0.176 | 1.318 | 0.185 | 2.260 |
| | (1.804) | (1.246) | (1.556) | (1.688) | (1.286) | (1.279) | (2.064) | (1.363) | (1.619) |
| Share pop. age 65+ | -0.486 | -0.408 | -0.371 | -0.389 | -0.026 | -0.108 | -0.665 | -0.715 | -0.582 |
| | (0.141) | (0.108) | (0.122) | (0.161) | (0.124) | (0.121) | (0.199) | (0.127) | (0.132) |
| Share pop. age 40-64 | -0.912 | -1.028 | -1.055 | -1.023 | -1.247 | -1.222 | -0.803 | -0.829 | -0.903 |
| | (0.195) | (0.184) | (0.192) | (0.190) | (0.226) | (0.189) | (0.224) | (0.165) | (0.195) |
| Share pop. age 0-17 | 0.613 | 0.315 | 0.201 | 0.822 | 0.481 | 0.401 | 0.222 | 0.043 | -0.059 |
| | (0.239) | (0.149) | (0.156) | (0.295) | (0.179) | (0.155) | (0.281) | (0.190) | (0.200) |
| Share pop. non-white | -0.181 | -0.133 | -0.130 | -0.145 | -0.133 | -0.163 | -0.214 | -0.124 | -0.103 |
| | (0.058) | (0.039) | (0.041) | (0.062) | (0.037) | (0.042) | (0.061) | (0.046) | (0.042) |
| Change in log pop. 1970-1990 | 0.470 | 0.311 | 0.302 | 0.541 | 0.413 | 0.367 | 0.425 | 0.251 | 0.269 |
| | (0.046) | (0.036) | (0.035) | (0.056) | (0.045) | (0.039) | (0.045) | (0.035) | (0.036) |
| Constant | 8.413 | 13.895 | 18.682 | -8.113 | -5.643 | 5.818 | 51.550 | 56.885 | 50.368 |
| | (15.161) | (11.609) | (12.956) | (17.009) | (12.706) | (12.137) | (17.360) | (11.417) | (12.987) |
| Region FE | X | X | X | X | X | X | X | X | X |
| Observations | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 |
| Adj. $R^2$ | 0.681 | 0.783 | 0.790 | 0.738 | 0.830 | 0.853 | 0.556 | 0.669 | 0.661 |

Note: See notes to Figure 5 for regression details.

Table A7: Regression Results for Foreign-Born Workers in Figure 5

| | | | | | Foreign-born | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | All individuals | | | HS or less | | | SC or more | |
| | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 |
| Trade shock 2000-2012 | -3.940 | -2.168 | -4.163 | 3.500 | 1.654 | -4.515 | -12.777 | -8.919 | -6.064 |
| | (4.092) | (2.218) | (2.072) | (6.347) | (3.089) | (2.543) | (4.913) | (3.405) | (3.267) |
| Manuf. share of employment | 0.054 | -0.283 | -0.169 | -0.444 | -0.667 | -0.241 | 0.590 | 0.330 | 0.114 |
| | (0.320) | (0.238) | (0.185) | (0.473) | (0.303) | (0.244) | (0.369) | (0.301) | (0.256) |
| Share pop. college educated | -0.516 | -0.545 | -0.508 | -0.563 | -0.822 | -0.634 | -0.700 | -0.609 | -0.673 |
| | (0.244) | (0.215) | (0.154) | (0.336) | (0.317) | (0.195) | (0.323) | (0.225) | (0.177) |
| Share pop. foreign born | -1.081 | -0.779 | -0.645 | -1.197 | -0.997 | -0.727 | -0.732 | -0.395 | -0.369 |
| | (0.159) | (0.098) | (0.112) | (0.282) | (0.149) | (0.160) | (0.207) | (0.134) | (0.121) |
| Share empl. female | 0.915 | 1.336 | 1.530 | 1.839 | 1.784 | 1.952 | 0.549 | 1.163 | 1.456 |
| | (0.298) | (0.291) | (0.228) | (0.613) | (0.430) | (0.328) | (0.385) | (0.280) | (0.252) |
| Share empl. routine jobs | 0.027 | -0.316 | -0.570 | 0.952 | -0.064 | -0.315 | -0.677 | -1.100 | -1.264 |
| | (0.617) | (0.425) | (0.430) | (0.711) | (0.555) | (0.462) | (0.835) | (0.489) | (0.544) |
| Offshorability index | 17.796 | 6.563 | 10.033 | 9.886 | 2.842 | 5.670 | 24.222 | 12.890 | 14.678 |
| | (4.784) | (2.892) | (3.391) | (7.677) | (4.431) | (4.560) | (5.170) | (3.137) | (3.481) |
| Share pop. age 65+ | 0.009 | -0.538 | -0.279 | 0.001 | -0.961 | -0.360 | 0.023 | -0.111 | -0.054 |
| | (0.374) | (0.371) | (0.320) | (0.706) | (0.579) | (0.456) | (0.409) | (0.328) | (0.305) |
| Share pop. age 40-64 | -1.327 | -1.450 | -1.567 | -1.075 | -2.063 | -2.285 | -2.218 | -1.686 | -1.519 |
| | (0.677) | (0.566) | (0.484) | (1.045) | (0.793) | (0.622) | (0.816) | (0.625) | (0.483) |
| Share pop. age 0-17 | -0.132 | -0.381 | -0.479 | 0.494 | -1.121 | -0.798 | 0.413 | 0.634 | 0.336 |
| | (0.713) | (0.537) | (0.408) | (1.212) | (0.768) | (0.600) | (0.848) | (0.609) | (0.469) |
| Share pop. non-white | 0.066 | 0.036 | -0.059 | 0.348 | 0.191 | 0.009 | -0.207 | -0.167 | -0.181 |
| | (0.152) | (0.124) | (0.086) | (0.242) | (0.170) | (0.107) | (0.154) | (0.137) | (0.128) |
| Change in log pop. 1970-1990 | 0.965 | 0.406 | 0.394 | 1.097 | 0.441 | 0.325 | 1.013 | 0.481 | 0.503 |
| | (0.100) | (0.096) | (0.072) | (0.158) | (0.130) | (0.079) | (0.124) | (0.113) | (0.091) |
| Constant | 46.492 | 47.683 | 38.434 | -77.871 | 60.805 | 31.159 | 126.307 | 68.256 | 54.599 |
| | (48.531) | (40.759) | (35.501) | (90.131) | (59.235) | (54.503) | (53.473) | (41.485) | (33.439) |
| Region FE | X | X | X | X | X | X | X | X | X |
| Observations | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 |
| Adj. $R^2$ | 0.508 | 0.561 | 0.641 | 0.390 | 0.478 | 0.555 | 0.318 | 0.414 | 0.534 |

Note: See notes to Figure 5 for regression details.

Table A8: Regression Results for CZs Below Mean Foreign-Born Share in Figure 6

| | CZs with Below Median Initial Foreign-Born Population | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Native born | | | | | | Foreign born | | | | | |
| | HS or less | | | SC or more | | | HS or less | | | SC or more | | |
| | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 |
| Trade shock 2000-2012 | 1.188 | -0.549 | -0.005 | -2.512 | 0.501 | 0.481 | 5.853 | 5.494 | -1.395 | -12.108 | -6.989 | -4.209 |
| | (1.501) | (0.981) | (0.941) | (1.683) | (0.710) | (0.685) | (9.152) | (5.174) | (3.662) | (6.496) | (4.279) | (3.245) |
| Manuf. share of employment | -0.078 | -0.106 | -0.097 | 0.045 | -0.125 | -0.082 | -0.455 | -0.741 | -0.267 | 0.500 | 0.169 | -0.087 |
| | (0.095) | (0.058) | (0.058) | (0.121) | (0.053) | (0.055) | (0.618) | (0.381) | (0.274) | (0.439) | (0.318) | (0.237) |
| Share pop. college educated | 0.120 | 0.008 | 0.061 | -0.481 | -0.497 | -0.438 | -0.830 | -0.598 | -0.294 | -1.006 | -0.801 | -0.960 |
| | (0.087) | (0.086) | (0.078) | (0.106) | (0.087) | (0.085) | (0.554) | (0.494) | (0.260) | (0.484) | (0.232) | (0.163) |
| Share pop. foreign born | -0.081 | -0.037 | 0.022 | -0.342 | -0.244 | 0.051 | -1.010 | -3.548 | -2.847 | 0.335 | 0.609 | 0.637 |
| | (0.306) | (0.174) | (0.172) | (0.285) | (0.150) | (0.158) | (1.194) | (1.000) | (0.687) | (0.880) | (0.684) | (0.613) |
| Share empl. female | 0.016 | 0.216 | 0.102 | 0.351 | 0.361 | 0.331 | 2.516 | 1.865 | 1.944 | 1.478 | 1.662 | 1.825 |
| | (0.121) | (0.106) | (0.100) | (0.110) | (0.096) | (0.093) | (0.695) | (0.481) | (0.427) | (0.462) | (0.329) | (0.285) |
| Share empl. routine jobs | -0.061 | 0.293 | 0.332 | -0.142 | -0.269 | -0.214 | -1.275 | -1.436 | -2.260 | -0.117 | -0.877 | -1.172 |
| | (0.336) | (0.246) | (0.221) | (0.297) | (0.187) | (0.168) | (1.754) | (1.560) | (1.140) | (1.178) | (0.853) | (0.687) |
| Offshorability index | -0.625 | -2.282 | -1.571 | 3.544 | 1.862 | 3.330 | 29.632 | 21.414 | 25.187 | 21.698 | 12.044 | 15.254 |
| | (1.986) | (1.606) | (1.415) | (1.857) | (1.504) | (1.496) | (11.246) | (9.677) | (7.858) | (6.859) | (4.934) | (5.080) |
| Share pop. age 65+ | 0.313 | 0.083 | 0.002 | -0.125 | -0.541 | -0.386 | -0.184 | -1.048 | -0.310 | 0.465 | 0.500 | 0.358 |
| | (0.183) | (0.148) | (0.136) | (0.155) | (0.141) | (0.152) | (1.026) | (0.957) | (0.522) | (0.580) | (0.552) | (0.502) |
| Share pop. age 40-64 | -0.968 | -0.974 | -0.948 | -0.908 | -0.647 | -0.637 | -1.072 | -2.723 | -2.572 | -2.366 | -2.173 | -1.762 |
| | (0.271) | (0.139) | (0.138) | (0.276) | (0.172) | (0.186) | (1.340) | (1.091) | (0.733) | (0.839) | (0.561) | (0.515) |
| Share pop. age 0-17 | 0.679 | 0.281 | 0.308 | 0.469 | -0.021 | -0.042 | -0.843 | -1.738 | -0.935 | -0.867 | 0.096 | 0.245 |
| | (0.295) | (0.170) | (0.151) | (0.280) | (0.154) | (0.173) | (1.435) | (1.009) | (0.654) | (1.246) | (0.755) | (0.608) |
| Share pop. non-white | -0.066 | -0.067 | -0.096 | -0.221 | -0.057 | -0.056 | 0.269 | 0.153 | -0.042 | -0.145 | -0.175 | -0.234 |
| | (0.055) | (0.036) | (0.041) | (0.053) | (0.034) | (0.036) | (0.257) | (0.248) | (0.140) | (0.202) | (0.171) | (0.166) |
| Change in log pop. 1970-1990 | 0.632 | 0.448 | 0.428 | 0.508 | 0.354 | 0.353 | 1.504 | 0.812 | 0.521 | 1.004 | 0.442 | 0.462 |
| | (0.057) | (0.039) | (0.037) | (0.052) | (0.044) | (0.046) | (0.271) | (0.260) | (0.151) | (0.219) | (0.169) | (0.143) |
| Constant | -4.173 | -12.575 | -9.567 | 41.325 | 51.519 | 39.649 | -25.419 | 124.053 | 85.993 | 67.813 | 41.119 | 32.026 |
| | (14.605) | (11.246) | (9.839) | (14.904) | (9.783) | (10.347) | (92.539) | (74.865) | (67.995) | (61.288) | (55.233) | (40.391) |
| Region FE | X | X | X | X | X | X | X | X | X | X | X | X |
| Observations | 598 | 598 | 598 | 598 | 598 | 598 | 598 | 598 | 598 | 598 | 598 | 598 |
| Adj. $R^2$ | 0.589 | 0.659 | 0.698 | 0.505 | 0.614 | 0.622 | 0.323 | 0.346 | 0.432 | 0.192 | 0.288 | 0.407 |

Note: See notes to Figure 6 for regression details.

## Table A9: Regression Results for CZs Above Mean Foreign-Born Share in Figure 6

| | CZs with Above Median Initial Foreign-Born Population | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Native born | | | | | | Foreign born | | | | | |
| | HS or less | | | SC or more | | | HS or less | | | SC or more | | |
| | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 | 2000-2007 | 2000-2012 | 2000-2018 |
| Trade shock 2000-2012 | 3.087 | 1.800 | 3.259 | -1.444 | -0.989 | -1.946 | -5.325 | -8.808 | -10.713 | -14.207 | -10.822 | -8.097 |
| | (2.575) | (1.451) | (1.622) | (3.174) | (1.850) | (1.896) | (5.374) | (3.693) | (3.528) | (6.896) | (5.978) | (4.125) |
| Manuf. share of employment | -0.245 | -0.208 | -0.426 | -0.040 | -0.146 | -0.029 | 0.418 | 0.344 | 0.391 | 1.164 | 0.691 | 0.585 |
| | (0.241) | (0.134) | (0.124) | (0.246) | (0.153) | (0.159) | (0.516) | (0.360) | (0.265) | (0.617) | (0.555) | (0.352) |
| Share pop. college educated | -0.208 | -0.166 | -0.279 | -0.400 | -0.453 | -0.395 | -0.495 | -0.178 | -0.224 | -0.757 | -1.060 | -0.976 |
| | (0.265) | (0.147) | (0.113) | (0.155) | (0.146) | (0.169) | (0.513) | (0.312) | (0.260) | (0.236) | (0.182) | (0.174) |
| Share pop. foreign born | -0.453 | -0.240 | -0.323 | -0.717 | -0.389 | -0.364 | -1.584 | -0.895 | -0.629 | -1.544 | -0.828 | -0.646 |
| | (0.177) | (0.079) | (0.102) | (0.104) | (0.082) | (0.094) | (0.197) | (0.177) | (0.208) | (0.230) | (0.221) | (0.201) |
| Share empl. female | -0.532 | -0.153 | -0.426 | -1.484 | -0.858 | -0.713 | 0.078 | 0.498 | 0.793 | -2.093 | 0.141 | 0.973 |
| | (0.700) | (0.334) | (0.333) | (0.328) | (0.280) | (0.376) | (0.776) | (0.534) | (0.548) | (0.525) | (0.616) | (0.471) |
| Share empl. routine jobs | 1.785 | 1.328 | 1.295 | 1.202 | 0.696 | 0.599 | -0.844 | -1.710 | -1.301 | -1.769 | -1.908 | -1.979 |
| | (0.347) | (0.348) | (0.247) | (0.279) | (0.218) | (0.256) | (0.816) | (0.398) | (0.299) | (0.807) | (0.683) | (0.369) |
| Offshorability index | -3.324 | -1.137 | 1.445 | 4.989 | 4.349 | 5.860 | 18.310 | 8.766 | 9.021 | 31.272 | 16.640 | 13.038 |
| | (3.919) | (2.651) | (2.467) | (3.533) | (2.289) | (2.444) | (6.955) | (3.734) | (3.796) | (5.254) | (5.131) | (4.221) |
| Share pop. age 65+ | -0.747 | -0.012 | -0.275 | -1.288 | -1.182 | -1.118 | -0.293 | -0.607 | -0.372 | -1.054 | -0.925 | -0.549 |
| | (0.411) | (0.292) | (0.250) | (0.356) | (0.237) | (0.244) | (0.621) | (0.538) | (0.534) | (0.730) | (0.523) | (0.555) |
| Share pop. age 40-64 | -0.679 | -0.911 | -0.884 | -0.558 | -0.993 | -1.439 | -0.678 | -0.876 | -0.987 | -0.730 | -0.677 | -1.347 |
| | (0.600) | (0.427) | (0.410) | (0.448) | (0.317) | (0.535) | (1.107) | (0.563) | (0.644) | (1.512) | (1.200) | (0.931) |
| Share pop. age 0-17 | 0.363 | 0.529 | -0.101 | -1.130 | -1.158 | -1.450 | -0.227 | -0.303 | -0.367 | -1.109 | -0.729 | -1.085 |
| | (0.586) | (0.538) | (0.385) | (0.427) | (0.214) | (0.336) | (1.157) | (0.620) | (0.670) | (1.164) | (0.767) | (0.796) |
| Share pop. non-white | -0.005 | -0.049 | -0.173 | -0.163 | -0.250 | -0.201 | 0.364 | 0.234 | 0.114 | 0.310 | 0.180 | 0.242 |
| | (0.144) | (0.075) | (0.077) | (0.102) | (0.084) | (0.073) | (0.275) | (0.156) | (0.176) | (0.211) | (0.156) | (0.105) |
| Change in log pop. 1970-1990 | 0.420 | 0.355 | 0.217 | 0.327 | 0.132 | 0.163 | 1.165 | 0.598 | 0.539 | 1.281 | 0.661 | 0.614 |
| | (0.077) | (0.063) | (0.052) | (0.100) | (0.080) | (0.088) | (0.193) | (0.104) | (0.108) | (0.126) | (0.118) | (0.100) |
| Constant | 10.977 | -12.627 | 36.543 | 170.787 | 158.233 | 162.984 | 111.610 | 98.103 | 64.285 | 356.185 | 207.123 | 163.581 |
| | (31.019) | (36.884) | (28.864) | (34.515) | (15.063) | (25.464) | (106.762) | (41.537) | (38.337) | (84.783) | (45.917) | (46.810) |
| Region FE | X | X | X | X | X | X | X | X | X | X | X | X |
| Observations | 124 | 124 | 124 | 124 | 124 | 124 | 124 | 124 | 124 | 124 | 124 | 124 |
| Adj. $R^2$ | 0.888 | 0.919 | 0.931 | 0.797 | 0.825 | 0.788 | 0.873 | 0.867 | 0.831 | 0.807 | 0.802 | 0.838 |

Note: See notes to Figure 6 for regression details.

Table A10: Regression Results for Workers Ages 18-39 in Figure 7

| | Ages 18-39 | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Native born | | | | | | Foreign born | | | | | |
| | All (18-39) | | HS or less | | SC or more | | All (18-39) | | HS or less | | SC or more | |
| | 1990-2000 | 1990-2018 | 1990-2000 | 1990-2018 | 1990-2000 | 1990-2018 | 1990-2000 | 1990-2018 | 1990-2000 | 1990-2018 | 1990-2000 | 1990-2018 |
| Trade shock 1992-2012 | -1.232 | -1.270 | 0.320 | -0.956 | -1.854 | -1.250 | -8.893 | -2.398 | -5.084 | -0.672 | -8.543 | -4.287 |
| | (1.811) | (1.011) | (1.908) | (1.137) | (2.150) | (1.067) | (6.431) | (2.195) | (8.198) | (3.345) | (5.954) | (2.318) |
| Manuf. share of employment | 0.110 | -0.001 | 0.124 | 0.048 | 0.067 | -0.026 | 1.556 | 0.081 | 1.748 | 0.069 | 0.594 | 0.039 |
| | (0.101) | (0.061) | (0.109) | (0.073) | (0.127) | (0.064) | (0.400) | (0.158) | (0.575) | (0.267) | (0.435) | (0.167) |
| Share pop. college educated | -0.192 | -0.110 | 0.097 | 0.040 | -0.831 | -0.500 | -1.454 | -0.743 | -1.631 | -0.868 | -1.280 | -0.818 |
| | (0.129) | (0.073) | (0.144) | (0.091) | (0.168) | (0.079) | (0.562) | (0.224) | (0.801) | (0.310) | (0.411) | (0.212) |
| Share pop. foreign born | -0.301 | 0.051 | -0.239 | 0.031 | -0.427 | -0.006 | -1.930 | -1.495 | -2.731 | -1.942 | -1.151 | -0.952 |
| | (0.092) | (0.080) | (0.086) | (0.075) | (0.120) | (0.079) | (0.353) | (0.181) | (0.480) | (0.269) | (0.246) | (0.146) |
| Share empl. female | -0.053 | 0.098 | -0.364 | -0.062 | 0.175 | 0.169 | 1.986 | 1.363 | 2.793 | 1.606 | 0.856 | 1.272 |
| | (0.140) | (0.100) | (0.138) | (0.106) | (0.194) | (0.106) | (0.703) | (0.275) | (1.145) | (0.402) | (0.457) | (0.242) |
| Share empl. routine jobs | 0.388 | 0.171 | 0.968 | 0.403 | 0.024 | 0.006 | -0.162 | -0.510 | 0.184 | -0.800 | -0.603 | -0.683 |
| | (0.212) | (0.124) | (0.223) | (0.198) | (0.278) | (0.119) | (1.374) | (0.645) | (1.496) | (0.658) | (1.633) | (0.768) |
| Offshorability index | 0.283 | 1.789 | -2.393 | 0.886 | 2.425 | 2.721 | 30.784 | 12.730 | 33.484 | 12.935 | 28.939 | 14.437 |
| | (2.007) | (1.279) | (2.028) | (1.472) | (2.723) | (1.143) | (10.296) | (5.078) | (12.998) | (6.908) | (9.815) | (4.674) |
| Share pop. age 65+ | -0.611 | -0.275 | 0.065 | 0.035 | -1.243 | -0.516 | -0.368 | -0.186 | -0.616 | -0.485 | -0.796 | 0.153 |
| | (0.388) | (0.144) | (0.347) | (0.153) | (0.427) | (0.144) | (0.922) | (0.348) | (1.421) | (0.584) | (0.560) | (0.270) |
| Share pop. age 40-64 | -0.617 | -0.824 | 0.064 | -0.903 | -1.062 | -0.701 | 4.071 | 0.649 | 3.285 | 0.007 | 2.305 | 0.299 |
| | (0.495) | (0.215) | (0.421) | (0.228) | (0.643) | (0.256) | (1.542) | (0.639) | (2.072) | (0.841) | (1.277) | (0.619) |
| Share pop. age 0-17 | -0.206 | -0.020 | 1.197 | 0.388 | -1.320 | -0.265 | 0.904 | -0.121 | 0.291 | -0.783 | 0.417 | 0.624 |
| | (0.381) | (0.195) | (0.387) | (0.185) | (0.472) | (0.228) | (1.314) | (0.525) | (1.971) | (0.847) | (0.887) | (0.390) |
| Share pop. non-white | -0.046 | -0.079 | -0.058 | -0.114 | -0.038 | -0.057 | 0.319 | -0.010 | 0.367 | 0.043 | 0.122 | -0.119 |
| | (0.070) | (0.047) | (0.072) | (0.050) | (0.089) | (0.049) | (0.277) | (0.094) | (0.394) | (0.126) | (0.209) | (0.111) |
| Change in log pop. 1970-1990 | 0.561 | 0.366 | 0.610 | 0.425 | 0.540 | 0.352 | 1.298 | 0.464 | 1.283 | 0.459 | 1.097 | 0.480 |
| | (0.074) | (0.033) | (0.077) | (0.044) | (0.078) | (0.031) | (0.276) | (0.090) | (0.396) | (0.117) | (0.189) | (0.092) |
| Constant | 9.196 | 11.246 | -75.661 | -16.632 | 94.073 | 44.920 | -162.542 | -20.033 | -195.112 | 5.399 | 9.257 | -8.808 |
| | (22.497) | (13.188) | (21.723) | (13.551) | (29.395) | (14.109) | (87.178) | (33.839) | (111.205) | (52.088) | (72.565) | (29.961) |
| Region FE | X | X | X | X | X | X | X | X | X | X | X | X |
| Observations | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 |
| Adj. $R^2$ | 0.669 | 0.785 | 0.726 | 0.830 | 0.619 | 0.707 | 0.574 | 0.756 | 0.576 | 0.735 | 0.317 | 0.564 |

Note: See notes to Figure 7 for regression details.

## Table A11: Regression Results for Workers Ages 40-64 in Figure 7

| | Ages 40-64 | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Native born | | | | | | Foreign born | | | | | |
| | All (40-64) | | HS or less | | SC or more | | All (40-64) | | HS or less | | SC or more | |
| | 1990-2000 | 1990-2018 | 1990-2000 | 1990-2018 | 1990-2000 | 1990-2018 | 1990-2000 | 1990-2018 | 1990-2000 | 1990-2018 | 1990-2000 | 1990-2018 |
| Trade shock 1992-2012 | -0.473 | -0.330 | -0.974 | 0.075 | -0.216 | -0.424 | -4.200 | -3.946 | -7.968 | -5.453 | 3.755 | -1.514 |
| | (0.942) | (0.814) | (1.154) | (0.780) | (1.264) | (1.007) | (4.865) | (2.424) | (7.804) | (3.482) | (4.727) | (2.283) |
| Manuf. share of employment | -0.028 | -0.016 | 0.063 | -0.036 | -0.080 | 0.016 | 0.838 | 0.362 | 1.567 | 0.599 | -0.203 | 0.015 |
| | (0.061) | (0.049) | (0.077) | (0.049) | (0.079) | (0.060) | (0.351) | (0.181) | (0.536) | (0.234) | (0.358) | (0.167) |
| Share pop. college educated | 0.130 | -0.023 | -0.229 | -0.179 | -0.464 | -0.391 | -1.135 | -0.703 | -0.911 | -0.850 | -1.528 | -0.686 |
| | (0.065) | (0.058) | (0.086) | (0.071) | (0.090) | (0.069) | (0.358) | (0.191) | (0.415) | (0.219) | (0.403) | (0.191) |
| Share pop. foreign born | -0.705 | -0.378 | -0.787 | -0.381 | -0.833 | -0.476 | -0.537 | -0.648 | -0.477 | -0.670 | -0.266 | -0.395 |
| | (0.047) | (0.045) | (0.065) | (0.043) | (0.058) | (0.048) | (0.328) | (0.155) | (0.433) | (0.215) | (0.288) | (0.159) |
| Share empl. female | 0.262 | 0.138 | 0.103 | 0.021 | 0.418 | 0.191 | 1.621 | 1.637 | 1.529 | 2.185 | 1.683 | 1.206 |
| | (0.092) | (0.069) | (0.083) | (0.062) | (0.149) | (0.102) | (0.513) | (0.276) | (0.667) | (0.388) | (0.462) | (0.233) |
| Share empl. routine jobs | -0.269 | 0.275 | -0.188 | 0.464 | -0.463 | 0.097 | -1.893 | -1.108 | -2.370 | -1.096 | -1.722 | -1.156 |
| | (0.176) | (0.198) | (0.239) | (0.230) | (0.216) | (0.222) | (0.706) | (0.537) | (1.005) | (0.607) | (0.948) | (0.607) |
| Offshorability index | -0.800 | 1.309 | -0.927 | -0.003 | -0.533 | 2.290 | 26.389 | 17.544 | 34.632 | 18.578 | 17.346 | 16.663 |
| | (1.602) | (0.819) | (1.841) | (1.004) | (2.355) | (1.284) | (7.447) | (4.789) | (9.583) | (5.808) | (8.560) | (4.319) |
| Share pop. age 65+ | -0.772 | -0.483 | -0.835 | -0.355 | -0.891 | -0.673 | -0.887 | -0.429 | -1.316 | -0.399 | -0.020 | -0.220 |
| | (0.140) | (0.076) | (0.177) | (0.081) | (0.213) | (0.121) | (0.816) | (0.444) | (1.096) | (0.575) | (0.678) | (0.357) |
| Share pop. age 40-64 | 0.498 | -0.533 | 0.627 | -0.666 | 0.034 | -0.701 | -0.560 | -1.153 | -0.156 | -1.566 | -0.906 | -0.880 |
| | (0.245) | (0.182) | (0.254) | (0.208) | (0.374) | (0.255) | (1.016) | (0.604) | (1.279) | (0.791) | (1.174) | (0.597) |
| Share pop. age 0-17 | 0.268 | 0.168 | 0.295 | 0.354 | -0.270 | -0.288 | -0.892 | -0.506 | -0.959 | -0.482 | 0.013 | 0.131 |
| | (0.195) | (0.111) | (0.230) | (0.127) | (0.227) | (0.150) | (1.103) | (0.622) | (1.447) | (0.848) | (1.020) | (0.503) |
| Share pop. non-white | -0.014 | -0.074 | -0.041 | -0.119 | -0.014 | -0.058 | 0.370 | 0.079 | 0.318 | 0.104 | 0.454 | 0.016 |
| | (0.042) | (0.035) | (0.047) | (0.036) | (0.057) | (0.043) | (0.229) | (0.144) | (0.316) | (0.182) | (0.155) | (0.125) |
| Change in log pop. 1970-1990 | 0.681 | 0.427 | 0.642 | 0.442 | 0.650 | 0.391 | 1.070 | 0.666 | 1.184 | 0.590 | 0.944 | 0.743 |
| | (0.050) | (0.037) | (0.055) | (0.037) | (0.059) | (0.043) | (0.206) | (0.118) | (0.284) | (0.155) | (0.166) | (0.106) |
| Constant | 3.820 | 11.478 | 0.016 | 3.874 | 80.867 | 61.357 | 74.863 | 34.904 | 50.956 | -1.843 | 96.987 | 57.372 |
| | (14.985) | (10.270) | (16.190) | (9.700) | (20.517) | (14.571) | (69.717) | (36.525) | (86.860) | (50.435) | (72.747) | (34.212) |
| Region FE | X | X | X | X | X | X | X | X | X | X | X | X |
| Observations | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 722 | 721 | 721 |
| Adj. $R^2$ | 0.868 | 0.831 | 0.840 | 0.868 | 0.793 | 0.777 | 0.520 | 0.661 | 0.475 | 0.630 | 0.333 | 0.564 |

Note: See notes to Figure 7 for regression details.