Places versus People: The Ins and Outs of Labor Market Adjustment to Globalization[*]

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Abstract

This chapter analyzes the distinct adjustment paths of U.S. labor markets (places) and U.S. workers (people) to increased Chinese import competition during the 2000s. Using comprehensive register data for 2000–2019, we document that employment levels more than fully rebound in trade-exposed places after 2010, while employment-to-population ratios remain depressed and manufacturing employment further atrophies. The adjustment of places to trade shocks is *generational*: affected areas recover primarily by adding workers to non-manufacturing who were below working age when the shock occurred. Entrants are disproportionately native-born Hispanics, foreign-born immigrants, women, and the college-educated, who find employment in relatively low-wage service sectors such as medical services, education, retail, and hospitality. Using the panel structure of the employer-employee data, we decompose changes in the employment composition of places into trade-induced shifts in the gross flows of people across sectors, locations, and non-employment status. Contrary to standard models, trade shocks reduce geographic mobility, with both in- and out-migration remaining depressed through 2019. The employment recovery stems almost entirely from young adults and foreign-born immigrants taking their first U.S. jobs in affected areas, with minimal contributions from cross-sector transitions of former manufacturing workers. Although worker inflows into non-manufacturing more than fully offset manufacturing employment losses in trade-exposed locations after 2010, incumbent workers neither fully recover earnings losses nor predominantly exit the labor market, but rather age in place as communities undergo rapid demographic and industrial transitions.

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1 Introduction

Regionally concentrated job loss is a major economic challenge of our time. Globalization (Autor et al., 2013), automation (Autor and Dorn, 2013; Acemoglu and Restrepo, 2020), broader secular shifts (Austin et al., 2016; Charles et al., 2019), and now the energy transition (Hanson, 2022) have caused local labor markets specialized in manufacturing to lose parts of their industrial core, leading to persistently lower earnings and employment rates, especially among non-college adults (Chetverikov et al., 2016; Amior and Manning, 2018; Abraham and Kearney, 2020). The entrenchment of economic distress has engendered social dislocation (Wilson, 2011), as manifested by locally elevated incidences of mortality (Pierce and Schott, 2020), single parenthood and child poverty (Autor et al., 2019), and political extremism (Colantone and Stanig, 2018b; Autor et al., 2020; Rodrik, 2020).

In this chapter, we examine the intertwined adjustment of places and people—labor markets and workers—to adverse labor demand shocks in the context of rising import competition from China, which is among the most-studied recent causes of deindustrialization.[1] By estimating the trade-induced flows of individuals between places, sectors, employment status, and job characteristics, we delineate the margins and magnitudes of labor market adjustment to adverse shocks for different types of people.

That China's rise severely disrupted local labor markets in high-income countries came as something of a surprise, to both economists and policymakers.[2] For the United States, initial impressions were that trade with low-wage countries would have only modest impacts (Freeman, 1995; Krugman, 2008). Trade models of the time suggested that an event like the China trade shock would reduce the relative earnings of low-wage workers in import-competing economies by reallocating factors away from labor-intensive manufacturing (Wood, 1995, 2018; Feenstra, 2015). The mobility of labor between sectors and regions would diffuse the shock across local labor markets, dampening its place-specific effects.[3]

We now know that trade shocks caused more intense pain than anticipated in regions specialized in manufacturing. Local labor markets specialized in industries which faced a large increase in Chinese import competition during the 1990s and 2000s experienced a differen-

[1] For earlier reviews of the literature, see Autor et al. (2016, 2021); Redding (2020); Dorn and Levell (2024a,b).

[2] China's dramatic manufacturing export growth sprang from the country's equally dramatic economic reforms (Naughton, 2007; Song et al., 2011; Storesletten and Zilibotti, 2014; Liu and Ma, 2023). Economists were quicker to detect China's trade boom than its broader disruptive consequences.

[3] Earlier literature considers how, because of labor market rigidities, expanded trade may lead to greater unemployment (e.g., Helpman and Itskhoki, 2010; Helpman et al., 2010; Davidson et al., 1999). The mechanisms considered in this work imply that variation in unemployment manifests across industries, rather than across regions (as found in a large body of recent literature). See also Helpman (2018) on the role of globalization in rising income inequality in high-income countries.

tial decline in manufacturing employment which was not compensated by a commensurate rise in non-manufacturing employment during the period when the trade shock unfolded. These regional effects were observed not only in the United States (Autor et al., 2013; Acemoglu et al., 2016) but in other high-income countries, including Germany (Dauth et al., 2014, 2017), Norway (Balsvik et al., 2015), Spain (Donoso et al., 2015), France (Malgouyres, 2017), the United Kingdom (Foliano and Riley, 2017), Italy (Citino and Linarello, 2022), and Australia (Coelli et al., 2023) as discussed in a comprehensive review by Dorn and Levell (2024b). The adverse labor market impacts of the China shock fell disproportionally on workers who were initially employed in import-competing manufacturing industries. While these workers had a greater propensity to move across firms and industries, they experienced lower earnings growth than comparable workers in other industries in the United States (Autor et al., 2014), Finland (Hakkala and Huttunen, 2016), Germany (Dauth et al., 2021), and the United Kingdom (De Lyon and Pessoa, 2021). Despite such scarring effects, net migration out of trade-exposed places was muted (Greenland et al., 2019; Autor et al., 2025).[4]

Because local-labor-market and worker-level perspectives in adjustment to changes in economic conditions are rarely integrated, there is much we do not know about how places adjust: who leaves; who arrives; how do industry composition and the quality of jobs evolve; and how long do these changes take to unfold. Characterizing these labor inflows and outflows may help elucidate why places struggle in the aftermath of adverse shocks and whether assistance of some kind may be merited.[5] And, beyond these outcomes, our knowledge of how the adjustment of people interacts with the adjustment of places is incomplete: whether exposed workers adjust in tandem with exposed places; whether workers leave while places languish; or whether regions rebound while workers struggle. Disentangling the distinct adjustment paths of labor markets and workers may help guide whether post-shock remediation should target places—e.g., location-specific investment subsidies as in Bilal (2023)—or people—e.g., subsidies for worker training as in Hyman (2018).[6]

The unified research design that we propose and apply, which builds on Dustmann et al. (2023), identifies the causal effects of the China trade shock on outcomes in local labor markets viewed from two different perspectives: (1) *places*, meaning trade-induced net changes in the stock of jobs in a local labor market, as measured by industrial composition, demo-

[4] One source of labor immobility in manufacturing regions may be the preponderance of individuals in these places who were born in the state (Zabek, 2024), which may be indicative of a low propensity to migrate.

[5] See, e.g., Neumark and Simpson (2015); Austin et al. (2016); Bartik (2020). For discussion of quantitative spatial models, see Redding and Rossi-Hansberg (2017) and Redding (2020).

[6] The classic reference in economics on policy targeting is Dixit (1985).

graphic composition, and earnings levels; and (2) *people*, meaning trade-induced flows ("ins and outs") of workers across labor markets, sectors, employment statuses, and earnings levels that give rise to these net changes. By merging a worker-level panel from the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program with the American Community Survey (ACS) and the 2000 and 2010 decennial census (Ruggles et al., 2004) via the Opportunity Databank (Chetty et al., 2020), we track changes in earnings and employment for individuals by their initial commuting zone (Tolbert and Sizer, 1996; Dorn, 2009), initial sector, initial earnings, education, and demographic characteristics. Our time period spans two decades, from 2000, the year before China joined the World Trade Organization, to the pre-pandemic year of 2019.

In trade-exposed commuting zones (CZs), we find persistent excess job losses in manufacturing (relative to the initial working-age population), which by the end of the period are more than offset by excess job gains in non-manufacturing.[7] More exposed places also had smaller net population outflows (or equivalently larger net population inflows), resulting in a larger decline in their employment-to-population ratios. Non-manufacturing job gains are stronger among women, the college-educated, members of minority racial and ethnic groups, and the foreign-born. They are further concentrated in services industries with relatively low-wage premiums, as estimated by Card et al. (2024). These industries include leisure and hospitality, retail trade, non-traded medical services, and K-12 education.

While trade-exposed places more than fully recover all employment losses after 2010, trade-exposed workers on average do not. Workers initially employed in manufacturing are more likely to exit employment and to take up lower-wage work outside of manufacturing, while being less likely to work in another CZ. Such maladjustment to import competition is disproportionately common among workers who are non-college-educated, initially low-earning, and initially employed in low-wage-premium industries. Combining our results on place effects and people effects, we find that, paradoxically, trade-exposed places experience both a jobs recovery—in terms of greater employment growth relative to the initial population—and rising joblessness—in terms of larger declines in employment rates among incumbents. This paradox is resolved by the absence of an out-migration response to import competition: in trade-exposed places, smaller outflows of older manufacturing workers to other commuting zones combine with larger inflows of workers, who are disproportionately minorities and foreign-born, into first-time employment. In the post-shock labor market, a new generation holds relatively low-paid jobs that, to a large extent, appear to provide services to local

[7] For related results using worker-level Census data, see Pierce et al. (2024), and for related results using establishment-level Census data, see Bloom et al. (2024).

families and the resident non-working old.

2 Related Literature

Despite benign expectations as to how the China trade shock would unfold, prior episodes of adjustment to trade shocks provided clues about the disruptions to come. In earlier decades, workers in trade-exposed industries (Grossman, 1982; Kletzer, 1998, 2001) and regions (Borjas and Ramey, 1995) had been displaced by import competition; those who lost jobs due to mass layoffs (whatever the cause) tended to earn permanently less than otherwise similar workers (Jacobson et al., 1993); and those who were less-educated were unlikely to leave places following downturns (Bound and Holzer, 2000).[8] In accordance with these patterns, import competition from China caused exposed workers to lose jobs in large part because of factory closures (Bernard et al., 2006; Acemoglu et al., 2016; Asquith et al., 2019), and to see their lifetime labor income reduced (Autor et al., 2014).

Manufacturing job losses were particularly large in the United States and the United Kingdom, which experienced a sharp increase in Chinese imports but no sizable growth of exports; losses were more limited in Germany and Switzerland, which strongly expanded exports to China (Dorn and Levell, 2024b). In Japan, local labor markets specialized in industries with large import growth from China experienced job gains due to large-scale imports of intermediate goods and expanding exports (Taniguchi, 2019; Kainuma and Saito, 2022).[9] Beyond research on the China shock, other work has studied the regional labor market impacts of trade liberalizations in India (Topalova, 2010), Brazil (Kovak, 2013; Dix-Carneiro and Kovak, 2017), and Finland (Costinot et al., 2024), and the effects of the North American Free Trade Agreement in the United States (Choi et al., 2024).[10]

Empirical research on import competition from China has drawn attention in part because it

[8] Related work examines how the scarring effects of job loss vary across the business cycle (Davis and von Wachter, 2011; Hershbein and Stuart, 2024) and countries (Bertheau et al., 2023); how the geographic mobility of labor has changed over time (Blanchard and Katz, 1992; Dao et al., 2017; Ganong and Shoag, 2017); the magnitude of moving costs between sectors and occupations (Artuç et al., 2010; Dix-Carneiro, 2014; Ashournia, 2018; Traiberman, 2019),; and the interplay of migration and housing markets in regional adjustment to adverse shocks (Howard, 2020; Notowidigdo, 2020a; Davis and Haltiwanger, 2024).

[9] Kiyota et al. (2021) estimate that most of the Japanese and South Korean job losses in industries exposed to final goods imports from China were offset by job gains in industries exposed to imports of intermediate goods. They also detect sizable job gains due to imports of intermediate goods in Germany but not in the U.S., the UK, or France. Studies for the U.S. (Acemoglu et al., 2016) and Australia (Blanco et al., 2020) find significant job losses in industries that sell their outputs to industries that compete with Chinese imports, and neutral employment effects in industries that source goods from import-competing sectors, while Aghion et al. (2021) observe weak employment gains through the latter channel in France.

[10] Additional worker-level studies include Utar (2014) on the removal of textile quotas in Denmark and Kovak and Morrow (2022) on the effects of the U.S.-Canada Free Trade Agreement on Canadian workers.

speaks to how globalization creates winners and losers, a concept familiar to economists since David Ricardo (Ricardo, 1815; Maneschi, 2008). To assess how trade affects welfare, recent literature embeds results from reduced-form empirical analysis—which identifies relative impacts of trade shocks across regions—in quantitative general equilibrium models in order to project changes in real income (Costinot and Rodríguez-Clare, 2014; Redding, 2020). Such projections do not come for free, however. One must specify the adjustment mechanisms through which local labor markets equilibrate in the aftermath of shocks. Approaches vary, first, in terms of the degree and speed of geographic labor mobility (Caliendo et al., 2019; Galle et al., 2023; Adão et al., 2019a); and, second, in terms of how and when the value of non-employment responds (Caliendo et al., 2019; Rodríguez-Clare et al., 2020; Amior and Manning, 2018; Kim and Vogel, 2020, 2021). Which form adjustment takes is materially important for quantifying the distributional consequences of globalization. Our results offer greater support for frameworks that allow for less mobility of people between places (e.g., Galle et al., 2023) and more persistent non-employment (e.g., Kim and Vogel, 2021).[11]

Recent work also calls attention to how the state of the macroeconomy affects labor market adjustment to import competition. In Rodríguez-Clare et al. (2020), the initial slackness of the labor market conditions the transitory behavior of unemployment, while in Dix-Carneiro et al. (2023) the endogenous magnitude of trade deficits affects the scale of manufacturing employment responses. The first result is reminiscent of findings in Davis and von Wachter (2011) on how the scarring effects of job loss are worse in recessions; the second result, which was originally considered by Borjas and Ramey (1995) in their empirical analysis of how rising U.S. trade deficits in the 1980s affected employment in durable manufacturing, extends the simple theoretical analysis of the role of trade deficits in the employment consequences of the China trade shock in Autor et al. (2013).

The economic hardship that commonly follows manufacturing decline has renewed interest in the use of trade- and place-based policies to alleviate regional economic distress. Recent literature provides little support for the use of import tariffs (Fajgelbaum et al., 2020; Fajgelbaum and Khandelwal, 2022), which appear to be ineffective in combating regionalized joblessness (Javorcik et al., 2022; Autor et al., 2024). By contrast, if the right conditions prevail, place-based policies designed to reduce spatial inequality may be welfare improving (Kline and

[11] In other contexts, less-educated labor in the United States does appear to be geographically mobile in response to adverse shocks, including the rise and fall of coal production (Black et al., 2005), mass layoffs (Foote et al., 2019), and large-scale immigrant inflows (Monras, 2020). Autor et al. (2025) find that the response of net population headcounts to the China trade shock is larger among the foreign-born (with impacts dissipating as one extends the time period from 2000-2007 to 2000-2018) than among the native-born (with impacts being null at all horizons). Because our analysis in this paper revolves around the LEHD, we do not assess impacts of trade exposure on changes in the size of overall CZ populations.

Moretti, 2014; Diamond and Gaubert, 2022). These conditions include localized spillovers that cause more-productive workers (Diamond, 2016; Fajgelbaum and Gaubert, 2020) or firms (Bilal, 2023) to concentrate in larger, higher-wage regions, and market frictions that leave some individuals stuck in smaller, lower-wage regions with correspondingly low levels of consumption. In such an environment, localized adverse shocks may have lasting impacts. By initiating a self-reinforcing process of industry deagglomeration (Dix-Carneiro and Kovak, 2017) or inducing occupational downgrading among the newly unemployed (Huckfeldt, 2022) and new labor market entrants (Wachter, 2020), they may dissuade new firms from entering and contribute to widening spatial disparities in earnings and well-being. As of yet, little work has assessed whether place-based policies are successful in attenuating the adverse impacts of exposure to globalization.

Help for unemployed workers may also be relevant for how local labor markets respond to adverse shocks, including targeted assistance to those who have been displaced by import competition (Hyman et al., 2024) or the regionally magnified impacts of national recessions (Chodorow-Reich et al., 2019; Boone et al., 2021; Acosta et al., 2023). Because we track unemployment insurance benefits imperfectly in our data, we will have little to say about their (potentially important) role in regional adjustment to job loss.[12]

A large literature has evaluated adjustment to the China trade shock over the medium-run (e.g., out to 2007), but the path of adjustment beyond this point (e.g., out to 2020) has received less attention. Evidence on local labor market consequences through 2007 establishes that import competition: (a) reduces local tax revenues and the provision of public services (Feler and Senses, 2017), which may diminish the attractiveness of a place to businesses; (b) leads to greater incidence of criminality (Dix-Carneiro et al., 2018), adverse health outcomes (Adda and Fawaz, 2020), and mortality tied to risky behaviors (Pierce and Schott, 2020), any of which may diminish the long-run quantity and productivity of labor; and (c) raises the fraction of children living in single-headed households and in poverty (Autor et al., 2019), which may impede the accumulation of human capital among the young. Chinese import competition also lowered consumer prices (Bai and Stumpner, 2019; Jaravel and Sager, 2019; Dorn and Levell, 2024b), which may help offset the adverse impacts of trade shocks on labor earnings. Because this chapter focuses exclusively on labor market outcomes, it does not speak to these broader impacts. Its contribution, instead, is to illuminate how trade-induced changes in local labor markets are connected to, but distinct from, impacts

[12]In this volume, see Le Barbanchon et al. (2024), who discuss literature on unemployment insurance and active labor market policies. Other related work evaluates the role of market and policy mechanisms in promoting labor mobility out of distressed places. See, e.g., Marinescu and Rathelot (2018) and Bastian and Black (2024).

on workers. By decomposing observed changes in the employment composition of trade-exposed places into underlying shifts in the gross flows of people across sectors, locations, and employment statuses, we show how the trajectory of trade-impacted places and trade-exposed workers have diverged since China's entry into the WTO in 2001.

3 Data Sources and Empirical Methods

3.1 Data sources

Our analysis uses a unique dataset built from administrative and demographic records held at the U.S. Census Bureau. Ours is the first research project to our knowledge to pool this full set of disparate data sources, although our primary data source, the LEHD, has at times been combined with one or more of the data sets we use (Abowd et al., 2018; Green et al., 2017; McKinney et al., 2022). We provide a brief summary of each data source and how we combine them.

We start with the Longitudinal Employer Household Dynamics (LEHD) employer-employee panel dataset, which derives from state unemployment insurance (UI) records. The LEHD's Employment History File (EHF) is a job-level database, where a job is a unique employer-employee combination, containing quarterly observations of earnings for a near-universe of the private wage-and-salary workers in participating states.[13] We conduct our analysis at an annual frequency and select the worker's employer as the employer that pays the highest annual earnings. We are able to follow the same worker over time across jobs using the Census Bureau's unique person identifier, the Protected Identification Key (PIK).[14] We use the LEHD's unique employer-state identifier (SEIN) to link each job to the LEHD's Employer Characteristics File (ECF), which includes information on the employer's industry and commuting zone (CZ). We therefore study place and people effects based on the location of the employer, and not the residence of the worker as in Autor et al. (2013) and related

[13] The LEHD covers most state and local government employees, but not federal workers.

[14] The Census Bureau applies PIKs via the Person Identification Validation System (PVS), which uses a probabilistic matching algorithm to place a 9-digit identifier from a master reference file to each observation in a data set. A PIK is unique and time-invariant, meaning that persons can be matched to their information whenever they appear in a PVS dataset. When records contain social security numbers (SSNs), names, and dates of birth, a match is first attempted using the SSN and then validated on name and date of birth. Administrative records with an SSN, such as the LEHD and federal tax data, have rates of PIK placement close to 100%. Data sources without SSNs, such as the demographic data we use, tend to have placement rates close to 90%. Wagner and Layne (2014) provide further detail on the PVS process. Differential PIK placements by demographic group have the potential to lead to bias in coefficient estimates (Bond et al., 2014). Because our study focuses on UI-covered workers (i.e., connected to an SSN in the core data), differential PIK placement is of less concern.

work, although the use of commuting zones as the geographic unit of analysis means that for most individuals the place of work and the place of residence coincide.

Our sample period is 2000 to 2019, which begins one year prior to China's accession to the World Trade Organization in 2001 and the ensuing reduction in China's trade barriers vis-à-vis the United States and the rest of the world (Pierce and Schott, 2016; Handley and Limao, 2017), and ends just before the onset of the Covid-19 pandemic in 2020. To ensure a balanced sample of states, we use the 43 mainland states that participated in the LEHD consistently during this time span.[15] We further restrict the data to workers with strictly positive annual earnings who are between the ages of 18 and 64 in the relevant earnings year and use the PIK to link individuals to the Opportunity Databank (OD) (Chetty et al., 2020).[16] The raw data we use from the OD are the Census Numident (the list of SSNs ever issued, where SSNs have been replaced by PIKs), short forms for the 2000 and 2010 Census (which cover the entire U.S. population), and federal income tax forms 1040 (for 1998 to 2019) and 1099 (for 2003 to 2019). The Numident provides information on worker year of birth, sex, and foreign-born status. We use the 2000 Census and 2005 to 2019 American Community Surveys (ACS) for data on racial and ethnic identity.[17] For several of our analyses, we focus on the surveyed subset of workers for whom educational attainment is available in the Census or ACS.[18] For workers who are surveyed multiple times, we take the most recent demographic information available.

[15]The excluded states and areas are Alabama, Alaska, Arkansas, the District of Columbia, Hawaii, Massachusetts, Mississippi and New Hampshire. These areas accounted for 7.8% of U.S. manufacturing employment in the BLS Current Employment Statistics of January 2000.

[16]See specifically the online appendix in Chetty et al. (2020).

[17]We categorize race and ethnicity groups as follows: White non-Hispanic, Black or African American non-Hispanic, Hispanic or Latino of any race, and Other Race non-Hispanic. These categories follow Office of Management and Budget official definitions, with the exception that we combine race categories other than White and Black or African American into a single group. This last group includes the non-Hispanic race categories Asian, American Indian or Alaska Native, and Native Hawaiian or Pacific Islander, in addition to those who report a race other than these categories or more than one race. In what follows, we simplify the terminology to "white," "Black," "Hispanic," and "other race."

[18]Because we only observe the college education indicator for the surveyed subsample of workers, we construct the total number of college-educated workers in the CZ by multiplying the total number of workers in the CZ by the share that is college-educated among the surveyed subsample; we follow the same procedure for non-college workers. Furthermore, some of our analyses require estimating the number of workers in a CZ that are both college-educated and belong to a particular earnings tercile. To construct such a measure, we multiply the total number of workers in the CZ who belong to the earnings tercile by the college-educated share among surveyed workers in that earnings tercile in the CZ. Within each CZ, this approach ensures that the sum of college and non-college workers in an earnings tercile equals the total number of workers in that earnings tercile. However, this approach does not ensure that the sum of college-educated workers across earnings terciles equals the total number of college-educated workers. A similar approach is taken to measure the number of college and non-college workers in a CZ who work in high-premium or low-premium jobs.

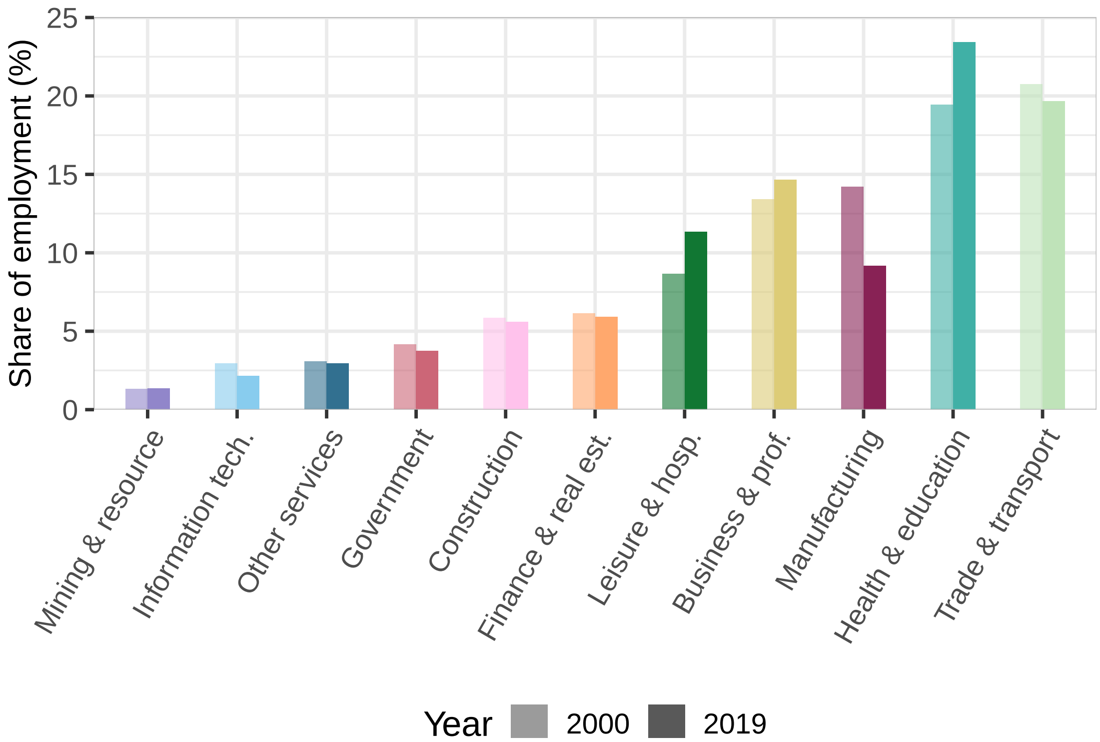


Figure 1: The Share of National Employment by Industry, 2000 and 2019.

Notes: This figure reports the share of U.S. private sector payroll employment by major industry in 2000 and 2019 among the 43 states included in our LEHD sample. These states comprise approximately 92.2% of U.S. private sector payroll employment in 2000 and 90.5% in 2019. Industries are ordered from least to greatest share of national employment in 2000. Lighter and darker bars correspond to employment in 2000 and 2019, respectively. See Table A.1 for share values.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

Our analyses also make use of data on import penetration by China in U.S. industries over 2000 to 2007 from Autor et al. (2021), industry wage premiums estimated in the LEHD by Card et al. (2024), the Personal Consumption Expenditure Index from the U.S. Bureau of Labor Statistics, and population counts by commuting zone, year, and demographic group constructed from the Survey of Epidemiology and End Results (SEER).

3.2 Changing employment and demographic composition in manufacturing and non-manufacturing

We first use the combined dataset to characterize the composition of employment in the U.S. and how it has changed over time. The share of employment encompassed by the manufacturing sector fell by more than one-third between 2000 and 2019, from 14.2% to 9.2%

of employment, as shown in Figure 1 and reported in Table A.1.[19] Conversely, the share of employment in health and education, leisure and hospitality, and business and professional services increased by multiple percentage points, though none of these sectors rose by as much as manufacturing fell.[20] Other major industries registered either little change or small declines in their employment shares.

Prior research establishes that rising Chinese import competition was a central contributor to the decline of U.S. manufacturing employment, especially in the period of 2000 to 2010 (Autor et al., 2013; Acemoglu et al., 2016; Pierce and Schott, 2016). Our longitudinal analysis asks whether the same individuals who left manufacturing jobs gained employment in other sectors, and whether the same CZs that lost manufacturing employment experienced job growth in other sectors. We further investigate how this structural transformation affected different demographic groups of workers, and whether jobs gained outside of manufacturing were comparable to the lost manufacturing jobs in terms of earnings levels.

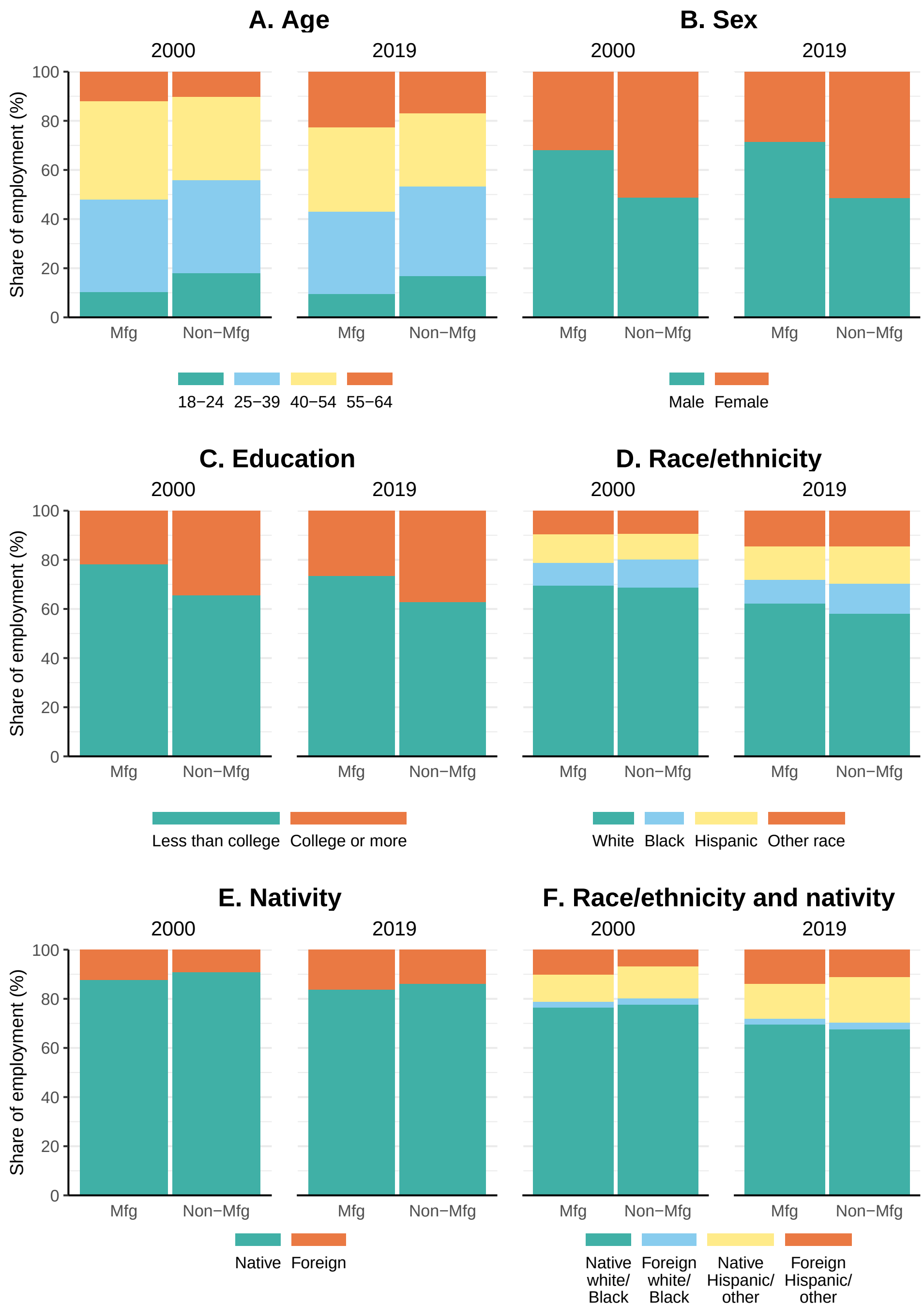
Figure 2 lays the foundation for what follows by enumerating the attributes of workers and jobs in the manufacturing and non-manufacturing sectors in the years 2000 and 2019. Each pair of bars reports shares of employment in 2000 and 2019 for manufacturing and non-manufacturing, broken down by subgroups of individuals within given demographic and earnings categories.

Figure 2a documents sharp contrasts in the demographic composition of manufacturing versus non-manufacturing workers. What stands out from the figure is not how much the composition of manufacturing or non-manufacturing employment changes between 2000 and 2019 but instead how much these sectors differ, both at the start and at the end of our sample time frame. Relative to those in non-manufacturing, workers in manufacturing in both periods are older, disproportionately likely to be male, less likely to have a four-year college degree, slightly more likely to be non-Hispanic white, less likely to be Black, and more likely to be foreign-born Hispanic.

Interest in manufacturing employment and manufacturing decline is motivated in part by the relatively high wages that this sector has historically paid to workers without college degrees. As economists have recognized since (at least) Slichter (1950), industries vary substantially in their average pay, even after accounting for worker and region characteristics. Figure 2b strongly reinforces the view that manufacturing remains a high-wage sector, measured in

[19] This decline is slightly larger than that reported in the BLS Current Employment Survey for the United States as a whole from 13.1% in 2000 to 8.5% in 2019.

[20] The largest increases in share were registered by Leisure and Hospitality (from 8.7% to 11.3% of employment) and Health and Education (from 19.4% to 23.4%).

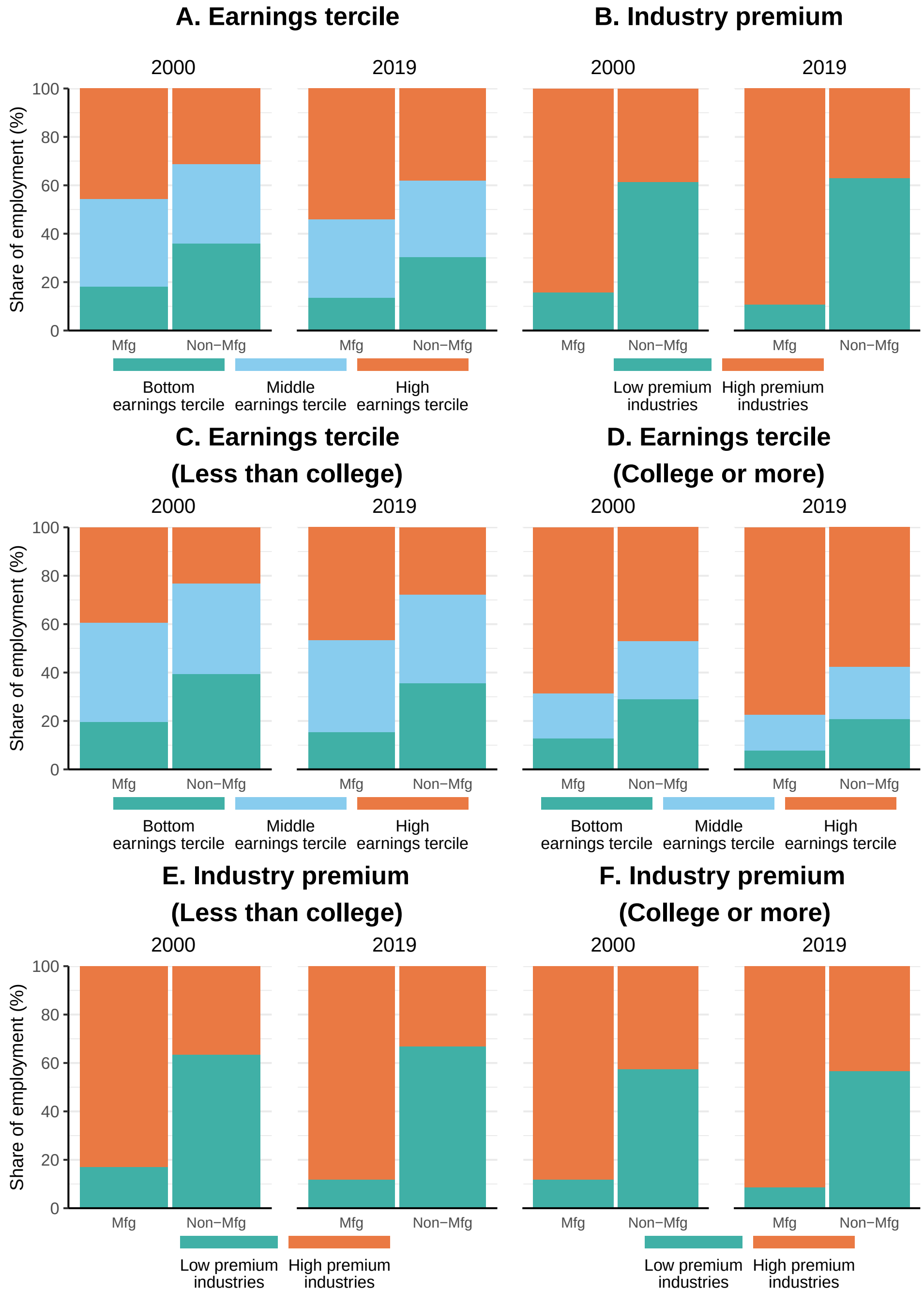


(a) Employment Share by Demographics

Figure 2: The Share of Manufacturing and Non-Manufacturing Employment by Demographic, Earnings Tercile, and Industry Premium, 2000 and 2019.

Notes: Panels A through F report the share of employment for manufacturing and non-manufacturing workers by demographic group in 2000 and 2019. Additional sample details are provided in the text. See Table A.3 for share values.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.



(b) Employment Share by Earnings Tercile and Industry Premium

Figure 2: The Share of Manufacturing and Non-Manufacturing Employment by Demographic, Earnings Tercile, and Industry Premium, 2000 and 2019.

Notes: Panels A through F display the share of employment for manufacturing and non-manufacturing workers by earnings tercile, industry premium, and educational attainment in 2000 and 2019. Earnings tercile thresholds are defined such that they divide workers into three earnings bins, each comprising one third of earners, in 2000. In subsequent years, those thresholds are fixed in real terms using the Personal Consumption Expenditure deflator. Employment is classified as high-premium if the wage premium reported by Card et al. (2024) for the worker's industry of employment exceeds the employment-weighted average premium for the U.S. economy. Additional sample details are provided in the text. See Table A.2 for share values.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

terms of unconditional individual earnings, further when subdividing workers into college and non-college subgroups, and again when characterizing employment by estimated industry wage premiums.

We first measure the unconditional earnings structure of employment by dividing workers into three earnings terciles, each comprising one-third of earners in 2000. We fix these thresholds in real terms over the ensuing years using the Personal Consumption Expenditure deflator.[21] In 2000, fully 46% of manufacturing workers were in the top tercile of the 2000 earnings distribution, as compared to 31% of non-manufacturing workers (see Table A.2). By 2019, these shares had risen to 54% and 38%, respectively, indicating a further divergence in these sectors. As of 2019, only 13% of manufacturing workers were in the bottom tercile of the year 2000 earnings distribution, as compared to 30% of non-manufacturing workers.

The contrast between manufacturing and non-manufacturing earnings is still more pronounced when workers are subdivided by education. Among non-college manufacturing workers in 2000, 40% were in the unconditional top earnings tercile, while 19% were in the bottom tercile. In non-manufacturing, by comparison, 23% of non-college workers were in the top tercile, with 39% in the bottom. These gaps persisted through 2019. Perhaps surprisingly, the manufacturing/non-manufacturing earnings gaps are even larger for college workers. In 2000, 69% of manufacturing workers with a four-year (or greater) degree were in the highest wage tercile and 13% were in the lowest tercile. Among college workers in non-manufacturing, 47% were in the highest tercile and 29% were in the lowest tercile. These differences were as pronounced in 2019 as they were in 2000.

These simple earnings contrasts do not account for differences in worker characteristics beyond education that may account for earnings differentials between manufacturing and non-manufacturing workers. To more definitively distinguish sectoral wage differentials from unmeasured differences in worker skills, we draw on work by Card et al. (2024), who update classic research by Krueger and Summers (1988) on measuring the inter-industry wage structure. Leveraging modern econometric methods and the vast scale of the LEHD database, Card et al. (2024) provide biased-corrected estimates of industry pay premiums purged of the influence of worker and firm selection.[22] Using estimates from Card et al. (2024), we classify each 4-digit NAICS industry as having either a high or low wage premium based on whether its estimated premium exceeds the employment-weighted average premium for the

[21] Given real earnings growth over these two decades, we expect the share of workers in the upper two terciles to rise between 2000 and 2019.

[22] Industry wage premiums reported in Card et al. (2024) are calculated using averages of estimated firm fixed effects within industries for the period 2010 to 2018, after correcting for selective mobility of workers between low- and high-wage firms. See also Abowd et al. (1999).

U.S. economy. We then impute to each worker the premium corresponding to her industry and subdivide workers into high- and low-wage-premium categories.

Remarkably, more than 84% of manufacturing workers in 2000 were employed in high-premium industries. In non-manufacturing, this share was 39%, less than half as large. Between 2000 and 2019, the high-premium share rose further to 89% in manufacturing, while falling very slightly to 37% in non-manufacturing. One might speculate that primarily college-educated workers cluster in high-premium manufacturing industries while non-college workers populate low-premium manufacturing industries. However, this is not the case. As shown in the bottom row of Figure 2b, the vast majority of both non-college and college manufacturing workers are in high-premium industries. In 2000, these fractions were 83% and 88% respectively, and in 2019, they were 88% and 92%. Conversely, the share of non-college workers in high-premium industries among non-manufacturing workers was 37% in 2000 and 33% in 2019. Among college workers, the corresponding shares were 43% in both 2000 and 2019.

The patterns of Figures 2a and 2b affirm the longstanding perception that manufacturing industries provide relatively high-paid jobs to relatively low-educated workers. In the empirical analysis, we will examine how trade-induced contractions in manufacturing employment in local labor markets causally affect (1) the stock of employment in high-wage jobs and in high-premium industries and (2) the flows of workers across regions, sectors, non-employment status, and earnings and industry wage premium levels. This enables us to assess whether high-wage employment gains ground in other sectors as manufacturing declines, and whether workers exiting manufacturing due to rising import competition: find similarly-paid jobs in other sectors; move instead to lower-paid sectors and lower earnings terciles; or alternatively exit employment altogether.

3.3 Measuring exposure to import competition

Our analytic approach exploits variation across commuting zones (CZs) in their mix of manufacturing industries to measure exposure to rising trade pressure. Following previous literature (Acemoglu et al., 2016; Autor et al., 2021), we define the growth of import penetration by China as perceived by a U.S. commuting zone as the change in import penetration at the U.S. national industry level weighted by initial CZ specialization in an industry. This measure is,

$$\Delta IP_{i,00-07} = \sum_j s_{i,j,00} \Delta IP_{j,00-07} \equiv \sum_j s_{i,j,00} \left(\frac{\Delta M^{cu}_{j,00-07}}{Y_{j,91} + M_{j,91} - X_{j,91}} \right), \quad (1)$$

where $s_{i,j,00} \equiv L_{i,j,00}/L_{i,00}$ is the share of industry j in the employment of CZ i in 2000, and $\Delta IP_{j,00-07}$ is the change in import penetration by China in U.S. industry j over 2000 to 2007. The change in industry import penetration is given by the ratio of the 2000–2007 increase of U.S. industry j imports from China ($\Delta M^{cu}_{j,00-07}$) to U.S. domestic absorption in industry j in 1991 (industry shipments, Y_j, plus imports, M_j, minus exports, X_j).[23]

As documented by Autor et al. (2021), most of the increase in U.S. import penetration by China after 1991 occurred between 2000 and 2007, which spanned the interval from China's accession to the WTO in 2001 to the onset of the global financial crisis in October of 2007.[24] We standardize this measure so that it has a mean of zero and standard deviation of one in the year 2000, weighting by initial employment in the CZ.

U.S. imports may change because of both shocks to U.S. product demand and shocks to foreign product supply (e.g., economic reforms in China). The latter is the external forcing variable of interest whereas the former is a confounder that may positively or negatively affect both domestic employment and import demand simultaneously.[25] Section 3.5 lays out our instrumental variables strategy for isolating the foreign-supply-driven component of the exposure variable from shocks to U.S. product demand. This section characterizes the observed variation.

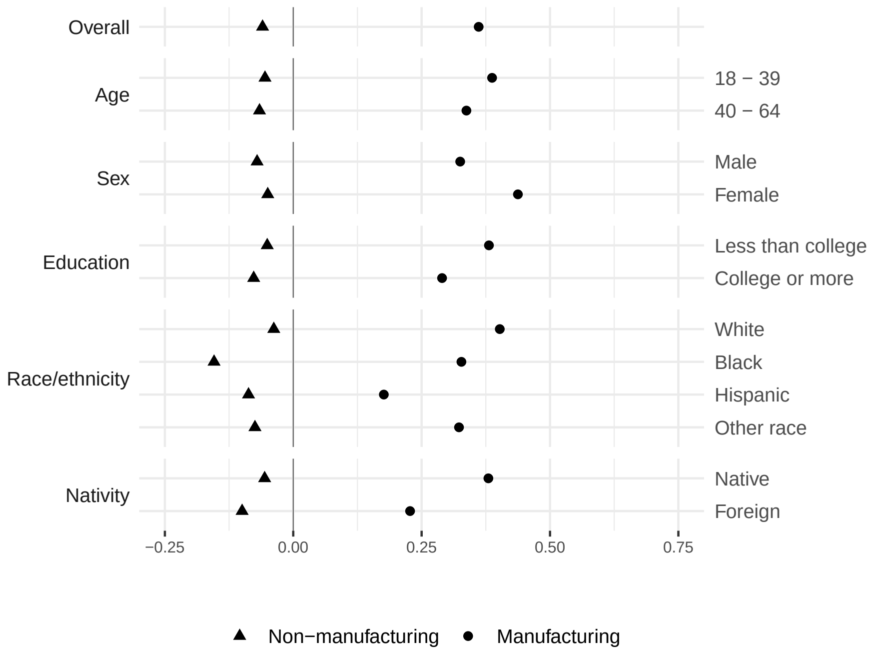
Figure 3 reports the estimated trade exposure calculated at the level of the CZ for workers employed in manufacturing and non-manufacturing in the year 2000, both overall and by demographic, earnings, and industry-premium group. While the exposure measure in equation (1) varies only across CZs, cross-group variation in this measure stems from differences in the demographics, earnings levels, and industry affiliations of workers living in more, versus less, trade-exposed CZs.

[23] We use the variable $\Delta IP_{i,00-07}$ from Autor et al. (2021), which is constructed based on Harmonized System (HS) trade data from UN Comtrade mapped to four-digit Standard Industrial Classification (SIC) industries, industry shipments data from the National Bureau of Economic Research manufacturing productivity database, and local labor market industry employment data from the County Business Patterns. Normalizing expression (1) by 1991 industry absorption rather than 2000 industry absorption addresses the concern that industry absorption in 2000 might be endogenous to the China shock of the 1990s. Acemoglu et al. (2016) and Autor et al. (2021) also adopt this normalization to avert the endogeneity concern.

[24] 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 7.9% in 2007 during the peak period of the China trade shock, and stabilized over the ensuing decade. Autor et al. (2021) find very similar impacts of trade exposure on CZ-level employment outcomes over 2000 to 2019 when using trade shocks defined over the 2000 to 2007, 2000 to 2012, and 2000 to 2014 time periods.

[25] In classical regression terms, the former may be correlated with the disturbance term in equation (5), $\epsilon_{i,t}$.

A. Demographic Groups



B. Earnings Terciles and Industry Premiums

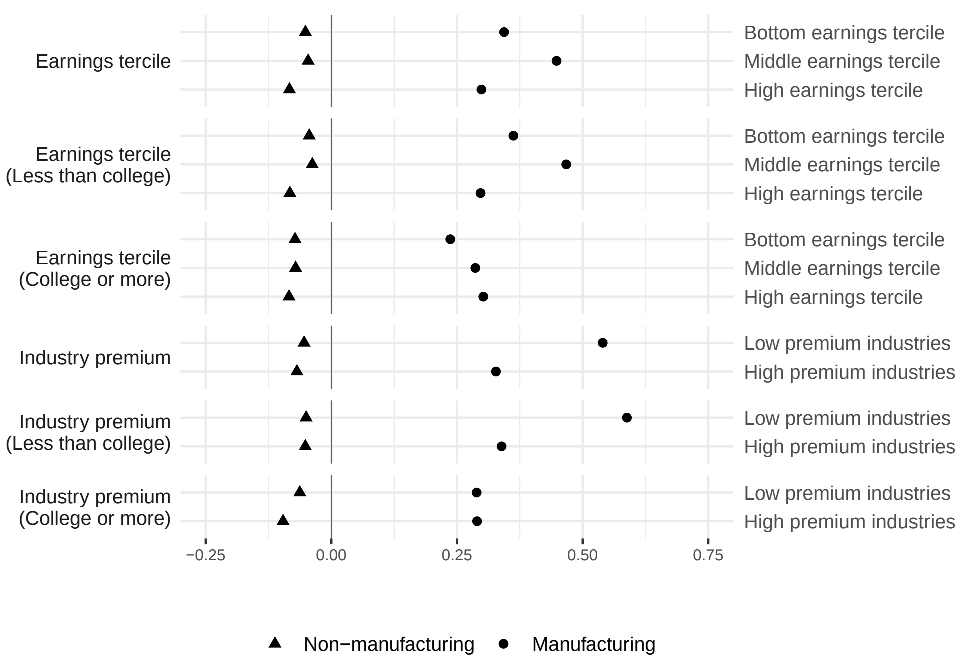


Figure 3: Trade Exposure of Workers Employed in Manufacturing and Non-Manufacturing, 2000.

Notes: This figure reports the average of CZ-level import penetration exposure, $\Delta IP_{i,00-07}$, as defined in equation (1), by demographic, industry, and job characteristics of the worker in 2000. See Table A.4 for values.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

While our trade exposure measure has mean zero by construction, the average manufacturing worker in 2000 lived in a commuting zone with exposure of $+0.36\sigma$, per Table A.4. For non-manufacturing workers, this average was -0.06σ. Figure 3 documents that there is substantial variation in trade exposure among manufacturing workers and minimal variation among non-manufacturing workers. Focusing on the former group, trade exposure is higher among women than men ($+0.44\sigma$ and $+0.33\sigma$); higher among non-college than college workers ($+0.38\sigma$ versus $+0.29\sigma$); higher among white than Black workers ($+0.40\sigma$ versus $+0.33\sigma$); higher among Black than Hispanic workers ($+0.33\sigma$ versus $+0.18\sigma$); and higher among native than foreign-born workers ($+0.38\sigma$ versus $+0.23\sigma$).[26]

Panel B documents that exposure also differs systematically across workers according to earnings levels and industry earnings premiums. Exposure is higher among middle-tercile than either low- or high-tercile manufacturing workers ($+0.47\sigma$, $+0.34\sigma$, and $+0.30\sigma$); higher among non-college than college workers in bottom and middle terciles (non-college low-, middle-, and high-tercile: $+0.36\sigma$, $+0.47\sigma$, and $+0.30\sigma$; college low-, middle-, and high-tercile: $+0.24\sigma$, $+0.29\sigma$, and $+0.30\sigma$); and higher among manufacturing workers in low-premium than high-premium industries ($+0.54\sigma$ versus $+0.33\sigma$). Within education groups, the contrast in exposure between manufacturing workers in low- and high-premium industries is particularly stark. Non-college workers in low- and high-premium industries face sharply different average exposure levels of $+0.59\sigma$ and $+0.34\sigma$, respectively. By contrast, average exposure of college graduates in manufacturing was $+0.29\sigma$ in both low- and high-premium industries. In short, trade exposure in manufacturing is most concentrated among middle-earnings, non-college, native-born workers.

3.4 Estimation framework

We begin by considering the effects of rising import competition on *places*, meaning trade-exposed local labor markets. We measure place effects in terms of net changes in both the quantity of employment and the demographic, sectoral, and earnings composition of employment in a commuting zone. Later, we examine how trade pressure affects the gross worker flows across sectors, locations, earnings levels, and employment status that, in sum, yield these net changes. Using the industry and the location of the employer from the LEHD, we decompose the total employment change in a CZ between 2000 and 2019 as:

[26] Exposure is also relatively high for workers of other race at $+0.32\sigma$, but this group is small and heterogeneous, combining native and foreign-born workers of various and multiple races, making this pattern hard to interpret.

$$\underbrace{\frac{\text{emp}_{cz}^{19} - \text{emp}_{cz}^{00}}{\text{pop}_{cz}^{00}}}_{\text{net emp change}} = \underbrace{\frac{\text{emp}_{\text{mfg in } cz}^{19} - \text{emp}_{\text{mfg in } cz}^{00}}{\text{pop}_{cz}^{00}}}_{\text{net emp change in mfg}} + \underbrace{\frac{\text{emp}_{\text{non-mfg in } cz}^{19} - \text{emp}_{\text{non-mfg in } cz}^{00}}{\text{pop}_{cz}^{00}}}_{\text{net emp change in non-mfg}}, \tag{2}$$

where emp denotes the employment count and pop denotes the population count. We use each component in equation (2) as an outcome $\Delta Y_{i,t}$ (the change in variable Y in commuting zone i over time interval t) in CZ-level regressions, and run corresponding regressions for each subperiod 2000–2001, ..., 2000–2019. Later, we further decompose net job flows into more detailed manufacturing and non-manufacturing subsectors.

In equation (2), we normalize employment changes by the initial working-age population in a CZ, which ensures that our decomposition of job flows between sectors, CZs, job types, and employment states is exact. Importantly, the normalization by initial population means that the impact of trade shocks on the components of equation (2) is not necessarily informative about the impact of these shocks on the employment-to-population ratio, which requires tracking how the denominator changes. If trade exposure also affects net migration (Greenland et al., 2019; Autor et al., 2025), trade-induced changes in net job flows and in the employment-population ratio may not align. To evaluate such alignment, we separately examine impacts of import competition from China on employment-population ratios, as in Autor et al. (2013) and related work. Formally, we decompose the change in the employment-to-population ratio into two terms reflecting the separate contributions of employment changes and population change:

$$\underbrace{\frac{\text{emp}_{cz}^{19}}{\text{pop}_{cz}^{19}} - \frac{\text{emp}_{cz}^{00}}{\text{pop}_{cz}^{00}}}_{\text{change in emp/pop ratio}} = \underbrace{\frac{\text{emp}_{cz}^{19} - \text{emp}_{cz}^{00}}{\text{pop}_{cz}^{00}}}_{\text{net emp change}} + \underbrace{\frac{\text{emp}_{cz}^{19}}{\text{pop}_{cz}^{19}} - \frac{\text{emp}_{cz}^{19}}{\text{pop}_{cz}^{00}}}_{\text{effect of pop change on emp/pop}}. \tag{3}$$

Here, the first term on the right of equation (3) is the net employment change measure from equation (2), reflecting the effect of employment changes, holding population constant. The second term reflects the effect of population changes, holding employment constant. We will evaluate how trade shocks affect each component of equation (3).

While equations (2) and (3) allow us to characterize how *places* are impacted by import competition, they are silent on the *channels* through which labor markets adjust and the *people* who make those adjustments. Over the two-decade analysis window, a substantial share of incumbent workers ages out of the 18–64 age bracket while an even larger number ages in. Simultaneously, workers flow across employment statuses, sectors, and local labor markets (CZs). These underlying trade-induced flows of people cannot be gleaned from changes in net stocks of workers within a place; they must be measured directly.

Building on the approach in Dustmann et al. (2023), we propose to leverage the panel structure of the employer-employee data to track the same workers over time and measure the channels through which their employment statuses change.

In Table 1, we define four channels through which labor market adjustments occur: flows between employment and non-employment, sectoral reallocation, geographic mobility, and aging in and out of the workforce. The effects of import competition on each of these channels sum to the effect on total employment in the local labor market, as shown in the following equation:

$$
\begin{aligned}
\underbrace{\frac{\text{emp}^{19}_{\text{mfg in }cz} - \text{emp}^{00}_{\text{mfg in }cz}}{\text{pop}^{00}_{cz}}}_{\text{net emp change in mfg}} &= \underbrace{\frac{\text{inflow}^{\text{non-employment}}_{\text{mfg in cz, 00-19}} - \text{outflow}^{\text{non-employment}}_{\text{mfg in cz, 00-19}}}{\text{pop}^{00}_{cz}}}_{\text{non-employment channel}} \\
&+ \underbrace{\frac{\text{inflow}^{\text{sectoral}}_{\text{mfg in cz, 00-19}} - \text{outflow}^{\text{sectoral}}_{\text{mfg in cz, 00-19}}}{\text{pop}^{00}_{cz}}}_{\text{sectoral reallocation channel}} \\
&+ \underbrace{\frac{\text{inflow}^{\text{geographic}}_{\text{mfg in cz, 00-19}} - \text{outflow}^{\text{geographic}}_{\text{mfg in cz, 00-19}}}{\text{pop}^{00}_{cz}}}_{\text{geographic mobility channel}} \\
&+ \underbrace{\frac{\text{inflow}^{\text{aging}}_{\text{mfg in cz, 00-19}} - \text{outflow}^{\text{aging}}_{\text{mfg in cz, 00-19}}}{\text{pop}^{00}_{cz}}}_{\text{aging channel}}
\end{aligned}
\tag{4}
$$

The first row of equation (4), which is the non-employment channel in Table 1, summarizes flows of workers in a CZ from non-employment to employment in manufacturing (inflow) and from manufacturing employment into non-employment (outflow).[27] (We provide a par-

[27] To be precise, the movements into non-employment that we observe consist of movements of workers out of our LEHD sample. Workers leaving the sample may transition into being jobless, self-employed, or employed outside of the 43 states in our sample. In an unreported analysis, we use data from IRS Form 1040 to find that the large majority of moves into non-employment as measured in equation (4) are in fact moves into being out of work. Movements from non-employment to employment correspondingly comprise individuals who were non-employed residents of the 43 states of our sample in 2000, and individuals who immigrated from other U.S. territories or from abroad.

allel analysis for non-manufacturing employment.) Since we consider employment only for individuals who are between the ages of 18 and 64 in a given year, we correspondingly define non-employment for the same age range. The 2000–2019 flows between employment and non-employment thus comprise only individuals who were in the age range of 18 to 64 in both 2000 and 2019, whereas individuals who were younger than 18 in 2000 or older than 64 in 2019 are counted toward the aging channel discussed further below. While equation (4) refers to the full outcome period of 2000–2019, we also analyze shorter time intervals from start year 2000 to every end year between 2001 and 2018 to study transitory and permanent transitions in employment status.[28] Temporary flows into non-employment are a common feature of adjustment in models involving nominal wage ridigities, as quantified for the China trade shock by Rodríguez-Clare et al. (2020). Permanent flows into non-employment, which may imply a lasting deterioration in work opportunities or in the attractiveness of work, are a feature of adjustment to trade shocks in Kim and Vogel (2020, 2021).

The second row of equation (4), which is the sectoral reallocation channel in Table 1, summarizes flows of workers (of working age during the start and end year) within a CZ from non-manufacturing into manufacturing (inflow) and from manufacturing into non-manufacturing (outflow). The trade-induced reallocation of labor across sectors has long been a feature of models of international trade. It is, for instance, central to the Stolper-Samuelson Theorem—a core result in the Heckscher-Ohlin trade framework (Feenstra, 2015)—and related recent extensions (Adão et al., 2022), in which changes in relative goods prices lead to changes in relative factor prices within national economies. Modern models of trade, inspired in part by empirical evidence of sizable costs to workers of changing jobs (Artuç et al., 2010; Dix-Carneiro, 2014; Traiberman, 2019), allow for the imperfect mobility of labor across sectors (Adão, 2015). Galle et al. (2023) allow for varying degrees of sectoral mobility in local labor market adjustment in their quantitative model of the China trade shock.[29]

[28] For instance, a worker who held a manufacturing job in 2000 and 2019 but was unemployed in 2010 would count towards the outflow from manufacturing to non-employment over the 2000–2010 period but not over the full 2000–2019 period.

[29] They further experiment quantitatively with allowing for transitions into non-employment (which they treat as akin to home production), finding that the extension has little impact on the estimated welfare consequences of the China trade shock.

Table 1: Inflow and Outflow Concepts for the Manufacturing Sector, 2000-2019

Direction	Notation	Definition
Channel: Non-employment		
Inflow	$\text{inflow}^{\text{non-employment}}_{\text{mfg in cz, 00-19}}$	Number of workers who were non-employed in 2000 and employed in manufacturing in the CZ in 2019.
Outflow	$\text{outflow}^{\text{non-employment}}_{\text{mfg in cz, 00-19}}$	Number of workers who were employed in manufacturing in the CZ in 2000 and non-employed in 2019.
Channel: Sectoral Reallocation		
Inflow	$\text{inflow}^{\text{sectoral}}_{\text{mfg in cz, 00-19}}$	Number of workers who were employed in non-manufacturing in the CZ in 2000 and employed in manufacturing in the same CZ in 2019.
Outflow	$\text{outflow}^{\text{sectoral}}_{\text{mfg in cz, 00-19}}$	Number of workers who were employed in manufacturing in the CZ in 2000 and employed in non-manufacturing in the same CZ in 2019.
Channel: Geographic Mobility		
Inflow	$\text{inflow}^{\text{geographic}}_{\text{mfg in cz, 00-19}}$	Number of workers who were employed in a different CZ in 2000 and employed in manufacturing in the CZ in 2019.
Outflow	$\text{outflow}^{\text{geographic}}_{\text{mfg in cz, 00-19}}$	Number of workers who were employed in manufacturing in the CZ in 2000 and employed in a different CZ in 2019.
Channel: Aging		
Inflow	$\text{inflow}^{\text{aging}}_{\text{mfg in cz, 00-19}}$	Number of workers who were below age 18 in 2000 and became employed in manufacturing in the CZ in 2019.
Outflow	$\text{outflow}^{\text{aging}}_{\text{mfg in cz, 00-19}}$	Number of workers who were employed in manufacturing in the CZ in 2000 and were older than age 64 in 2019.

Notes: Workers who are below the age of 18 in 2000 or above the age of 64 in 2019 are always counted towards the aging channel regardless of their employment status, sector, or location in that year. For analyses of shorter outcome periods with start year 2000 and end year $t = 2001, 2002, ...2018$, the inflow and outflow concepts shown in this table are defined based on an individual's age, location, employment status, and sector in year 2000 and in year t.

The third row of equation (4), which is the geographic mobility channel in Table 1, summarizes flows of workers (of working age during the start and end year) from outside the CZ into manufacturing jobs within a CZ (inflow) and from manufacturing in a CZ to employment in another CZ (outflow). The migration of labor in response to localized shocks has long been thought to be a primary mechanism through which spatial labor market equilibrium is attained (Moretti, 2010; Redding and Rossi-Hansberg, 2017). Long-run geographic labor mobility is prominent, e.g., in the Caliendo et al. (2019) quantitative model of regional adjustment to the China trade shock. As discussed above, recent evidence has reduced optimism about how much outmigration occurs in response to adverse labor demand shocks.

The fourth row of equation (4), which is the aging channel in Table 1, summarizes flows of workers who were below age 18 in 2000 and were employed in manufacturing in a CZ in 2019 (inflow) and of workers who were employed in manufacturing in a CZ in 2000 and who were above age 64 in 2019 (outflow).[30] The aging channel, which can be seen as the generational component of labor market adjustment, accounts for the entry of new generations of youths into the labor market upon attaining working-age, as well as the exit of older generations from the working-age population upon attaining age 65. While the aggregate size of generations aging in and out of the national labor market is largely pre-determined, the entry of youths into particular CZs and sectors reflects individual choices. Such a generational perspective on labor market adjustment to import competition has been largely absent in literature on the consequences of globalization.[31]

3.5 Causal identification

To quantify the impact of import competition from China on flows of workers between sectors, CZs, job types, and employment status, we estimate first-difference models of the form,

$$\Delta Y_{i,t}^{f} = \mu_t + \beta_t \Delta IP_{i,00-07} + \delta_t X_{i,00} + \epsilon_{i,t}. \tag{5}$$

The outcome variable, $\Delta Y_{i,t}^{f}$, is labor flow type f for time interval t in CZ i, where we estimate impacts of trade exposure on net employment, as given by equation (2); employment-

[30] Workers who are below the age of 18 in 2000 or above the age of 64 in 2019 are always counted towards the aging channel regardless of their actual employment status, sector, or location in that year. For example, if a worker was employed in manufacturing at age 17 in year 2000, and employed in non-manufacturing at age 18 in year 2001, this worker would count towards aging inflows into non-manufacturing in year 2001.

[31] See Adão et al. (2024) on intergenerational adjustment to technology shocks in an overlapping generations framework.

population ratios, as given by equation (3); and the labor market adjustment channels, as given by equation (4). To understand the dynamics of market-level and worker-level adjustment to trade shocks, we fit regressions separately for each time period $t = 2000$–$2001, ..., 2000$–2019, as in Autor et al. (2021). Each coefficient in equation (5) thus carries a time subscript. The coefficient β_t captures how the change in import penetration from China for commuting zone i, $\Delta IP_{i,00-07}$, affects labor flows for a CZ. The vector of control variables, $X_{i,00}$, contains Census division fixed-effects as well as the CZ share of employment in manufacturing in 2000 (Borusyak et al., 2022b), such that β_t is identified by the local *mix* of manufacturing industries rather than the overall level of manufacturing employment. Because the outcome variable is a change over time, Census division fixed-effects can be interpreted as controls for region-specific linear time trends. We further verify that the main results are not sensitive to region-specific time trends. All regressions are weighted by employment in the CZ in 2000.[32]

These estimates of the impact of import competition on both places and people should be understood as *relative* effects in two respects: first, since the estimating equation compares outcomes of more-exposed relative to less-exposed CZs and incumbent workers, the comparison intrinsically abstracts from any common effect of trade exposure affecting all places equally (Wolf, 2019); second, and closely related, the regression further abstracts from any potential interactions among, or spillovers between, CZs in their responses to trade shocks. Both of these considerations are potentially important and are carefully explored by Adão et al. (2019a) and Borusyak et al. (2022a).

As discussed above, our trade exposure measure, the growth of import penetration by China between 2000 and 2007 as perceived by a U.S. commuting zone, is calculated as the change in import penetration by industry at the national level weighted by the initial specialization of the CZ in that industry. To identify the foreign-supply-driven component of U.S. imports from China, we follow Autor et al. (2013) and Acemoglu et al. (2016) in instrumenting U.S. import exposure, $\Delta IP^{cu}_{i,00-07}$, using non-U.S. China exposure, $\Delta IP^{co}_{i,00-07}$, which we measure using the industry-level growth of Chinese exports to eight other high-income countries:[33]

$$\Delta IP^{co}_{i,00-07} = \sum_j s_{i,j,90} \Delta IP^{co}_{j,00-07}. \tag{6}$$

[32]Throughout the analysis, we omit the commuting zone that contains Silicon Valley, San Jose-Sunnyvale-Santa Clara. This CZ, which had high exposure to the China shock owing to its substantial computer hardware industry, is an outlier in terms of high-wage employment growth in non-manufacturing.

[33]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.

where $\Delta IP^{co}_{j,00-07} = \Delta M^{co}_{j,00-07}/(Y_{j,88}+M_{j,88}-X_{j,88})$. This expression differs from (1) by using imports by other high-income markets ($\Delta M^{co}_{j,00-07}$) in place of U.S. imports ($\Delta M^{cu}_{j,00-07}$), the 3-year lag of industry absorption ($Y_{j,88} + M_{j,88} - X_{j,88}$) in place of its year 1991 value, and the 10-year lag of CZ industry employment shares, $s_{i,j,90} \equiv L_{i,j,90}/L_{i,90}$, in place of year 2000 values.

Analyses of the China trade shock have used $\Delta IP^{co}_{i,00-07}$ as a shift-share instrument in local labor market regressions (e.g., Autor et al., 2013). 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 Adão et al. (2019b) present a related method for estimating standard errors. Conversely, Goldsmith-Pinkham et al. (2020) study a different setting in which industry shifts are taken as given while initial industry employment shares are assumed to be exogenous.

Based on the framework in Borusyak et al. (2022b), for the instrument, $\Delta IP^{co}_{i,00-07}$, to be orthogonal to the residual, $\epsilon_{i,t}$, in equation (6), it must hold that $\mathbb{E}\left[\sum_j \bar{s}_{j,\tau} \Delta IP^{co}_{j,00-07} \bar{\epsilon}_{j,t}\right] = 0$, where $\bar{s}_{j,\tau}$ is the national employment share of industry j in some pre-period year τ, and $\bar{\epsilon}_{j,t} \equiv \sum_{i'} s_{i',j,\tau}\epsilon_{i',t}/\sum_i s_{i',j,\tau}$ 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 $\Delta IP^{co}_{i,00-07}$ and unobserved shocks $\bar{\epsilon}_{j,t}$ is zero (exogeneity of the shifts), or if the employment shares $s_{i,j,\tau}$ are exogenous and uncorrelated with these shocks (exogeneity of the shares). The substantial industry-level variation in the timing and intensity of the China trade shock documented by Autor et al. (2014, 2021) suggests that our approach is more consistent with assuming shift exogeneity than share exogeneity. To check for orthogonality, Borusyak et al. (2022b) recommend regressing current shocks on past outcomes, which are likely correlated with current residuals. Autor et al. (2013), Acemoglu et al. (2016), Autor et al. (2021), and Borusyak et al. (2022b) perform such validation exercises for CZs and industries and fail to reject orthogonality in the large majority of instances.[34]

[34] See Borusyak et al. (2024) for a recent discussion of the literature.

4 Place Effects: The Effects of Trade Shocks on the Level and Composition of Employment

This section reports estimates of the impact of trade exposure on the quantity and composition of employment within commuting zones. It provides to our knowledge the most granular and comprehensive analysis available of the evolution of both the level and composition of employment in more versus less trade-exposed local labor markets over the nearly two decades after China joined the World Trade Organization in 2001. We underscore that the results in this section document the causal effect of the China trade shock on *places*. Since the set of workers in a place changes considerably over the course of 2000–2019 due to entry and exit from non-employment, cross-CZ and international migration, and aging in and aging out of the labor force, this analysis does not shed light on which workers bear the incidence of manufacturing contraction or subsequent non-manufacturing employment growth. We address those questions in Section 5.

4.1 Employment, population, and industrial composition

We begin in Figure 4 with estimates of equation (5) for the evolution of total employment relative to initial employment in panel A (equation 2) and the employment-to-population ratio in panel B (equation 3) for each year between 2001 and 2019 relative to 2000. For clarity, we suppress standard error bands in the figures. (Figure 9 reports point estimates and standard errors for all impact estimates in this section, found in Figures 4 through 8, for the years 2000–2010 and 2000–2019.)

The two panels of Figure 4 present four key results that frame our subsequent discussion. First, the induced fall in manufacturing employment in trade-exposed CZs that commences with China's post-2000 trade expansion is sizable, persistent, and cumulative. More than 90% of trade-induced manufacturing job losses are concentrated in highly trade-exposed manufacturing subsectors (Figure 5, panel B), referring to the most-exposed third, weighted by employment.[35] A CZ with trade exposure of plus-one standard-deviation ($+1\sigma$) saw an average fall of 0.8 percentage points (pp) in manufacturing employment as a share of initial CZ working-age population between 2000 and 2010. This loss cumulated further to 1.4pp

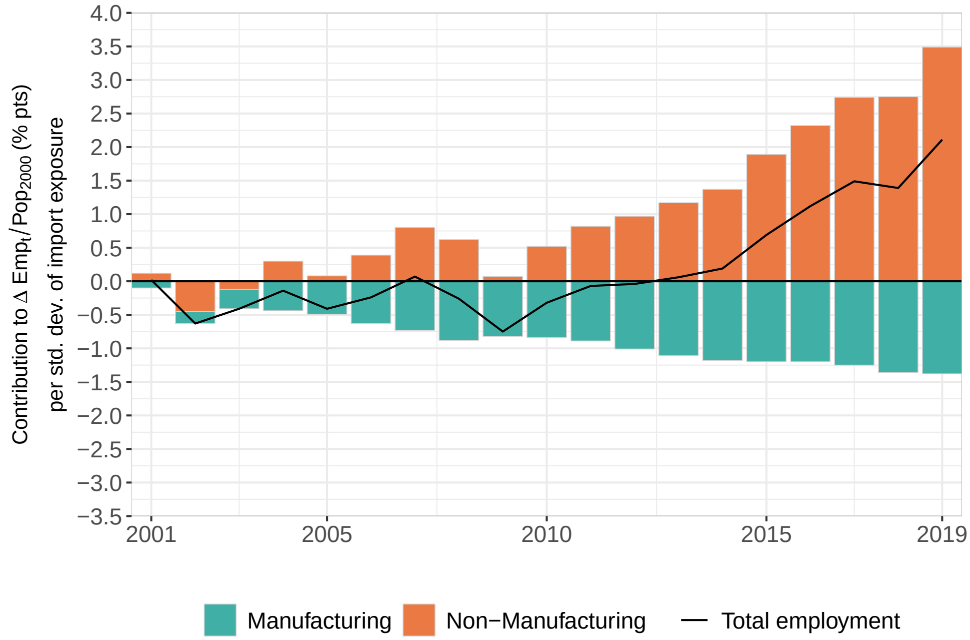
[35] These include: NAICS 313, Textile Mills; NAICS 314, Textile Product Mills; NAICS 315, Apparel; NAICS 316, Leather and Allied Products; NAICS 326, Plastics and Rubber (which includes Plastic Footwear and Toys); NAICS 334, Computer and Electronic Products; NAICS 335, Electrical Equipment, Appliances, and Components; NAICS 337, Furniture; and NAICS 339, Miscellaneous (e.g., games, sports equipment). These industries accounted for 33.2% of all manufacturing employment in 2000 and were, on average, three times as exposed to the China trade shock as the remaining set of less-exposed manufacturing industries.

by 2019. Trade-exposed local labor markets thus see a secular manufacturing employment decline that neither plateaus nor reverses during our outcome window. The effect size is large. Manufacturing comprised 14.2% of employment in 2000 and employed 10.6% of working-age adults. A fall of 1.4pp per $+1\sigma$ of trade exposure is therefore substantial, amounting to the net displacement of one-in-seven manufacturing workers.

A second main result is that growth in non-manufacturing employment in trade-exposed CZs eventually offsets these manufacturing losses, but not for the first decade of the outcome window. Between 2000 and 2010, non-manufacturing employment rises on average by 0.5pp as a share of initial working-age population in CZs at $+1\sigma$ of trade exposure, offsetting approximately 60% of the manufacturing decline. After 2010, however, the growth of non-manufacturing employment in trade-exposed CZs is rapid; by 2019, non-manufacturing employment rises differentially by an average of 3.5pp in CZs at $+1\sigma$ exposure. Thus, a third key finding is that employment per initial working-age population *increases* differentially in trade-exposed CZs, gaining 2.1pp per $+1\sigma$ over the 2000–2019 period. The entirety of this gain accrues between 2011 and 2019, a decade after the onset of the post-2000 trade shock.

The fourth central result, visible in the lower panel of Figure 4, is that the employment-to-population ratio (EPOP) does *not* on average rebound in trade-exposed CZs. One decade into the 21st century, the EPOP is 1.4pp lower on average in CZs at $+1\sigma$ of trade exposure. After 19 years have elapsed, this deficit remains slightly above 1pp. In Figure 4, what accounts for the seeming discrepancy between panel A (rising overall employment in trade-exposed CZs) and panel B (falling EPOP in trade-exposed CZs)? As we will show below, two factors appear paramount. One is that incumbent workers in trade-exposed CZs are significantly less likely to take jobs outside of their initial CZ, which contributes to a relative rise in population in more exposed CZs. More significant still is that trade-exposed CZs see an influx of U.S.-born Hispanic workers and foreign-born non-Hispanic workers, particularly after 2010, many of whom were below working age in 2000, at the outset of our sample. The (eventual) employment rebound in trade-exposed labor markets should be understood not as labor market tightening but rather as growth of the working-age population, leading to sizable employment growth but a modest fall in EPOP among working-age adults.

A. Total Employment



B. Employment-to-Population Ratio

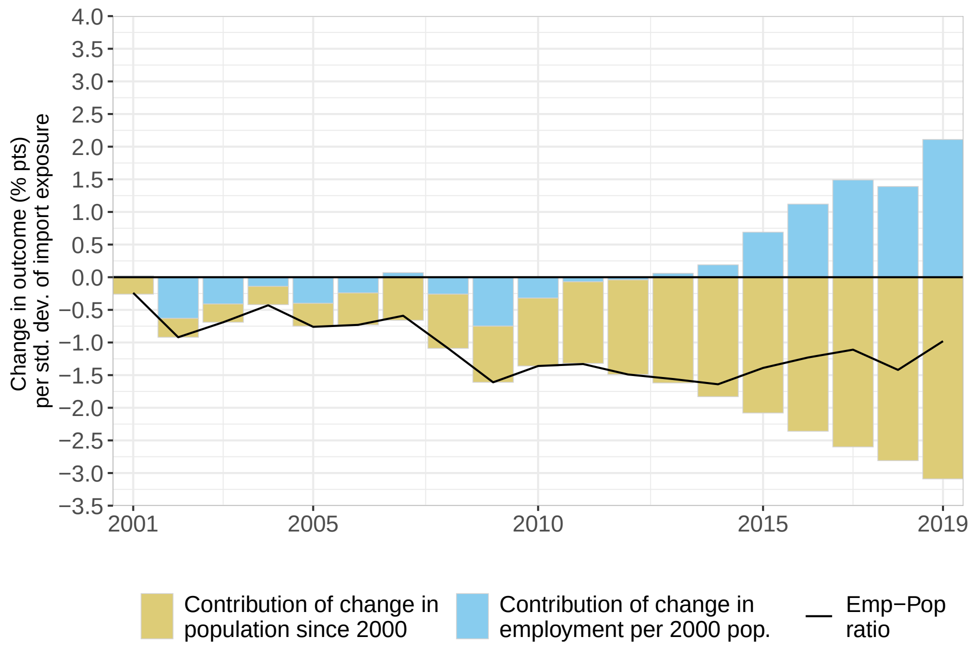
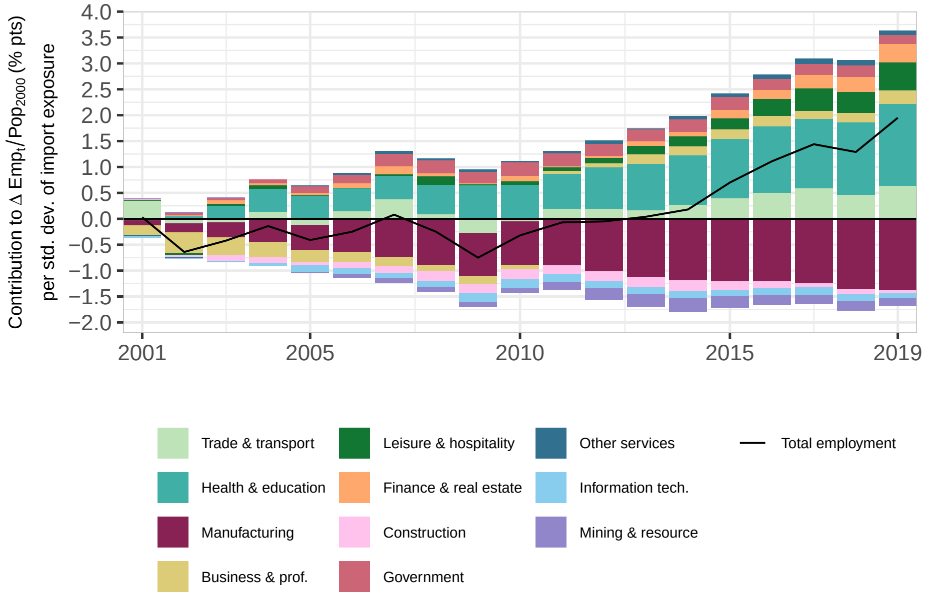


Figure 4: Impact of CZ-Level Trade Exposure on CZ Employment and Employment to Population Ratio.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). In Panel A, the outcome variables are defined using the components in equation (2), and in Panel B, the outcome variables are defined using the components in equation (3). All outcome variables are denominated by the population size of the CZ in 2000. All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

A. Total Employment by Supersector



B. Total Employment for Selected Subsectors, 2019

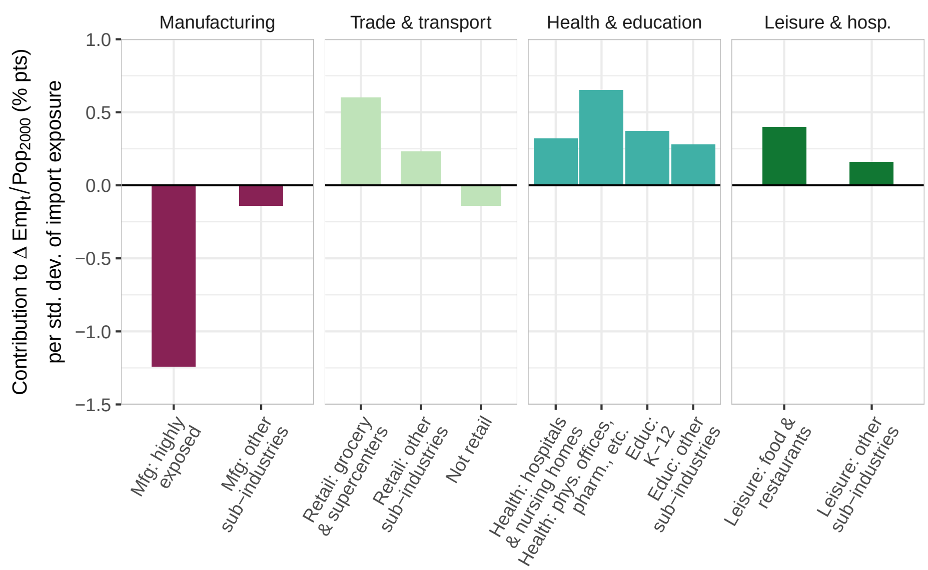


Figure 5: The Impact of CZ-Level Trade Exposure on CZ Employment by Sector and Subsector.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). In panel A, the outcome variable is the change in employment in the CZ between 2000 and the indicated year on the x-axis, divided by the population size of the CZ in 2000, as defined in equation (2). Estimates are reported by supersector and, in panel B, the effect for selected subsectors between 2000 and 2019. All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000. See Figure 15 for estimates by sex. For 2019 point estimates with standard errors by supersector and subsector, see Table A.6 and Table A.7 respectively.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

If not in the manufacturing sector, where does the post-2010 employment rebound in trade-exposed CZs occur? Figure 5 documents that more than half of all gross employment gains accrue to the health and education sectors, particularly physicians offices and pharmacies; hospitals and nursing homes; K-12 education; and other education subsectors. The next largest contributor is retail trade, dominated by grocery stores and supercenters, followed by other retail sub-industries. Finally, leisure and hospitality accounts for the bulk of the remainder, particularly food and restaurants. Unlike the manufacturing industries experiencing employment contractions, these are relatively low-wage-premium industries with relatively few high earners, as our analysis below underscores.

In conjunction with the high resolution of the LEHD data, these aggregate fact patterns provide a compelling opportunity to chart the contours of the transition out of manufacturing in trade-exposed local labor markets: which age, gender, education, race, ethnicity, and nativity groups gain and lose employment; which terciles of the earnings distribution expand and contract; and how the distribution of employment across high- and low-premium industries adjusts. Characterizing these changes is critical to understanding how trade shocks reshape local labor markets. We perform this analysis in two steps, first regarding demographics and second regarding industry composition.

4.2 Changes in the demographic composition of employed workers

To measure the impacts of rising import competition on the demographic composition of places, we estimate the components of equation (2) separately by age, sex, education, race, ethnicity, and nativity of the workers in the CZ. Each outcome is denominated by the initial CZ working-age population in the year 2000, so that the components of each demographic breakdown sum to the total effect seen in Figure 4. We report impacts in percentage point (pp) changes in employment per initial CZ population per $+1\sigma$ of trade exposure, noting as documented in Figure 3 that average exposure differs substantially across demographic groups. The six panels of Figure 6 show estimates. Table A.5 reports point estimates with standard errors. Additionally, Figure 9 summarizes these results by reporting point estimates with standard errors for each outcome over two time intervals, 2000–2010 and 2000–2019.

We begin with two age brackets, ages 18–39 and ages 40–64, as seen in panel A of Figure 6. Whereas the fall in local manufacturing employment induced by the trade shock is roughly evenly borne by younger (18–39) and older (40–64) workers, the subsequent expansion of non-manufacturing employment is dominated by rising employment of workers over age 40. Over the full 2001–2019 time interval, essentially all gross job gains in trade-exposed CZs are accounted for by rising employment of workers ages 40–64. Conversely, all gross losses between 2001 and 2015 are borne by workers 18–39. After 2015, these losses turn to modest gains. These net impacts are large for workers ages 40–64: Relative to the mean CZ, a CZ at $+1\sigma$ exposure is predicted to see a relative increase of 1.6pp in the ratio of employed workers ages 40–64 to initial working-age population. The corresponding effect on employment of workers 18–39 is only 0.4pp. By implication, the average age of workers rose differentially between 2000 and 2019 in more trade-exposed CZs. As we show in Section 5, this net increase in employment of older workers reflects two forces: an induced *decline* in outward geographic mobility of incumbent workers in trade-exposed CZs, leading to a form of "aging-in-place"; and a sharp fall in the inflows into trade-exposed CZs of non-Hispanic white workers who were under age 18 in 2000.

The change in the age structure of employment in trade-exposed CZs coincides with an equally sizable shift in sex composition (panel B). Although the decline in manufacturing employment as a share of initial working-age population was only slightly larger among men than women (0.70pp and 0.68pp respectively per $+1\sigma$ of exposure), both non-manufacturing job gains and aggregate job gains accrued overwhelmingly to women.[36] Of the 2.1pp net relative gain in CZ-level employment as a fraction of initial working-age population per $+1\sigma$ trade shock, 1.54pp accrued to increased employment of women versus 0.57pp to men. Using public-use SEER data on CZ-level working-age population, we find only a modest decline of 0.4% in the male relative to female working-age population in CZs with $+1\sigma$ greater trade exposure, implying that the differential growth in female employment primarily reflects a differential rise in women's employment-to-population ratios rather than a shift in the gender composition of residents. The relative and absolute rise in female employment stems entirely from differential increases in employment of women in non-manufacturing.[37]

[36]The fact that males made up 68% of manufacturing employment in 2000 (Figure 2a), and yet trade-induced manufacturing losses were almost evenly split across sexes, means that the incidence of declining manufacturing fell disproportionately on women. This pattern, also reported in Autor et al. (2019), partly reflects the outsized collapse of the textile sector, which disproportionately employed women.

[37]In Section 5.2, we provide a detailed analysis of the subsectors in which males and females gain employment.

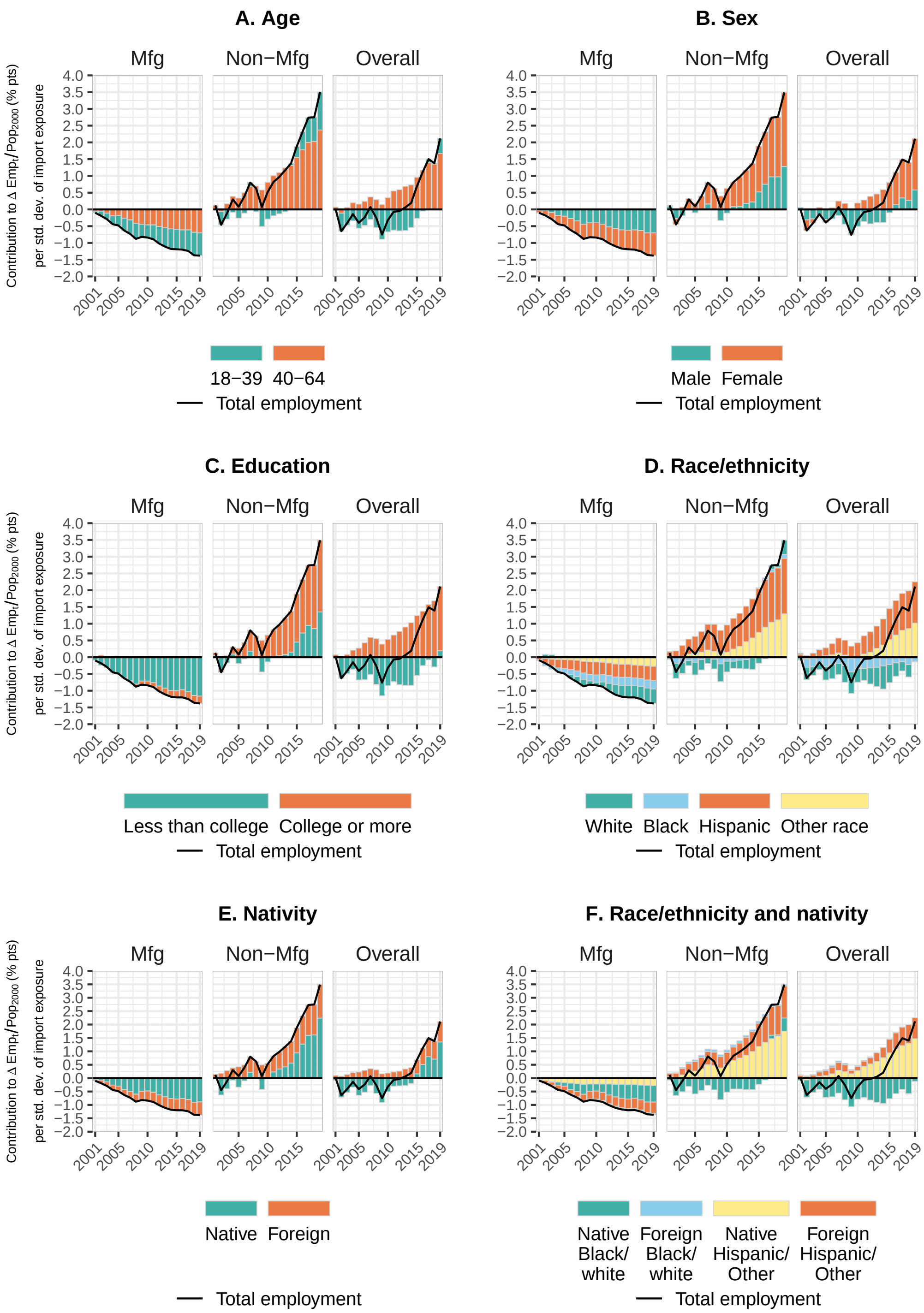


Figure 6: The Impact of CZ-Level Trade Exposure on CZ Employment by Age, Sex, Education, Race/Ethnicity, Nativity, and Race/Ethnicity × Nativity.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). Estimates are shown by age, sex, education, race/ethnicity, nativity, and race/ethnicity × nativity. The outcome variable is the change in employment in the CZ between 2000 and the indicated year on the x-axis, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000. See Table A.5 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

The reconstitution of the educational composition of employment in trade-exposed CZs is at least as pronounced as the change in sex composition, as shown in panel C of Figure 6. Almost the entirety of the 1.4pp relative decline in manufacturing per $+1\sigma$ of trade exposure is accounted for by a loss of non-college employment, and these losses are not offset by gains in the non-manufacturing sector. Between 2000 and 2019, 60% of the gain in non-manufacturing employment in more trade-exposed ($+1\sigma$) CZs accrued to college graduates (2.1pp of 3.5pp). Summing over the manufacturing and non-manufacturing sectors, more than 95% of trade-induced net job additions are found among college graduates. Moreover, for the bulk of the two-decade outcome window, there is essentially no rebound of non-college employment. The non-college employment recovery in trade-exposed CZs, commencing in 2015, took almost one-and-a-half decades to materialize. Nevertheless, by 2019, employment of non-college workers (as a share of the initial population) had fully re-converged between more and less trade-exposed CZs. Simultaneously, the balance of employment had substantially shifted towards college-educated workers.

The next three panels of Figure 6 report changes in CZ-level employment by race, ethnicity, and nativity that emanate from the China trade shock. While, similar to gender, trade-induced losses in manufacturing employment are distributed roughly evenly across race and ethnicity groups, this is not the case for non-manufacturing gains. Both white and Black employment remain depressed relative to initial working-age population in trade-exposed CZs out to 2019. Accordingly, the gradual offset of manufacturing job losses by gains in non-manufacturing is entirely accounted for by employment growth among two groups: Hispanics of any race and non-Hispanics of other race (primarily Asians). Panel E reveals that about two-thirds of these offsetting gains accrue to native-born U.S. workers, with the remaining third accounted for by foreign-born workers. Panel F puts these pieces together, documenting that the large net gains in both foreign-born employment and native-born employment are accounted for by Hispanic and other-race workers.

To probe these stark changes in the education, race, ethnicity, and nativity of workers in trade-exposed CZs, Figures 7a and 7b further subdivide these impacts into subgroups defined by education $\times$ nativity $\times$ race/ethnicity. Figure 7a reveals that the entire incidence of trade-induced employment declines was borne by non-Hispanic white and Black, native-born, non-college adults. There are no net employment declines among native-born Hispanics or among foreign-born adults of any race or ethnicity. The fall in native non-college Black employment as a share of initial working-age adult population is remarkably large. Black workers comprise only 9% of manufacturing employment and 11% of non-manufacturing employment in 2000, while the corresponding shares for white workers are several times larger at 69% and 62%, respectively (Table A.3).[38] Despite these vast differences in representation, and bearing in mind that all net job losses are among non-college workers, the share of net employment losses accounted for by non-college Black workers are nearly as large as the share due to non-college white workers.[39] Thus, native-born Black workers absorb a large share of trade-induced job losses, as first reported in Kahn et al. (2022). In Section 5, we will probe these patterns further.

Given that employment relative to initial CZ-populations rises eventually (after 2010) in relatively trade-impacted CZs, these large absolute employment losses among non-college Black and white workers imply even larger gains among other groups. As documented in Figure 7b, three demographic groups accounted for essentially the entire employment increase in trade-exposed CZs: non-college, native-born Hispanics (a 0.85pp gain per $+1\sigma$ exposure); college-educated, native-born Hispanics (a 0.50pp gain per $+1\sigma$ exposure, per Table A.8); and college-educated, foreign-born other-race workers (a 0.82pp gain per $+1\sigma$ exposure).

In sum, although employment more than fully rebounds in trade-exposed local labor markets, the demographic groups on the upside of that rebound are distinct from those on the downside. Almost all net employment declines are borne by native-born non-college white and Black workers. Almost all net employment gains accrue to college-educated workers, female workers, and workers who were either native-born Hispanics or foreign-born other-race workers (primarily Asian). Section 5 unpacks this transformation by tracking flows of workers across sectors, locations, employment statuses, and countries. Beforehand, we consider how the trade shock reshapes earnings structures in exposed labor markets.

[38]See Borjas and Ramey (1995) for evidence on the differentially adverse impact of trade shocks in the 1980s on the relative employment of Black workers.

[39]The corresponding shares for Hispanics are 12% and 11% respectively; and for foreign-born, 12% and 9%, respectively.

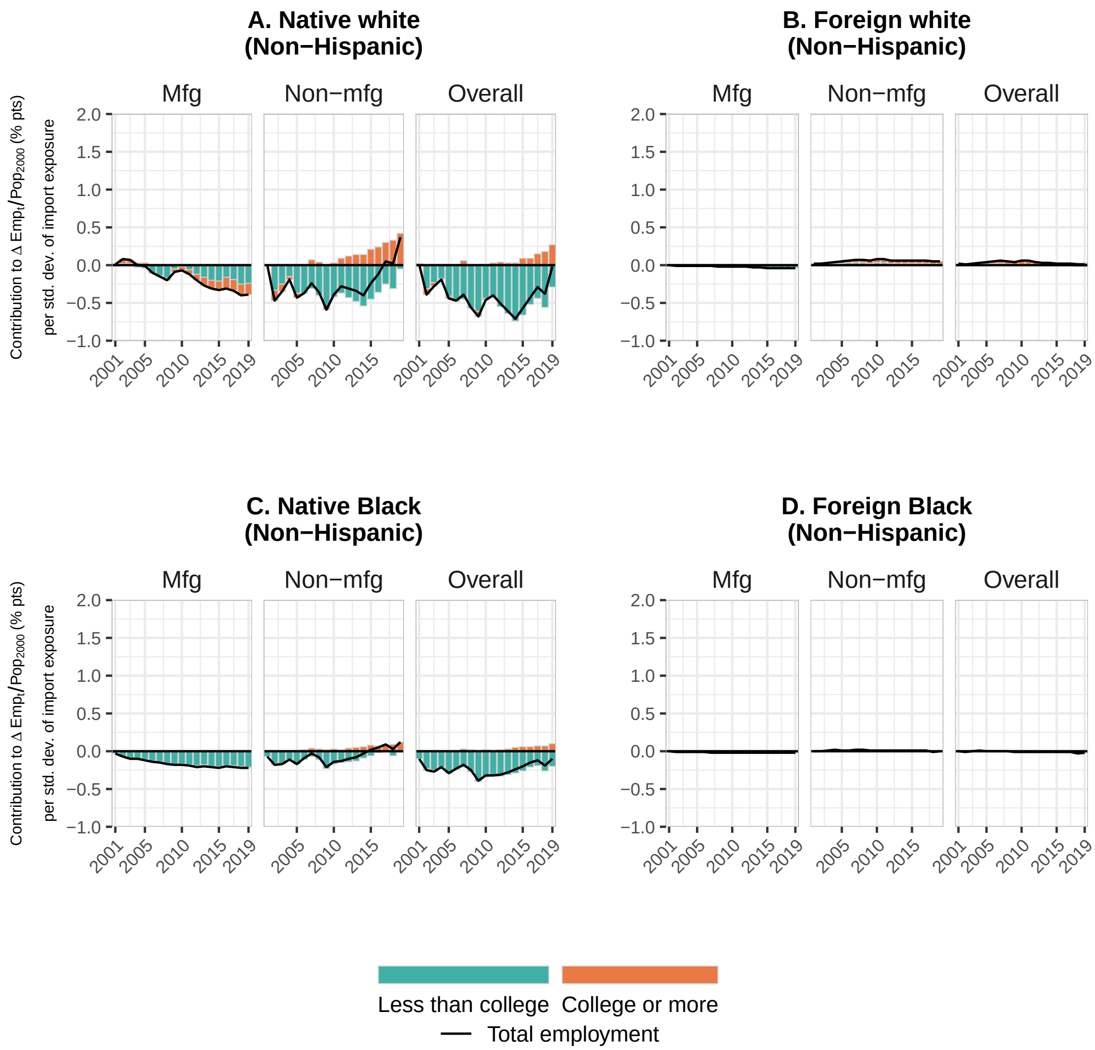


Figure 7a: The Impact of CZ-Level Trade Exposure on CZ Employment by Education, Race/Ethnicity, and Nativity: Non-Hispanic White and Black.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). Estimates are shown by education for race/ethnicity-by-nativity combinations: native Hispanic, foreign Hispanic, native other race, and foreign other race. See the text for definitions of race/ethnicity categories. The outcome variable is the change in employment in the CZ between 2000 and the indicated year on the x-axis, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000. See Table A.8 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

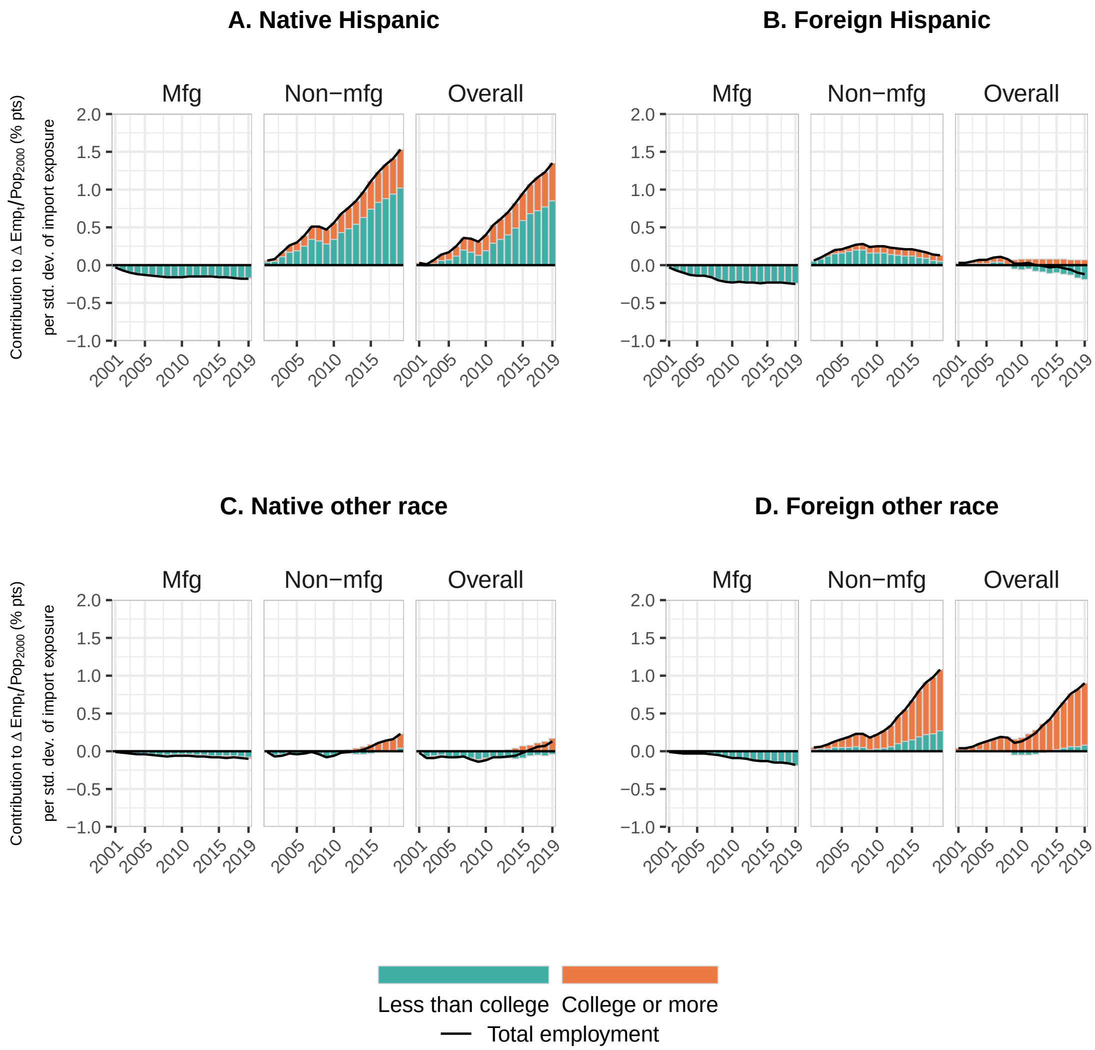


Figure 7b: The Impact of CZ-Level Trade Exposure on CZ Employment by Education, Race/Ethnicity, and Nativity: Hispanic and Other Race.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). Estimates are shown by education for race/ethnicity-by-nativity combinations: native Hispanic, foreign Hispanic, native other race, and foreign other race. See the text for definitions of race/ethnicity categories. The outcome variable is the change in employment in the CZ between 2000 and the indicated year on the x-axis, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000. See Table A.8 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

4.3 Changes in earnings and industry composition

Manufacturing workers are disproportionately found at higher earnings terciles. While this pattern could simply reflect their higher skill levels, both classic and recent literature (Krugman, 2008; Card et al., 2024) document that, among the set of industries that pay above-mean wage premiums to their workers, manufacturing industries are heavily overrepresented, as seen in Figure 2b. We explore whether, by placing pressure on manufacturing employment, trade exposure erodes earnings structures in affected CZs. Specifically, we fit equation (5) to data on the evolution of CZ-level employment by earnings tercile and industry premium, overall and by education, between 2000 and 2019. Figure 8 presents these results.

Panel A of Figure 8 shows that most trade-induced job reductions in manufacturing reflect a loss of mid- and high-earnings jobs. Of the 1.38pp fall in manufacturing employment per working-age population per $+1\sigma$ trade exposure, more than 80% reflects a loss of middle-tercile (-0.57pp) and high-tercile employment (-0.58pp), with the remainder (-0.23pp, 17%) in low-tercile employment. The loss of middle- and high-tercile jobs in manufacturing is consistent with the initial earnings distribution of manufacturing employment: as shown in Figure 2b, only 18% of manufacturing workers were in the lowest earning tercile in 2000.

By contrast, jobs that comprise the eventual employment rebound in trade-exposed CZs are disproportionately found at low earnings terciles. Of the 3.5pp increase in non-manufacturing employment per $+1\sigma$ of exposure that results over the next two decades, 44% accrues to low-tercile employment, 36% to mid-tercile employment, and only 20% to high-tercile employment. Summing across manufacturing and non-manufacturing sectors, low-tercile jobs account for 62% of the 2.1pp net employment gain per $+1\sigma$ trade exposure, with 32% accounted for by mid-tercile jobs, and only 6% by high-tercile jobs. Trade-exposed CZs suffer a substantial deterioration in average job quality, even as overall employment expands.

These changes in the earnings distribution in trade-exposed CZs could potentially reflect a compositional shift towards lower-educated, lower-paid non-college workers. Panels B and C of Figure 8 indicate that the opposite is the case. As shown in Panel B, almost the entirety of the manufacturing job loss in trade-exposed locations reflects a decline in non-college manufacturing employment, and almost all of that decline is in middle-tercile and, to a lesser extent, high-tercile employment. Summing across manufacturing and non-manufacturing sectors, there is a substantial net loss in high-tercile employment among non-college workers in trade-exposed CZs. The modest positive net employment gains among non-college workers after 2015 accrue almost entirely to low-tercile employment. Conversely, there is no meaningful decline in employment of college-educated workers in manufacturing in trade-exposed CZs (panel C), while the ensuing rise in non-manufacturing employment of college-educated workers is sizable. Moreover, the majority of this net gain (54%) is in high-tercile employment. By implication, the *lack* of a net change in high-tercile employment in trade-exposed CZs (panel A) reflects the offsetting effects of a sharp fall in high-tercile employment among non-college workers and a contemporaneous rise in high-tercile employment among college-educated workers, indicating substantial churn in CZ earnings distributions.

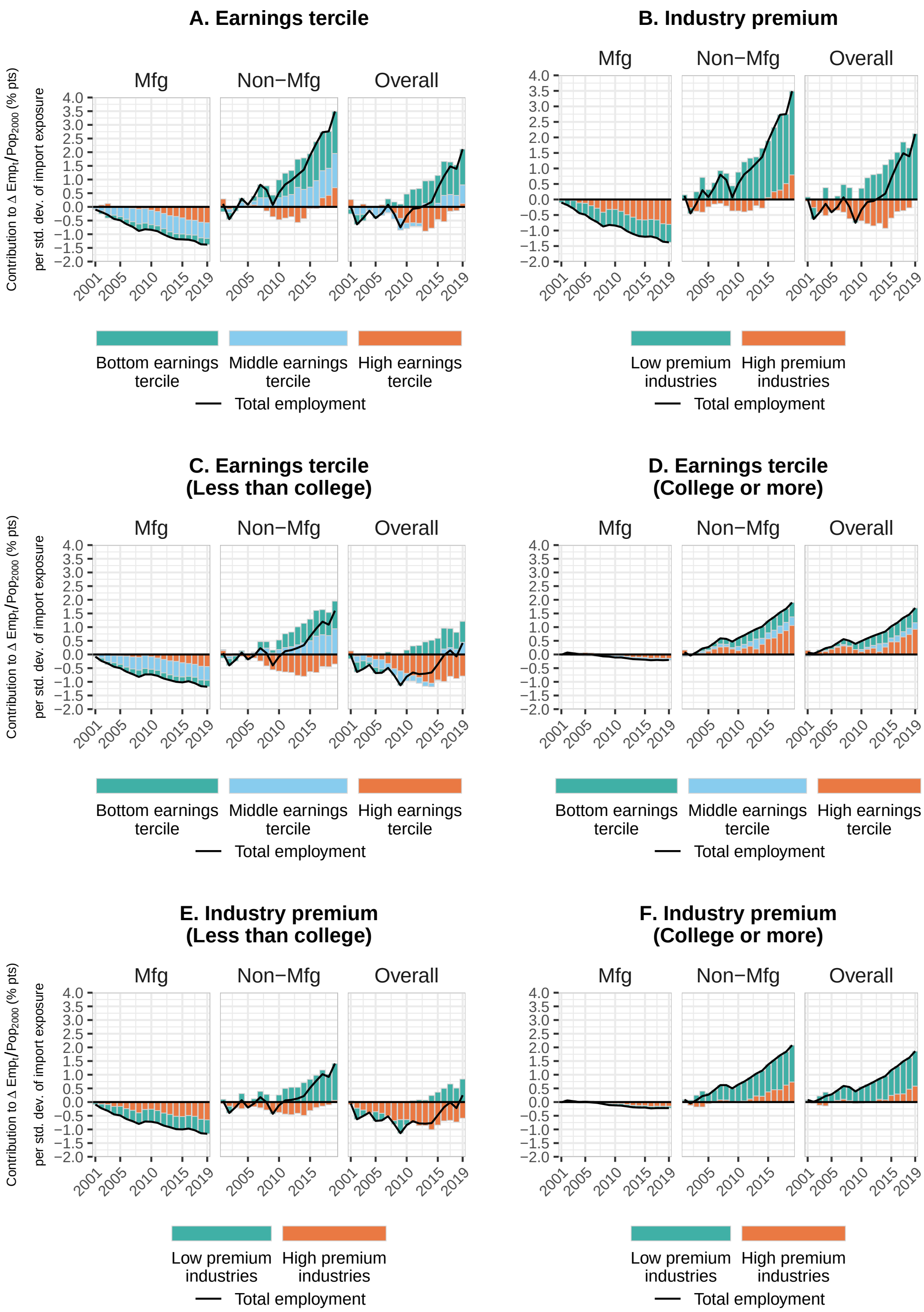


Figure 8: The Impact of CZ-Level Trade Exposure on CZ Employment by Earnings Tercile and Industry Premium.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). Estimates are shown by earnings tercile, industry premium, and educational attainment, as defined in the text. The outcome variable is the change in employment in the CZ between 2000 and the indicated year on the x-axis, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000. See Table A.9 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

Although the educational composition of employment in trade-exposed labor markets shifts substantially towards college-educated workers after 2000, our estimates do not preclude the possibility that the observed downward shift in earnings distributions reflects in part adverse selection of low-productivity college graduates into trade-exposed locations. As a measure of wage change that is free from demographic effects, panels B, E, and F of Figure 8 report estimates of the impact of trade exposure on employment in high- and low-premium *industries*.

Nearly 60% of the decline in manufacturing employed in trade-exposed CZs reflects a net job loss in high-premium industries. Conversely, 77% of the corresponding growth in non-manufacturing employment in trade-exposed CZs is in low-premium sectors. Across all sectors, all net employment growth in trade-exposed CZs occurs in low-premium industries. Focusing on changes in the industrial structure of non-college and college employment amplifies this conclusion. Each $+1\sigma$ of trade exposure reduces high-premium non-college employment by 0.59pp and raises low-premium non-college employment by 0.84pp. Conversely, each $+1\sigma$ of trade exposure raises low-premium college employment by 1.28pp and high-premium college employment by 0.58pp. Thus, to the degree that trade-exposed CZs see net gains in high-premium employment, it occurs among college-educated workers only. Non-college employment falls in high-premium industries and rises in low-premium industries.

Figure 9, which summarizes the impact estimates reported in Figures 4 through 8 (adding standard errors), underscores the following results: Manufacturing employment losses in trade-exposed CZs accumulate throughout the entirety of our outcome window, accompanied by large, enduring declines in employment-to-population ratios. Nevertheless, these same CZs experience differential employment growth relative to *initial* population, where this growth is driven entirely by rising non-manufacturing employment. Employment growth in these CZs over-represents older workers, college graduates, women, Hispanics, members of races other than white and Black, and foreign-born residents. These gains are concentrated in low-paid employment and in low-premium sectors. Measured either by the evolution of employment across earnings terciles or between high- and low-premium industries, shifts in the earnings composition of non-college employment in trade-exposed CZs are largely unfavorable. Conversely, employment of college graduates grows at all earnings terciles and in both low- and high-premium industries.

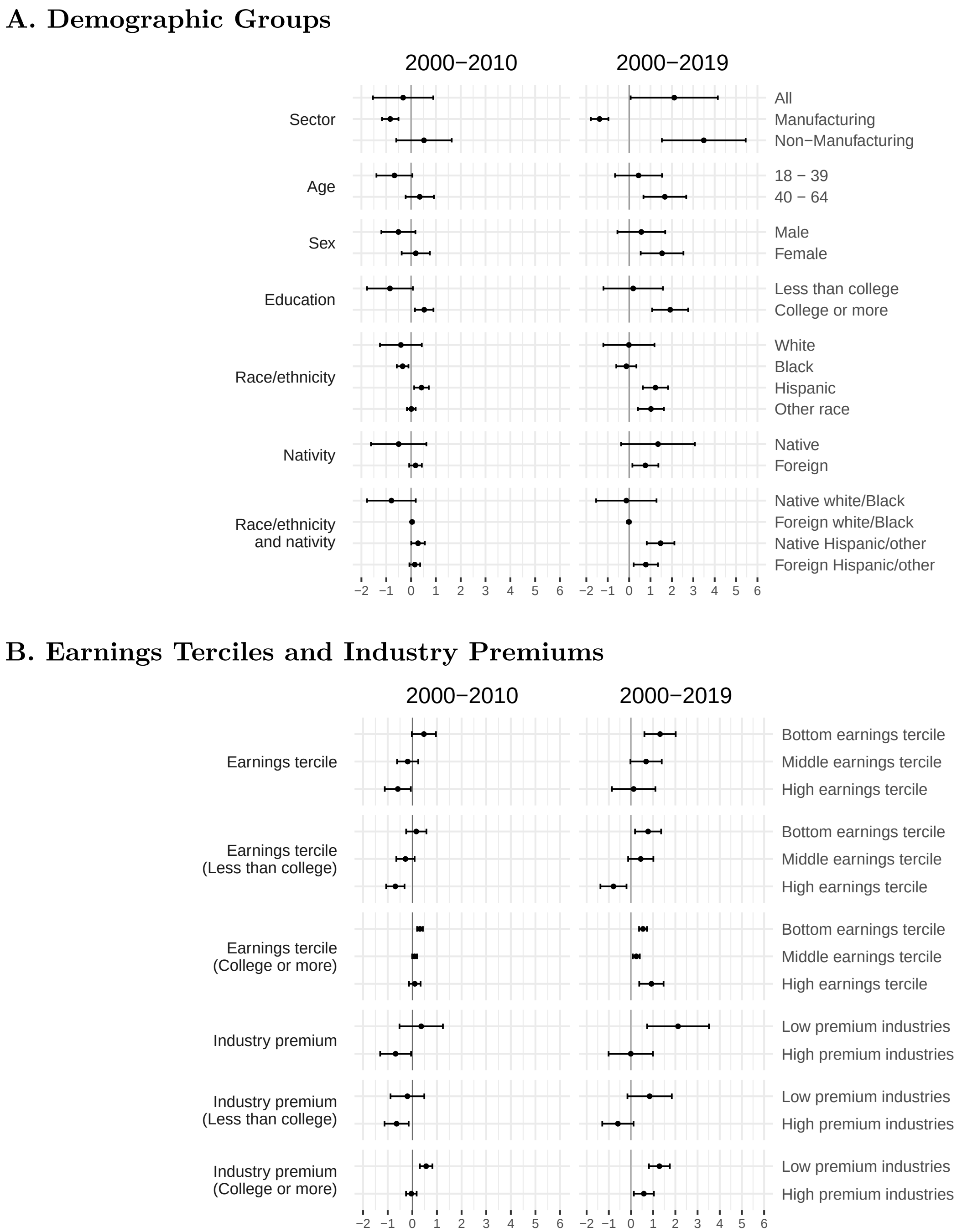


Figure 9: The Impact of CZ-Level Trade Exposure on CZ Employment by Demographic, Earnings Tercile, and Industry Premium.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). Horizontal bars display ±1.96 standard errors. The outcome variable is the change in employment in the CZ between 2000 and the indicated year in 2010 and 2019, for each column respectively, divided by the population size of the CZ in 2000, as defined in equation (2). The employment to population ratio outcome in panel A is defined in equation (3). See Table A.10 for point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

Our results connect to recent quantitative analyses of the long-run consequences of the China trade shock. The enduring negative impacts of the China trade shock on manufacturing employment in trade-exposed CZs would seem to sit uneasily with results showing that on net globalization led to an expansion of U.S. manufacturing employment in the 2000s (e.g., Feenstra et al. 2019). To generate such gains, the general equilibrium impacts of globalization would have to be consistent with an overall decline in U.S. manufacturing employment. Galle et al. (2023) highlight adverse welfare impacts of the China trade shock on workers in exposed sectors and regions, broadly in line with our results. Yet, it is still uncommon for quantitative models to differentiate among workers beyond their initial sector and region. The concentrated impacts of import penetration by China on the employment of non-college native-born white workers, for instance, may partially account for the documented connection between regional trade exposure and greater support for political extremism, especially on the right (Colantone and Stanig, 2018a,b; Autor et al., 2020). Allowing for greater worker heterogeneity would potentially enrich quantitative trade models (akin perhaps to the analytical insights gained from introducing firm heterogeneity).

5 People Effects: The Ins and Outs of Local Labor Market Adjustment to Trade

The results in Section 4 document how the count and composition of jobs in local labor markets adjust to sharp changes in competitive conditions emanating from rising trade pressure. They do not, however, inform the question of how workers adjust to these same pressures. Over the two-decade analysis window, a substantial share of incumbent workers ages out of the 18–64 age bracket while an even larger number ages in. Simultaneously, workers flow across employment statuses, sectors, and local labor markets (CZs). These underlying trade-induced flows of people cannot be gleaned from changes in net stocks of workers within a place; they must be measured directly.

We perform this measurement by leveraging the panel structure of the employer-employee data to track the "ins and outs" of worker flows along the four dimensions enumerated in Table 1: flows between employment and non-employment; flows across sectors; flows between places (i.e., local labor markets, across borders); and flows into and out of the 18–64 age bracket. Since the effect of import competition on each of these channels sums to the net effect on total employment in each market (equation 4), this analysis provides an exact decomposition of the sources of the net employment changes described above.

Analysis of the flows of people across and within trade-exposed locations yields three key sets of results, which we summarize briefly before elucidating them in detail.

1. **Expected margins of adjustment**

   - Consistent with the assumptions of a large literature, trade pressure reshapes the flow of workers across places. Yet, these flow responses are opposite to expectations. Refuting the notion that worker out-mobility is an important margin of adjustment, workers in trade-exposed CZs become *less likely* to take jobs outside of their initial CZs. Simultaneously, workers employed in other locations become less likely to enter trade-exposed CZs. Reductions in both geographic inflows and outflows are driven by the mobility responses of native-born whites and Blacks, as well as by non-college workers.

   - Surprisingly, a second anticipated margin of adjustment, worker reallocation from manufacturing to non-manufacturing, also plays a comparatively minor role. Less than 15% of the trade-induced fall in manufacturing employment—and less than 6% of the growth in non-manufacturing employment—between 2000 and 2019 reflects reallocation of workers from manufacturing.

   - A third expected margin of adjustment, outflows of incumbent workers to non-employment in trade-exposed CZs also makes a modest net contribution to employment change—smaller, for example, than the contribution of declining cross-CZ inflows of workers from other CZs. Most incumbents transitioning to non-employment exit from non-manufacturing rather than from manufacturing.

2. **Unexpected margins of adjustment**

   - The strong employment rebound in trade-exposed local labor markets that commences after 2010 derives almost entirely from two unexpected sources: inflows into trade-exposed CZs of young adults who were below working age at the time of China's WTO accession; and entry of foreign-born workers who were already of working age in 2000 but who obtain their first (recorded) U.S. job in trade-exposed locations after 2000.

   - These new entrants (both young and adult) are demographically distinct from incumbents: they are substantially more likely to be native-born Hispanics, foreign-born immigrants, women, and college-educated. Conversely, the long-run decline in manufacturing employment in trade-exposed locations operates mostly through reduced entry of young, native-born, white, non-college-educated men.

   - The combination of falling out-migration of initial CZ incumbent workers and rising inflows of young native-born Hispanics, foreign-born adults, women, and non-college workers, means that the workforce demographics of trade-exposed CZs shift strongly away from modal manufacturing incumbents, who are white, native-born, non-college-educated men.

3. **Changes in earnings structure**

   - The shift towards low-wage employment and low-premium industries in trade-exposed commuting zones reflects changes in both the allocation of new entrants and the trajectories of incumbents.

- Newly working-age adults entering trade-exposed labor markets flow differentially into low-premium sectors. Simultaneously, incumbent workers in these locations who are initially found in low-paid employment and in low-premium industries become significantly less likely to out-migrate to other regions or transition upwards to high-tercile earnings or high-premium industries.
- Conversely, workers who are initially in mid-tercile employment and employed in high-premium sectors become more likely to transition downward to low-tercile employment and low-premium sectors.

5.1 Aggregate flows

Figure 10 enumerates the contribution of each component of equation (4)—flows between employment and non-employment, flows across sectors, flows between places (i.e., local labor markets, across borders), and flows into and out of the 18–64 age bracket—to the overall trade-induced change in employment in local labor markets. Table A.11 displays each flow's 2019 point estimate and standard error. We first summarize these aggregate patterns in this subsection. Section 5.2 documents how these aggregates reflect the distinct (and often countervailing) responses of different demographic groups defined by nativity, race and ethnicity, gender, and education. Section 5.3 then characterizes how trade pressure reshapes the quality of jobs by analyzing worker flows among earnings terciles and across low-premium and high-premium industries.

Worker mobility across commuting zones

A foundational assumption of research on labor market adjustment to globalization is that workers facing adverse shocks to local employment will tend to relocate to less-exposed labor markets, which serves to maintain spatial economic equilibrium (Redding and Rossi-Hansberg, 2017; Redding, 2020).[40] In the case of the China trade shock to U.S. labor markets, we find that the opposite is true: workers in trade-exposed CZs become *less likely* to take jobs outside of their initial CZs. The positive coefficients of the dark blue series in Figure 10, and corresponding Table A.11, indicate a larger number of incumbent workers remaining in their CZs.[41] Within the first two years of the onset of a $+1\sigma$ trade shock, worker

[40]By construction, the average CZ-level trade shock in our sample is zero. Hence, any worker employed in a CZ with a positive shock is by definition facing an above average shock.

[41]Throughout Figure 10, positive bars indicate employment gains that result either from greater inflows to employment or reduced outflows from employment. Negative bars indicate employment losses due to

outflows to other-CZ employment decline by 0.4pp to 0.6pp as a share of initial working-age population. The reduction in outflows endures for approximately a decade, after which it begins to attenuate. By the end of the outcome window in 2019, cumulative gross migration outflows from trade-exposed CZs remain 0.29pp *lower* per $+1\sigma$ exposure.[42]

Ironically, the migration response to rising trade exposure *does* reduce employment in trade-exposed commuting zones—not however by spurring out-migration but instead by deterring in-migration of workers from other CZs. As shown in the light blue series in Figure 10, each $+1\sigma$ trade exposure is estimated to reduce the *inflow* of workers into trade-exposed CZs by approximately 0.6pp between 2000 and 2019. Distinct from what we observe for outflows, this effect builds for almost a decade and is highly persistent: a decade after onset, worker inflows to trade-exposed CZs have fallen by 1pp per $+1\sigma$ exposure; two decades after onset, gross inflows are depressed by 0.58pp. Since each $+1\sigma$ exposure also deters cross-CZ incumbent outflows by 0.29pp, the net cross-CZ worker flow effect reduces local employment by -0.29pp between 2000 and 2019 ($-0.58\text{pp} + 0.29\text{pp}$).

While it is not surprising that worker inflows into CZs undergoing adverse shocks decline (see e.g., Howard 2020), what explains the decline in outflows? One explanation is that financial constraints and (or) strong local kinship and friendship ties inhibit workers who are affected by trade shocks from moving fluidly across locations (Koenen and Johnston, 2024; Zabek, 2024). A second is that the structure of transfer payments, combined with trade-induced falls in the local cost of living, provide displaced workers with an incentive to remain in their original location (Notowidigdo, 2020b). A third is that the alternative locations in which trade-affected workers might potentially seek new employment are adversely trade-affected simultaneously, and hence do not offer an attractive outside option (Borusyak et al., 2022a).

Our evidence does not directly adjudicate among these explanations, but it offers a related insight. The fact that trade exposure persistently reduces inward mobility confirms that shocks reduce outward mobility from other locations by deterring would-be entrants from migrating to adversely-affected labor markets.[43] This is potentially consistent with Borusyak et al. (2022a), who hypothesize that workers are deterred from leaving trade-impacted locations by simultaneous adverse shocks to their potential destination locations. Our analysis

increased outflows from employment or lower inflows to employment.

[42] Consistent with the lower outwards mobility shown here, Autor et al. (2014) find that workers exposed to Chinese import competition become less likely to generate earnings from employers outside their initial CZ.

[43] Similarly, in their study of how native employment responded to an increase in immigrants in Germany, Dustmann et al. (2023) find that it is reduced inflows of natives to exposed regions, rather than increased outflows of natives from exposed regions, that explains most of the change in native employment in exposed regions.

does not, however, reveal *where* these entrants would have come from absent the trade shock—from otherwise trade-exposed CZs (as per Borusyak et al. 2022a), from abroad, or from CZs that are neither more nor less trade-exposed. This subject merits further study.

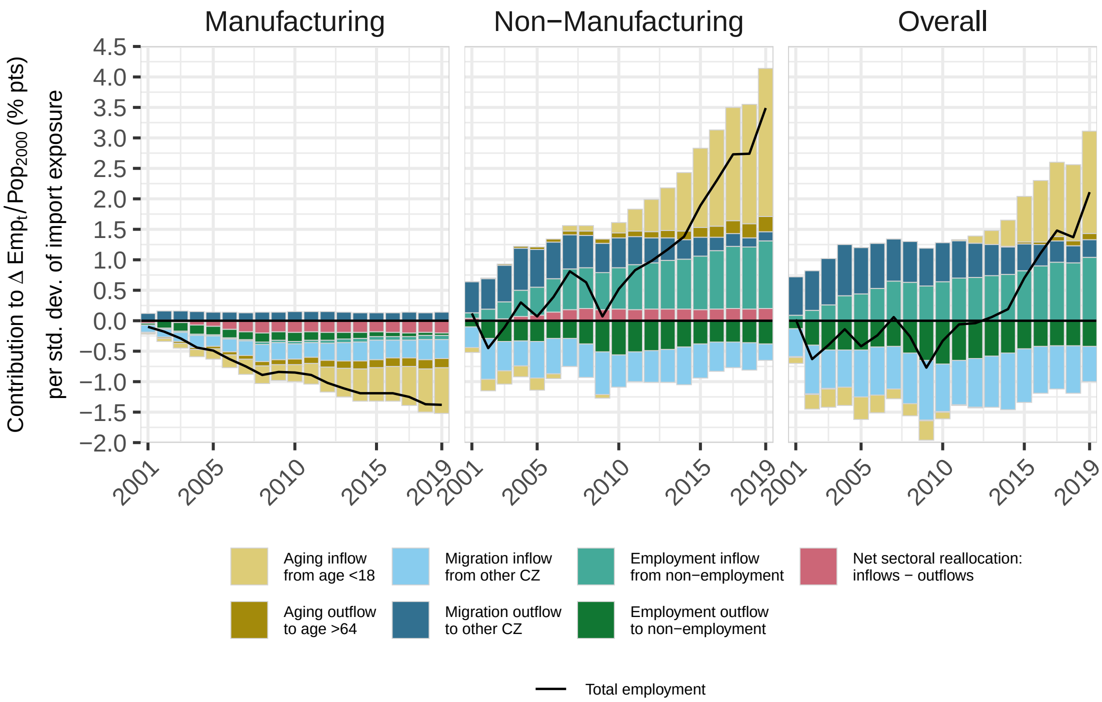


Figure 10: The Impact of CZ-Level Trade Exposure on Gross CZ Employment Flows.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). The outcome variable is the change in employment in the commuting zone between 2000 and the indicated year on the x-axis, divided by the population size of the CZ in 2000, as defined in equation (4). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000. Positive bars indicate employment gains that result either from greater inflows to employment or reduced outflows from employment. Negative bars indicate employment losses due to increased outflows from employment or lower inflows to employment. See Table A.11 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

Worker reallocation across sectors

A second aggregate channel of adjustment depicted in Figure 10 is sectoral reallocation. By definition, this channel has equal and opposite effects on employment in the manufacturing and non-manufacturing sectors (first and second panel of the figure) and hence does not affect overall CZ employment (third panel). The plum-colored bars in Figure 10 depict the effect of a $+1\sigma$ trade shock on within-CZ net flows of workers between manufacturing and non-manufacturing. Trade pressure induces workers to flow from manufacturing to non-manufacturing, as anticipated. But this effect is *surprisingly small*: each $+1\sigma$ of trade exposure is estimated to induce net manufacturing to non-manufacturing worker flows of 0.20pp relative to initial working-age population (per Table A.11). This is only 14% as large as the net decline in manufacturing employment per $+1\sigma$ trade shock (equal to -1.38pp, per Table A.10), and is only 6% as large as the net increase in non-manufacturing employment in the same locations (equal to $+3.49$pp). By implication, cross-sector mobility of former manufacturing workers plays only a small role in the movement out of manufacturing—and almost no role in the steep growth in non-manufacturing—in trade-exposed CZs.

In a related analysis of establishment-level Census data, Bloom et al. (2024) find that approximately 40% of the trade-induced reallocation of jobs from manufacturing to non-manufacturing that occurs between 1997 and 2007 stems from employment shifts across establishments of the same firms (e.g., firms reallocate business activity from manufacturing facilities located in one set of CZs to service-sector operations located in other CZs). The results in Figure 10 suggest that little of this within-firm, cross-sector reallocation involves reallocation of workers initially employed in trade-exposed manufacturing. This is evident from the fact that exposed manufacturing workers are unlikely to transition to employment outside of their initial sector, whether they remain in their 2000 CZ or move elsewhere. Indeed, they are *less* likely than non-exposed manufacturing workers to abandon their initial regional and sectoral position. We infer that firms that undertake regional and sectoral job reallocations in response to rising trade pressure likely shift relatively few incumbents from manufacturing to non-manufacturing, implying that their non-manufacturing job additions derive from other labor pools.[44]

Worker outflows to non-employment

Figure 10 shows that trade pressure increases the probability that incumbent workers transition to non-employment (dark green series). A $+1\sigma$ trade shock increases outflows to non-employment (i.e., a reduction in workers employed) by as much as 0.6pp as a share of initial working-age population (panel C). This effect is strongly persistent. It accumulates between 2000 and 2010 and ebbs only modestly thereafter. We estimate that as of 2019, an excess of 0.42pp of incumbent working-age adults per a $+1\sigma$ shock remains unemployed or out of the labor force (per Table A.11).

[44] Our analysis does not constrain firms to remain in the same sector, nor does it classify workers as remaining in their initial sector if their employer changes sectors. If a manufacturing firm changes to the non-manufacturing sector between 2000 and 2019, its incumbent workers undergo a sectoral transition in our data. Only a small share of incumbent manufacturing workers transitions to non-manufacturing—either within or between firms—implying that such reclassification-with-ongoing-employment events must be rare.

Yet, a surprisingly small share of the outflows to non-employment occur from the manufacturing sector, as shown in panel C of Figure 10.[45] During the first few years after the onset of the shock, outflows of manufacturing workers to non-employment peak at 0.15pp per $+1\sigma$ trade exposure, explaining 34% of the total initial contraction in manufacturing. However, outflows to non-employment diminish over time, amounting to a statistically insignificant 0.04pp per $+1\sigma$ by 2019.[46] These findings are consistent with spatial equilibrium models in which local unemployment of former manufacturing workers gradually dissipates after the initial shock (Rodríguez-Clare et al., 2020; Kim and Vogel, 2021).

Inflows of first-time workers

Perhaps the most surprising finding of the analysis in Section 4 is that trade-exposed CZs make steep employment gains relative to initial population after 2010, as seen in Figure 4 above. Although CZ-level employment-to-population ratios *fall* by 0.98pp per $+1\sigma$ trade exposure between 2000 and 2019, total employment per initial working-age population rises by more than 2.11pp in these same CZs (see also Table A.10). The combination of rising employment per initial population and falling employment per contemporaneous population implies that employment growth must primarily reflect new worker entry rather than rising employment among incumbents. Where do these new workers come from?

Figure 10 provides an initial answer. The two largest contributors to gross employment inflows are: (1) adults who were of working age in 2000 but had not previously been observed in employment in our sample of CZs, and (2) youth who were under 18 in 2000 and began entering the workforce in trade-exposed CZs around 2010. We discuss these in turn.

While we noted above that outflows to non-employment rise in more trade-exposed CZs relative to less trade-exposed CZs, Figure 10 shows that labor market *inflows* of adult workers from non-employment (bright green series) rise by even more than outflows to non-employment. These inflows build gradually but steadily—and ultimately substantially—from the onset of the outcome window to its end in 2019. A $+1\sigma$ shock is estimated to raise inflows from non-employment by 1.04pp between 2000 and 2019 as a share of initial CZ working-age population (per Table A.11). Workers flowing in from non-employment are adults who were already of working age in the year 2000 but were not employed in any CZ of our sample at that time. As we explore further below, this category includes both foreign-born workers who entered the U.S. labor force in trade-impacted CZs after 2000 and U.S.-born working-age

[45] Below, we investigate outflows to non-employment from non-manufacturing, finding that it can be explained by return migration of the foreign-born.

[46] Section 7 provides a more detailed analysis of the transition paths of manufacturing incumbents.

adults who had attained working age but were not in the paid labor force in 2000, perhaps due to school, family, or military service. Because we observe CZ locations only for employed adults, we cannot ascertain where these new labor-force entrants resided immediately prior to entry—whether in the same CZ, in another CZ, or outside of the United States. We can observe, however, whether these workers are native-born or foreign-born, which proves highly relevant below.

Just as important as the entry from non-employment of adult workers into trade-exposed CZs are inflows of young workers who were below working age in the year 2000 ('aging inflows'). As shown by the light amber bars in Figure 10, these young entrants make a differentially positive contribution to CZ employment in trade-exposed local labor markets. As enumerated in Table A.11, each $+1\sigma$ of trade exposure predicts a 2.43pp differential contribution of aging inflows to employment in the non-manufacturing sector between 2000 and 2019—the most significant driver of long-term growth in non-manufacturing employment.

What explains the disproportionate inflow of young adults into the workforces of trade-exposed CZs? One potential explanation that is *not* supported by the data is a preexisting correlation between demographic structure and trade exposure. If, hypothetically, trade-exposed CZs contained larger youth populations at the onset of the 21st century, they would experience a differential inflow of young adult workers after 2000 that was only incidentally related to the unfolding trade shock. We find no correlation, however, between trade exposure from 2000 forward and youth populations prior to 2000.[47] Reinforcing this conclusion, Figure 10 documents that the influx of young workers into trade-exposed CZs commences a full decade after the onset of the trade shock. We infer that these aging inflows, commencing with a ten-year lag, are largely an economic response to the labor market impacts of trade, and we explore their demographic makeup in much greater detail below.[48]

Diminished inflows of young workers also emerge as the largest contributor to the long-term *decline* in manufacturing employment. As shown in the first panel of Figure 10, each $+1\sigma$ trade exposure predicts a 0.75pp fall in the employment of youth in manufacturing who attained age 18 during the outcome window. This effect is numerically large, explaining 56% of the contraction in manufacturing employment between 2000 and 2019. On net, aging

[47] Regressing the ratio of pre-market CZ residents (ages 0–17) to working-age CZ residents (ages 18–64) on the incipient trade shock measure in the year 2000, we obtain a coefficient of -0.003 with a p-value of 0.41. This regression uses SEER data and includes the vector of control variables used in the main empirical model, equation (5).

[48] We document above that trade exposure reduces geographic mobility from exposed CZs. If the dependent children of induced non-movers become more likely to enter the trade-exposed CZ's labor force when reaching adulthood, then aging inflows would be boosted. Analysis of these pathways requires linking children and parents, which is beyond the scope of our analysis.

inflows contribute 1.68pp per $+1\sigma$ to overall employment in the CZ by 2019, despite their negative contribution to manufacturing employment.[49]

Figure 6 above documented that the age composition of employment in trade-exposed CZs shifts decidedly towards adults ages 40–64. This pattern, further detailed in Figure 11, may seem paradoxical in light of the stepped-up entry into trade-exposed CZs of workers who were below working age in the year 2000. This tension highlights the utility of tying changes in the composition of workers in a place to the underlying flow of people across places and employment statuses. As we show next, the changing age composition of trade-exposed CZs reflects the net effect of countervailing forces set in motion by trade shocks, with increased inflows of young native-born Hispanic workers and *reduced* outflows of older, native-born white and Black workers.

5.2 Gross worker flows and net demographic changes

This section documents the materially important role played by inflows of young, native-born Hispanics, foreign-born immigrants, women, and college-educated workers in the generational transformation of the workforce in trade-exposed locations. To facilitate comparisons of the results in this section with the place-level effects in Section 4 above, Figure 11 reports the net employment change of each demographic group induced by $+1\sigma$ trade exposure (denominated as always by initial CZ working-age population). We reemphasize that these results correspond to net employment changes in more versus less trade-exposed local labor markets. They do not speak to aggregate changes in employment, either overall or for any demographic group; indeed, our trade-exposure measure is normalized to mean zero, meaning that the average effect on total employment is zero by construction.

Flows by race, ethnicity and nativity

Figure 11 reinforces the message of Section 4 that the nativity, racial, and ethnic composition of employment in trade-exposed CZs changes substantially between 2000 and 2019, with a flattening of employment of native-born whites and Blacks and a steep rise in employment of foreign-born Hispanic and other-race workers. This section shows how trade-driven shifts

[49]Even absent geographic mobility, the set of working-age adults in each CZ is reshaped over time by demographic change. Adults surpassing age 64 exit the working-age bracket ('aging outflows') and are excluded from the count of employed in each year, while youth attaining age 18 during the outcome window and entering employment are newly counted among the employed ('aging inflows'). Although aging inflows are largely predetermined at the national level, trade pressure may directly affect the local labor markets and sectors in which new labor market entrants choose to work. Aging inflows are not *fully* mechanical at the national level because they are affected by immigration (a major factor), emigration (a minor factor), mortality, and births.

in the demographics of worker flows give rise to these net changes.

Figure 12 highlights the role of race, ethnicity, and national origin by subdividing worker flows into four mutually exclusive race and ethnicity by nationality groups: native-born whites and Black workers; native-born Hispanic and other-race workers; foreign-born white and Black workers; and foreign-born Hispanic and other-race workers. This partition of the data crystallizes three points.

First, although net employment of native-born white and Black workers changes relatively little in more trade-exposed CZs, migration flows of these workers from and to other CZs falls substantially (by 0.99pp and 0.91pp per $+1\sigma$, reported in Table A.12). By implication, a disproportionate share of native-born whites and Blacks employed in trade-exposed CZs are, by 2019, long-term incumbents.

Second, more than the entirety of the influx of young (under 18 in 2000) native-born workers into trade-exposed CZs reflects rising employment of native-born Hispanic and other-race workers (panel E of Figure 12). From 2000 forward, inflows of young workers in this group surge, contributing 2.23pp of employment per $+1\sigma$ exposure by 2019. Simultaneously, inflows of young, native-born white and Black workers drop by 1.56pp per $+1\sigma$ exposure (per Table A.12). Thus, the racial and ethnic composition of employment of new labor market entrants shifts strongly away from native-born white and Black workers and towards native-born and foreign-born Hispanic and other-race workers.

Third, panels A and E of Figure 12 show that rising foreign-born inflows—both adult workers from non-employment and young workers aging into the sample—are comprised entirely of Hispanic and other-race adults. Figure 13 delves further into these induced changes in racial, ethnic, and nativity composition. To satisfy disclosure restrictions, this figure reports impacts of trade exposure on worker flows by race and ethnicity (white, Black, Hispanic, other) but does not subdivide these further by nativity.[50]

[50]For reference, Figure A.1 displays the effects of trade exposure on the inflows of native-born versus foreign-born workers, not subdivided by race and ethnicity.

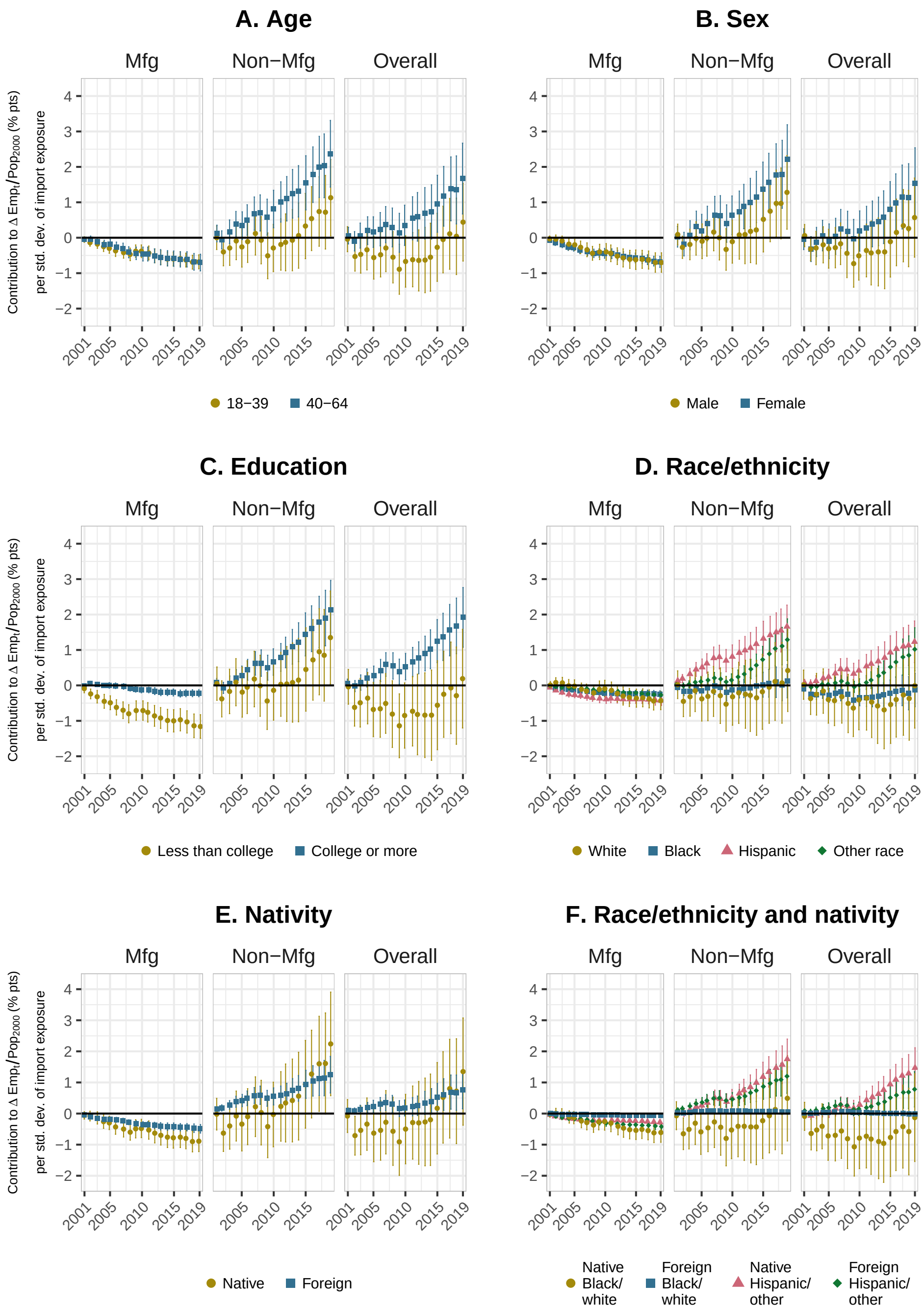


Figure 11: The Impact of CZ-Level Trade Exposure on CZ Employment by Demographic Group.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). Estimates are shown by age, sex, education, race/ethnicity, nativity, and race/ethnicity × nativity. Vertical bars display ±1.96 standard errors. The outcome variable is the change in employment in the CZ between 2000 and the indicated year on the x-axis, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000. See Table A.5 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

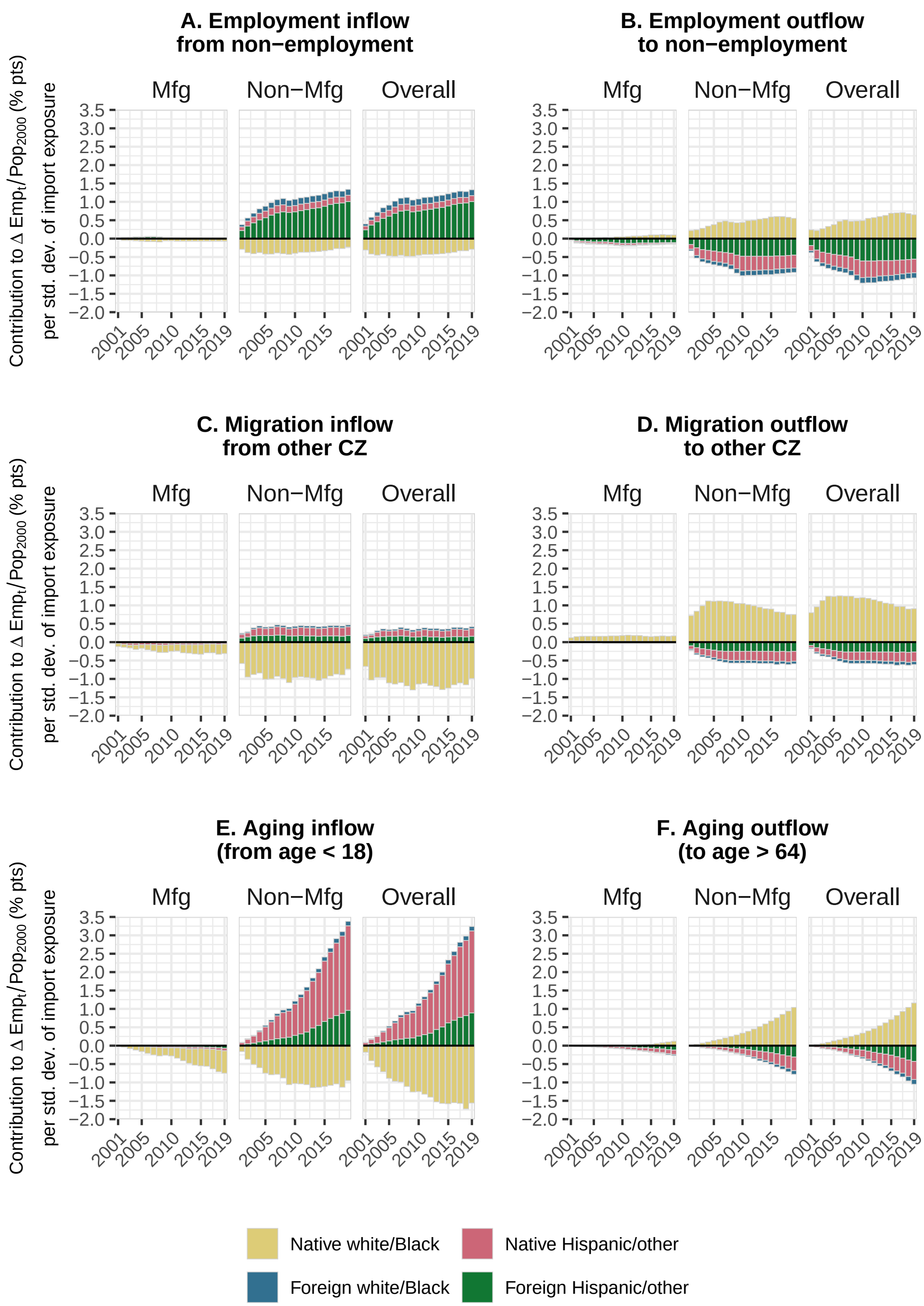


Figure 12: The Impact of CZ-Level Trade Exposure on Gross CZ Employment Flows by Race/Ethnicity × Nativity.

Notes: See note to Figure 10. Estimates are shown by race/ethnicity and nativity. Greater inflows of workers which raise CZ employment are indicated with positive bars in panels A, C and E. Greater outflows of workers which reduce CZ employment are indicated with negative bars in panels B, D and F. See Table A.12 for 2019 point estimates.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

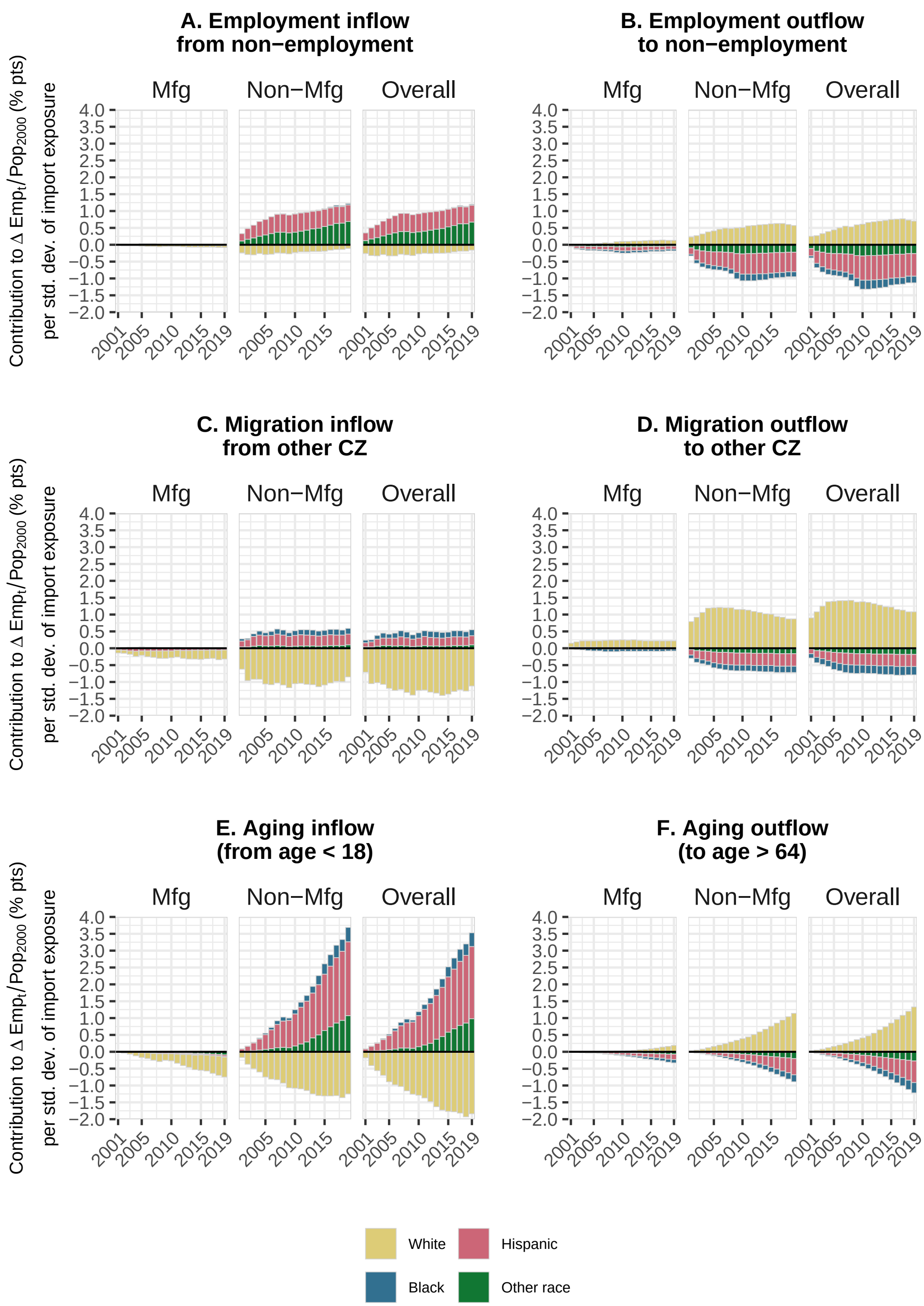


Figure 13: The Impact of CZ-level Trade Exposure on Gross CZ Employment Flows by Race/ethnicity.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). The outcome variable is the change in employment in the commuting zone between 2000 and the indicated year on the x-axis, divided by the population size of the CZ in 2000, as defined in equation (4). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000. See Table A.13 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

We showed above that inflows of adult workers from non-employment rise in trade-exposed CZs. Panels A and B of Figure 13 reveal that this pattern is driven entirely by greater inflows of Black, Hispanic, and other-race workers, with a strong countervailing effect contributed by white workers. Combined inflows from non-employment of Black, Hispanic, and other-race workers rise by 1.10pp per $+1\sigma$ exposure while combined outflows of these workers to non-employment jumps by 1.13pp (see Table A.13). Opposite to this pattern, inflows from non-employment of white workers fall by 0.16pp per $+1\sigma$ exposure while outflows of white workers to non-employment also fall by 0.65pp, most of which is driven by increased persistence of white workers in non-manufacturing employment.

Reinforcing this point, panels C and D of Figure 13 reveal that cross-CZ flows of white workers provide a strong countercurrent to those of Hispanics and other race workers. Rising trade pressure reduces cross-CZ employment inflows of white workers by 1.12pp per $+1\sigma$ but it increases combined migration outflows of Black, Hispanic, and other-race workers by 0.79pp (Table A.13). Thus, the drop in cross-CZ worker inflows into trade-exposed CZs is driven entirely by white workers; cross-CZ inflows of workers from other race and ethnic groups *rise*. Panel D provides the mirror image pattern for worker outflows to employment in other CZs. Outflows of white workers fall by 1.08pp per $+1\sigma$ exposure while outflows of Black, Hispanic, and other-race workers rise by 0.79pp. Thus, the migration responses of Black, Hispanic, and other-race workers to rising local labor market trade pressure accords with conventional wisdom, showing increased mobility on both inflow and outflow margins. Conversely, whites show sharply reduced mobility on both dimensions: they are less likely to enter leave trade-exposed CZs and less likely to leave.

Panels E and F of Figure 13 further underscore the distinct flow responses of white workers relative to other groups. In panel E, we see that inflows of young white workers fall by 1.84pp per $+1\sigma$ exposure. By implication, inflows of young workers into trade-exposed CZs are driven exclusively by Black, Hispanic, and other-race workers, who contribute 0.41pp, 2.14pp, and 0.98pp, respectively, to employment growth per $+1\sigma$ exposure. Triangulating between panels E of Figures 12 and 13 provides a complementary insight: most young native-born entrants into trade-exposed CZs are Hispanic workers, while most young foreign-born entrants are other-race workers (neither white, Black, nor Hispanic). Finally, panel F shows that falling aging outflows of white workers and rising aging outflows of Blacks, Hispanics, and other-race workers exert offsetting effects on total CZ employment.

These patterns place in sharp relief the distinct nature of adjustment in trade-exposed CZs of whites relative to other groups. Inflows of whites into trade-exposed CZs decline along all margins: inflows from non-employment, inflows from other CZs, and inflows of newly working-age adults. Simultaneously, outflows of white workers to non-employment, to other-CZ employment, and to post working-age status, all decelerate. Conversely, both inflows and outflows of Black, Hispanic, and other-race workers in trade-exposed CZs increase along all margins—employment/non-employment, cross-CZ mobility, working-age status. Thus, the long-term incumbency of white workers in trade-exposed CZs rises even as their employment shares shrink. Conversely, the incumbency of non-white groups declines as their employment shares grow.

Inflows of women and college graduates

Figure 11 documents that about three-fourths of the differential net employment increase in trade-exposed CZs stems from a rapid rise in female employment. Specifically, female employment rises by 1.54pp per $+1\sigma$ exposure while male employment increases by only 0.57pp (see Table A.5). Figure 14 reveals that this gender contrast emanates from the differential labor force entry of two groups: adult women entering from non-employment (that is, not working as of 2000); and young female entrants who were below working age in 2000.[51] Although the entry of adult women into employment in trade-exposed CZs could in theory reflect an "added worker effect," whereby women enter the workforce to buffer adverse shocks to household earnings (Ashenfelter and Heckman, 1974), additional analysis indicates that this is not the case. Rather, this trend is entirely driven by differential entry of adult female foreign-born immigrants. Meanwhile, rising employment of young female labor market entrants in trade-exposed CZs reflects entry of foreign-born and native Hispanic women.

The differential growth of female employment in trade-exposed CZs likely reflects in part the ongoing employment shift out of manufacturing, in which males are overrepresented, and towards healthcare, education, retail trade, and leisure and hospitality, where women tend to be overrepresented. As documented in Figure 15, however, it is not the case that trade-induced manufacturing employment contractions are substantially more severe among men than women; in fact, their magnitudes relative to CZ populations are almost indistinguishable. What differs instead is the degree to which women disproportionately drive employment in the sectors that expand in trade-exposed locations. In each of the three largest growth subsectors in trade-exposed CZs—within retail, healthcare, and K-12 education—the employment contribution of women is more than twice that of men: 1.43pp versus 0.62pp per $+1\sigma$ exposure (per Table A.7).[52]

[51] Net inflows of adult women from non-employment amount to 0.43pp per $+1\sigma$ exposure versus 0.19pp for men, per Table A.11. Net inflows of young adult women account for 1.12pp per $+1\sigma$ versus 0.57 for men.
[52] Across the 11 subsectors reported in Figure 15, women's and men's employment losses are 0.67pp and

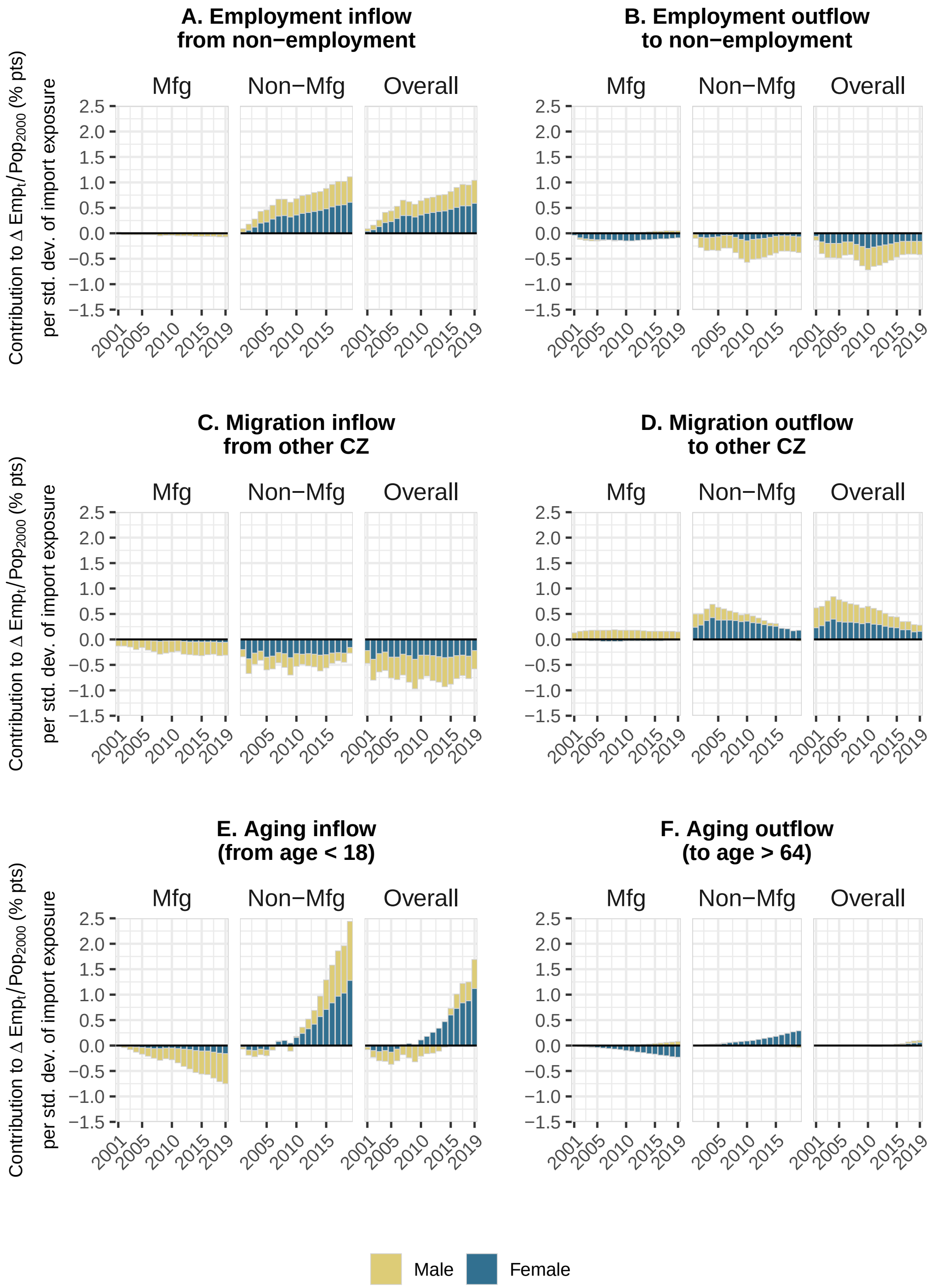


Figure 14: The Impact of CZ-Level Trade Exposure on Gross CZ Employment Flows by Sex.

Notes: See note to Figure 10. Estimates are shown by sex. Greater inflows of workers which raise CZ employment are indicated with positive bars in panels A, C and E. Greater outflows of workers which reduce CZ employment are indicated with negative bars in panels B, D and F. See Table A.11 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

0.71pp, respectively, while their gains are 1.98pp and 0.87pp.

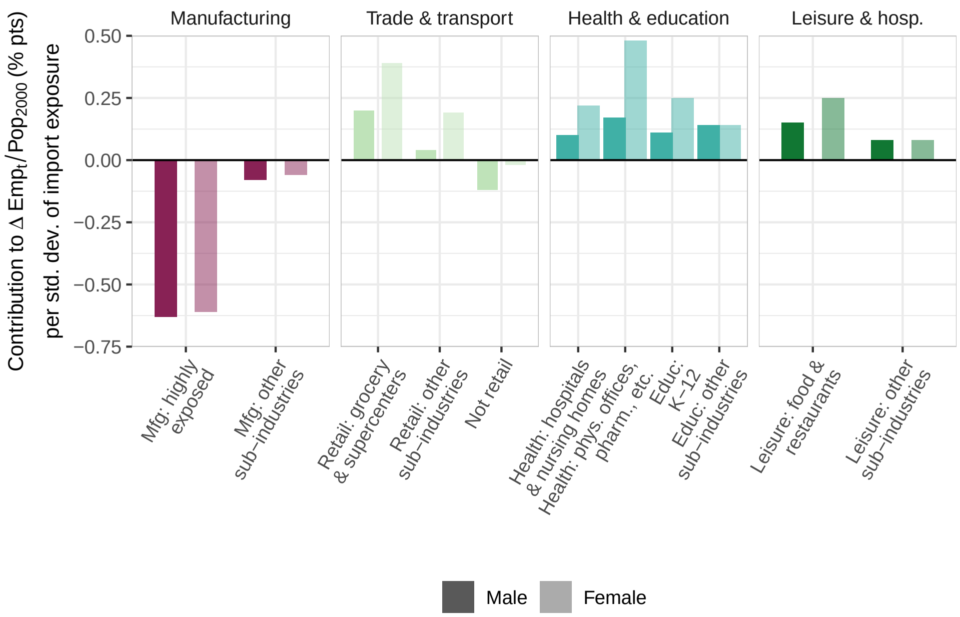


Figure 15: The Impact of CZ-Level Trade Exposure on CZ Employment by Sex and Subsector, 2019.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). The outcome variable is the change in employment in the CZ between 2000 and 2019, divided by the population size of the CZ in 2000, as defined in equation (2). See Table A.7 for 2019 subsector point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

A final, substantial margin of demographic adjustment in trade-exposed CZs is education. Figure 11 documents that non-college employment falls steeply in trade-exposed CZs, reaching a nadir of -1.11pp per $+1\sigma$ exposure, prior to beginning a slow return to parity that is not complete until 2019. Simultaneously, employment of college graduates rises steadily and robustly throughout the entire outcome window, reaching 1.92pp per $+1\sigma$ trade exposure by 2019 (per Table A.5). Figure 16 documents the sharp shifts in worker flows that give rise to these net changes. Consistent with the pattern observed for native-born workers, falling non-college employment in trade-exposed CZs does *not* reflect increasing out-migration to other CZs. Rather, it stems from greatly diminished in-migration from other CZs, as well as diminished entry of young, non-college workers. The opposite pattern prevails for college-graduate workers: cross-CZ inflows and outflows of college-educated workers both rise, accompanied by a rise in entry by newly working-age college graduates and adult college graduates entering from non-employment.

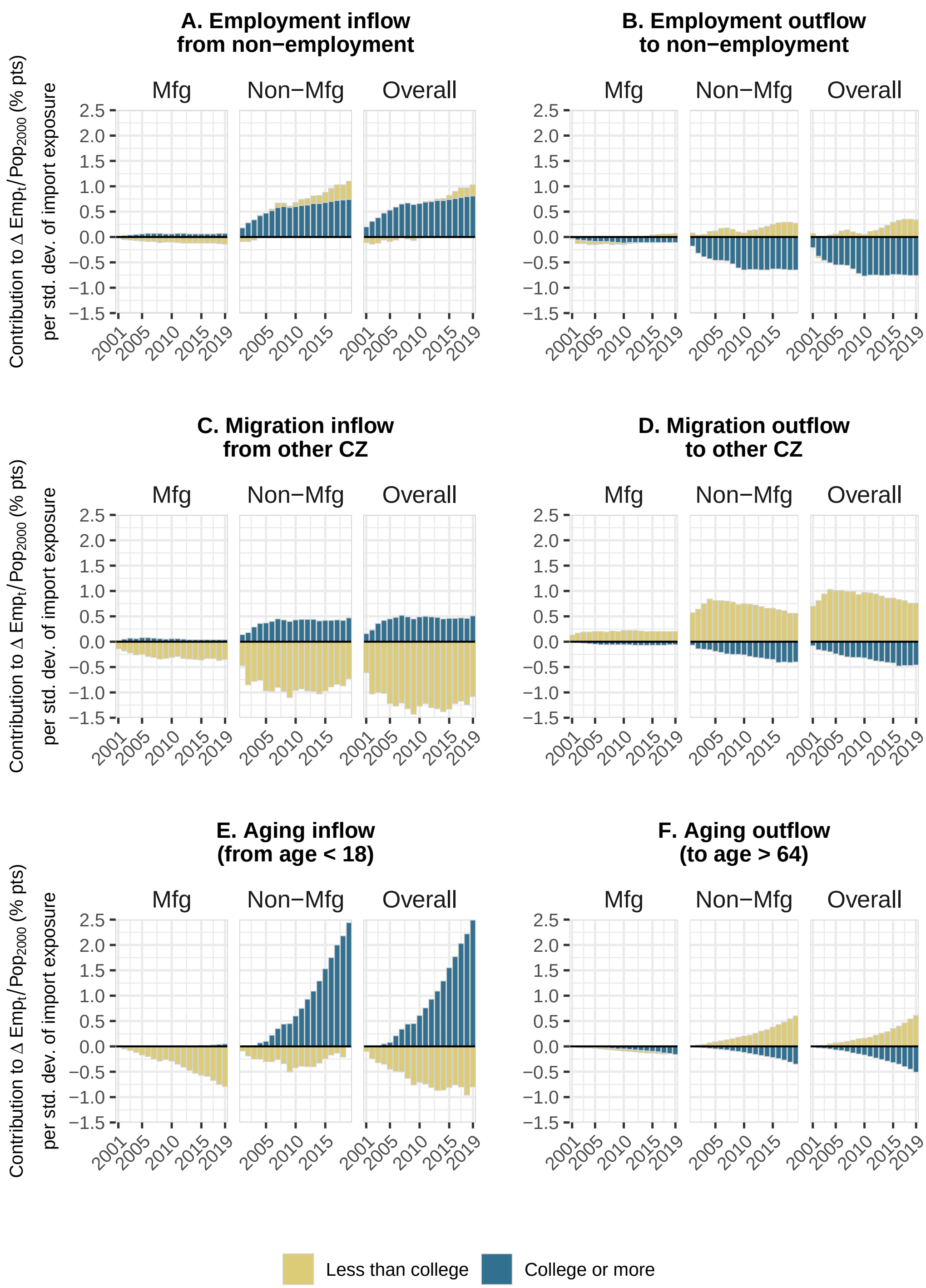


Figure 16: The Impact of CZ-level Trade Exposure on Gross CZ Employment Flows by Education.

Notes: See note to Figure 10. Estimates are shown by education: less than college and college or more. Greater inflows of workers which raise CZ employment are indicated with positive bars in panels A, C and E. Greater outflows of workers which reduce CZ employment are indicated with negative bars in panels B, D and F. See Table A.11 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

We saw above that a substantial component of declining manufacturing employment in trade-exposed CZs reflects decreased inflows of workers who were not yet of working age in 2000. Figure 16 reveals that this decrease has a distinct educational undercurrent. All of the decline in inflows of young adults into the manufacturing sector is due to reduced entry of young *non-college* workers. Similarly, the entire rise in inflows of young adults into non-manufacturing reflects the entry of young *college-educated* workers. Finally, nearly all of the worker inflows from non-employment to manufacturing, and outflows from non-manufacturing to non-employment, reflect increased flows of college-educated workers. Thus, the generational transformation of the workforce in trade-exposed CZs includes a substantial shift towards college-educated workers.

Summary measures of demographic shifts in employment

Putting these pieces together, changes in worker flows in trade-exposed labor markets deliver a demographic and generational transformation over the course of two decades. Though employment of native-born whites shows little net change, the *composition* of native-born whites shifts significantly towards long-term incumbents, with a marked decline in contributions from adult entrants and young native-born entrants. Simultaneously, employment of native-born Hispanic and foreign-born immigrant workers grows rapidly. Inflows by workers from these groups are dominated by young, first-time labor market entrants and foreign-born adults joining the U.S. workforce for the first time. A disproportionate share are women and college graduates.

Seen from the perspective of native white and Black workers, particularly non-college males, the racial, ethnic, international, gender, and educational composition of the workforce in trade-exposed CZs will appear to change rapidly. This perception is likely intensified by the slowing turnover among native-born white and Black workers—especially non-college men—in these same locations. Conversely, seen from the perspective of newly-entering native-born Hispanic and foreign-born immigrant workers, their white and Black coworkers disproportionately represent long-term incumbents, non-college adults, and men. Figure 17 depicts the differential change in the demographic composition of the adult workforce in trade-exposed CZs by fitting equation (5) to a summary measure of demographic shifts: the change in the log odds ratio that a randomly selected worker w in a given CZ i in year t belongs to a specific demographic group J, $\ln\left(\Pr[w_{ijt} \in J]/\left(1 - \Pr[w_{ijt} \in J]\right)\right)$. The first series (beige circular markers) in Figure 17 finds no significant change in the prevalence of native-born white workers as a share of overall employment in trade-exposed CZs. The second series (blue square markers) documents a differential fall of 2 log points per $+1\sigma$ exposure

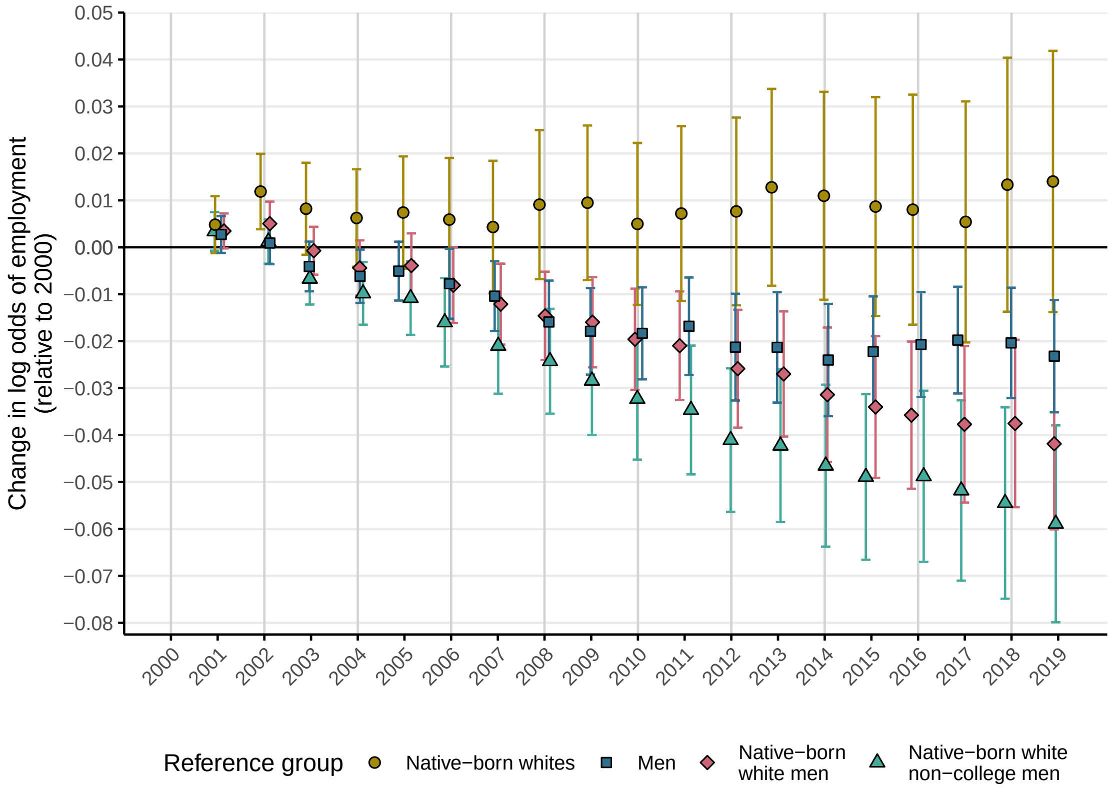


Figure 17: The Impact of CZ-Level Trade Exposure on the Prevalence of Specific Demographic Groups in Employment.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). The outcome variable is the change in log odds of employment relative to 2000 levels for each reference group compared to all others, e.g. native-born whites compared to native-born non-whites and foreign-born individuals. Vertical bars display ± 1.96 standard errors. All regressions include controls for Census division indicators and the 2000 manufacturing employment share in CZ. See Table A.14 for 2010 and 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

in the prevalence of male workers (see See Table A.14). This effect cumulates between 2000 and 2014, then stabilizes thereafter. The third series (red diamonds) plots the employment trajectory of native-born white men (i.e., the intersection between the first two series). The employment prevalence of this latter group tracks that of males overall from 2000 through 2010 but then continues falling. By 2019, this net decline reaches 4 log points by 2019 per $+1\sigma$ exposure.

The final series in the figure (green triangles) further narrows the focus to native-born white non-college men. The prevalence of this demographic group as a fraction of the workforce falls steadily and steeply throughout the outcome window, reaching a nadir of 6 log points per $+1\sigma$ exposure by 2019. As shown in Figure A.2, these trends are steeper still for older workers from these demographic groups. Nearly two decades after China's 2001 WTO accession, the employment prevalence of native-born white male non-college workers in trade-exposed labor

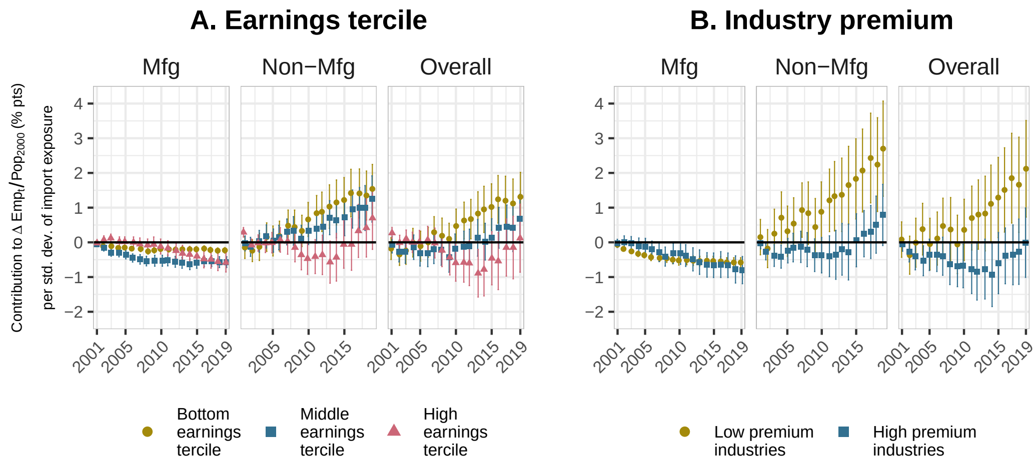


Figure 18: The Impact of CZ-Level Trade Exposure on CZ Employment by Earnings Tercile and Industry Premium.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). Estimates are shown by earnings tercile and industry premium, as defined in the text. Vertical bars display ±1.96 standard errors. The outcome variable is the change in employment in the CZ between 2000 and the indicated year on the x-axis, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000. See Table A.9 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

markets falls by 8 log points among workers age 40–64 per $+1\sigma$ exposure, and by 5.2 log points among workers age 18–39. Though these patterns convey no normative content, they may contextualize the perception among non-college native-born voters (particularly males) that rising trade pressure contributes to a loss of traditional labor market roles (Autor et al., 2020; Bonomi et al., 2021; Grossman and Helpman, 2021; Bouët et al., 2024).

5.3 Flows across earnings levels and industry premiums

The employment composition of trade-exposed CZs shifts along numerous demographic and sectoral dimensions between 2000 and 2019, summarized in Figure 11. One common currency for synthesizing these changes is to consider flows into and out of employment according to earnings tercile and industry premium. Figure 18 reports trade-induced net employment changes in each of these categories. Figures 19 and 20 report trade-induced gross flows, with corresponding point estimates and standard errors given in Table A.15.

Figure 18 shows that most of the relative employment growth in trade-exposed CZs occurs in the bottom tercile of the earnings distribution, amounting to 1.31pp per $+1\sigma$ exposure, as compared to 0.80pp for the other two earnings terciles combined (per Table A.9). In Figure 19, we find that the largest single contributor to these compositional shift is *falling* gross out-migration to other CZs of incumbent workers in bottom-tercile jobs to employment in other CZs, amounting to 0.63pp per $+1\sigma$ exposure (per Table A.15). At the same time, there is a substantial reduction of in-migration from other CZs to low-earning employment. Thus, the bottom tercile of the earnings distribution in trade-exposed CZs increasingly over-represents long-term CZ incumbents. Figure 18 also indicates a modest net increase in middle-tercile employment, driven by non-manufacturing. As shown in Figure 19, the growth of middle-tercile employment rising inflows of adult workers from non-employment (likely foreign-born immigrants) and inflows of newly working-age entrants (many of whom are also foreign-born). Figure 19 reveals that the sharp fall and then belated rebound of high-tercile employment seen in Figure 18 reflects employment outflows of high-tercile workers to both employment in other CZs and to non-employment, where the latter effect potentially corresponds to return migration (Akee and Jones, 2024). High-tercile employment in trade-exposed CZs does not reach its nadir until 2014. Over the subsequent five years, young adult entrants—whom we found to be college-educated—flow rapidly into high-tercile employment in non-manufacturing, leading ultimately to a reconvergence of high-tercile employment between more versus less trade-exposed CZs.[53]

Figure 20 offers one more perspective on relative changes in the earnings composition of trade-impacted CZs by focusing on employment in low and high-premium sectors. All relative employment growth between 2000 and 2019 in trade-exposed CZs occurs in low-premium sectors, as documented in Figure 18. Figure 20 shows that the growth of low-premium employment is driven by a combination of young adults (under 18 in the year 2000) entering the labor market and working-age adults flowing in from non-employment. Both categories are likely dominated by native-born Hispanics and foreign-born immigrants. We also detect a modest net sectoral reallocation of incumbent workers from high-premium manufacturing jobs to low-premium non-manufacturing jobs.[54] Conversely, the differential fall in high-premium employment in trade-exposed CZs is proximately accounted for by declining in-migration from other CZs and rising net exits to non-employment. Finally, we find that the majority of the decline in manufacturing jobs is accounted for by diversion of young entrants away from high-premium manufacturing industries, approximately offset by the increase in high-premium non-manufacturing employment among young entrants.

[53]Recall from Figure 4 that the working-age employment-to-population ratio in trade-exposed CZs drops differentially even as the ratio of employment to initial working-age population rises. It is plausible therefore that the share of the working-age population in high-tercile jobs does not rebound in trade-exposed CZs to its initial level.

[54]Net sectoral reallocation is shown in Table A.15.

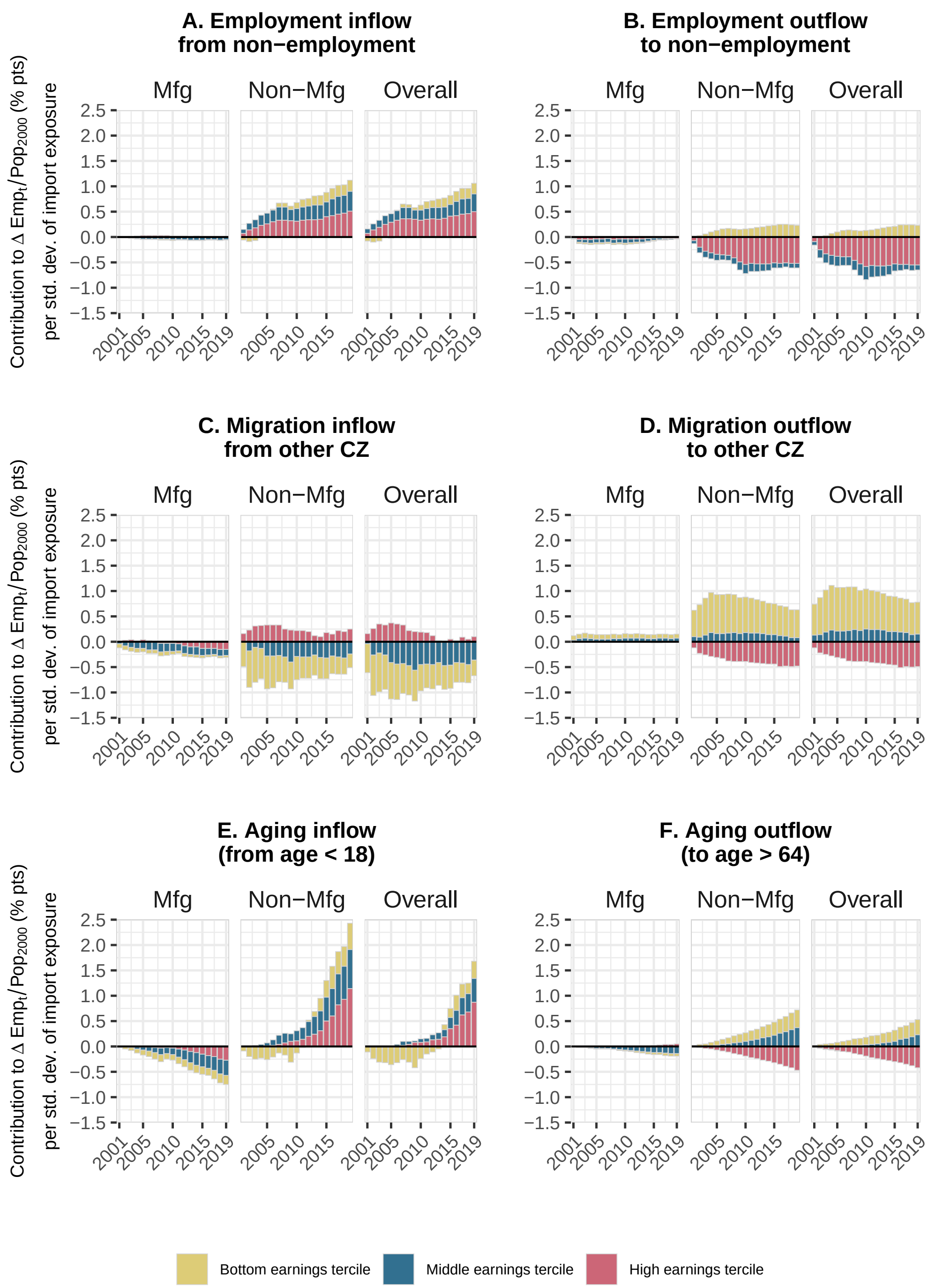


Figure 19: The Impact of CZ-Level Trade Exposure on Gross CZ Employment Flows by Earnings Tercile.

Notes: See note to Figure 10. Estimates are shown by earnings tercile: bottom, middle, and high. Earnings tercile thresholds are defined such that they divide workers into three earnings bins, each comprising one third of earners, in 2000. In subsequent years, those thresholds are fixed in real terms using the Personal Consumption Expenditure deflator. Greater inflows of workers which raise CZ employment are indicated with positive bars in panels A, C and E. Greater outflows of workers which reduce CZ employment are indicated with negative bars in panels B, D and F. See Table A.15 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

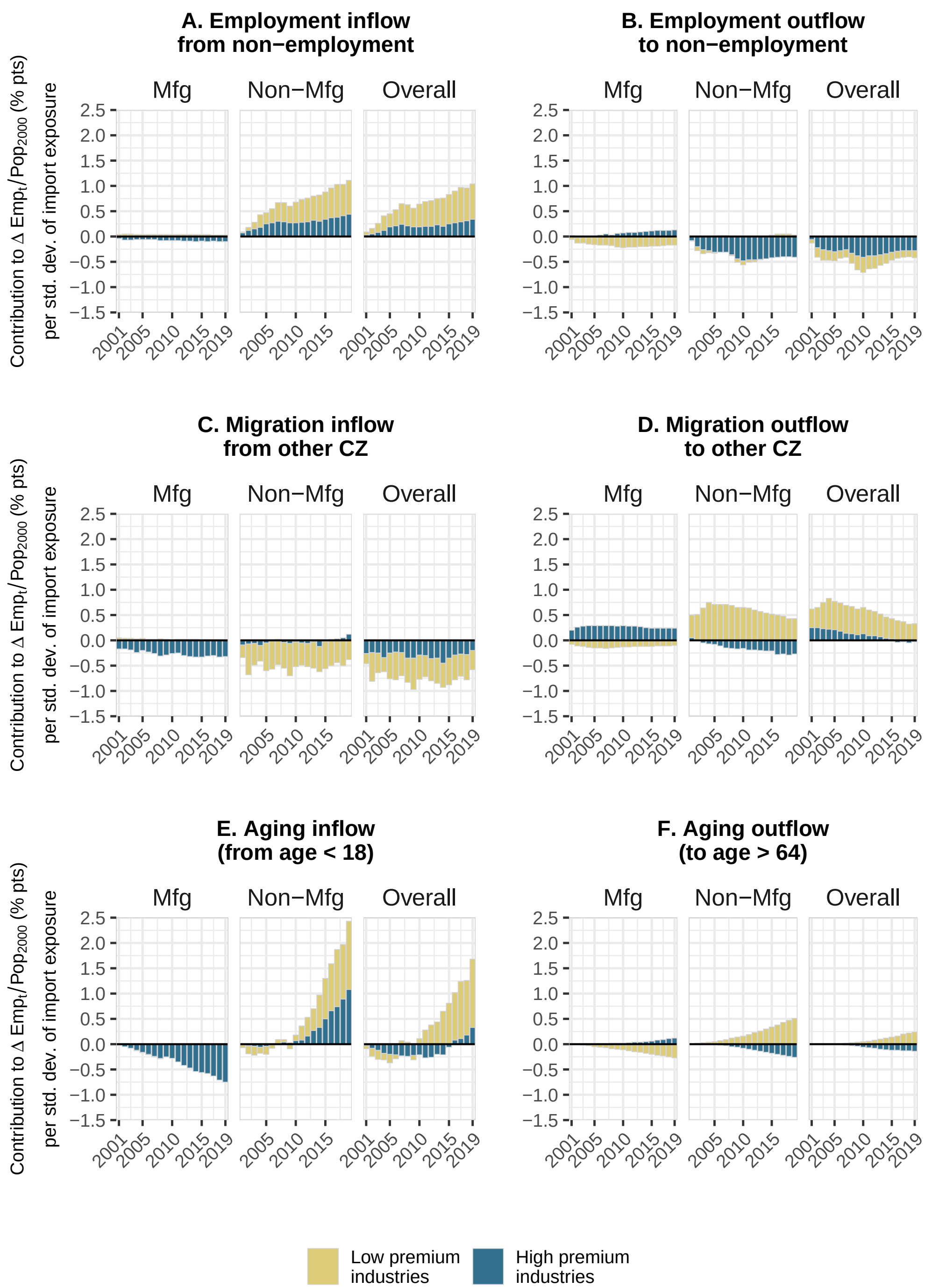


Figure 20: The Impact of CZ-Level Trade Exposure on Gross CZ Employment Flows by Industry Premium.

Notes: See note to Figure 10. Employment is classified as high-premium if the wage premium reported by Card et al. (2024) for the worker's industry of employment exceeds the employment-weighted average premium for the U.S. economy. Greater inflows of workers which raise CZ employment are indicated with positive bars in panels A, C and E. Greater outflows of workers which reduce CZ employment are indicated with negative bars in panels B, D and F. See Table A.15 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

These figures, in combination, highlight two underlying dynamics that drive the rapid growth of low-tercile and low-premium employment in trade-exposed CZs. The first is a conventional one: newly working-age labor market entrants—largely native-born Hispanics and foreign-born immigrants, as shown above—flow into low-paid employment and low-premium sectors. The second dynamic is less expected: workers in low-tercile and low-premium employment in trade-exposed CZs become less likely to either exit the labor force or decamp to employment elsewhere. Thus, incumbent workers in trade-exposed CZs appear increasingly anchored to their initial locations, even as the age, gender, educational, ethnic and racial, regional, and national composition of their co-residents shifts rapidly.

6 The Trajectories of Manufacturing Incumbents

The analysis above quantifies how trade exposure reshapes the stock of employment in more- versus less-exposed local labor markets, and how these impacts stem from changes in worker flows across sectors, employment statuses, local labor markets, national boundaries, and generations of workers. In this final empirical section, we narrow the analysis to the causal effects of trade pressure on the labor market outcomes of adult incumbent workers who were employed in the manufacturing sector in year 2000. This focus enables a sharp characterization of the labor market trajectory of workers who were putatively most directly exposed to rising trade pressure: manufacturing workers employed in CZs that, due to their patterns of industry specialization, faced rising import competition from China.[55]

We redefine the outcome variable in equation (5) to focus exclusively on start-of-period manufacturing employees of working-age. We denominate the outcome variable by the initial count of these incumbents, removing from that count in each year workers who have aged out of the 18–64 bracket; see Appendix B for further details.[56] We estimate models of the form,

$$\Delta Y_{k,i_{00},t} = \mu_t + \beta_t \Delta IP_{i_{00},00-07} + \delta_t X_{i_{00},00} + \epsilon_{k,i_{00},t}, \tag{7}$$

where $\Delta Y_{k,i_{00},t}$ is the change in the change in the employment status between year 2000 to year t of worker k, who is initially employed in manufacturing in CZ i_{00} in 2000. The exposure variable, $\Delta IP_{i_{00},00-07}$, is the growth of import exposure between 2000 and 20007

[55]One could effectively back out impacts on incumbent workers from the results in Sections 4 and 5, but restricting the sample to incumbents puts their experiences in sharp relief.

[56]In all other regression analyses, the denominator is the working-age population of the CZ in year 2000.

for CZ i_{00}, where k was employed in 2000.[57] The vector $X_{i_{00},00}$ controls for Census division indicators and the 2000 manufacturing employment share in CZ i_{00}.

Figure 21 indicates that employment rates of incumbent manufacturing workers fall by close to -1ppt per $+1\sigma$ exposure between 2000 and 2010.[58] By 2019, employment of exposed incumbents mostly re-converges to that of manufacturing incumbents in non-exposed labor markets. However, the sectoral composition and geographic location of employment has not. For each $+1\sigma$ exposure, the share of incumbents remaining in manufacturing employment within the same CZ falls by 1.19ppt, while the share taking employment in another CZ falls by an even larger 1.63ppt. Offsetting these effects is an increase of 2.49ppt in the share entering employment in non-manufacturing within the same CZ. This effect is large relative to other channels depicted but small relative to the aggregate growth in non-manufacturing employment in their surrounding CZs.[59] These results confirm that the predominant margins of adjustment among trade-exposed manufacturing workers are increased sectoral mobility (out of manufacturing), decreased geographic mobility, and reduced employment.

We next consider heterogeneity in the trajectory of trade-exposed manufacturing workers according to their initial earnings, as seen in Figure 22. Panel A shows that the causal effect of trade exposure on the evolution of employment and earnings differs markedly by workers' initial earnings. Manufacturing workers in the bottom tercile of the national wage distribution in 2000 see a sharp reduction in employment, which is explained primarily by a fall in their entry rate into high-tercile employment and secondarily by a fall in their retention rate in low-tercile employment. We detect similar impacts of trade exposure on manufacturing workers initially in the middle earnings tercile: a fall in overall employment, a steep reduction in entry into high-tercile employment, and a modest decline in retention in their initial earnings tercile. Middle-tercile workers also become more likely to fall into the bottom-tercile of earnings. Impacts on high-tercile manufacturing incumbents are smaller than for the other two groups but not negligible. Their employment rate falls during the first decade of the outcome window. It then rebounds and nearly retains parity by 2019 with comparison workers in non-exposed CZs. All net job losses among high-tercile workers in

[57] As in the prior CZ analysis, $\Delta IP_{i_{00},00-07}$ is defined according to equation (1) and is instrumented with $\Delta IP^{co}_{i_{00},00-07}$ as defined in equation (6).

[58] We use 'ppt' to refer to percentage point changes relative to the set of adults in the risk set who remain in the working-age range in the relevant year. This is distinct from 'pp' above, which refers to percentage point changes relative to initial CZ working-age population.

[59] Recall that Figure 21 is denominated by initial manufacturing employment whereas all prior figures are denominated by CZs' initial working-age population. The growth in non-manufacturing employment in trade-exposed CZs depicted in Panel A of Figure 4 of 3.5pp per $+1\sigma$ exposure is roughly an order of magnitude larger than the trade-induced flows (per $+1\sigma$ exposure) of year 2000 manufacturing incumbent workers into non-manufacturing.

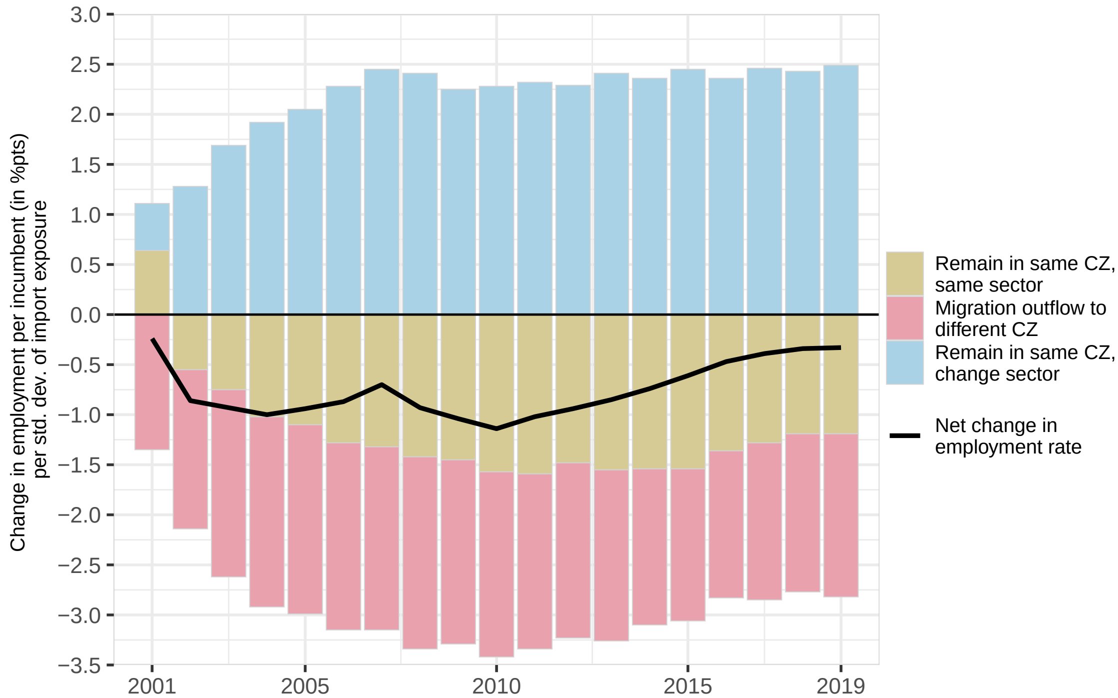


Figure 21: The Impact of CZ-Level Trade Exposure on Employment, Sectoral Mobility, and Geographic Mobility of Workers Employed in Manufacturing in 2000.

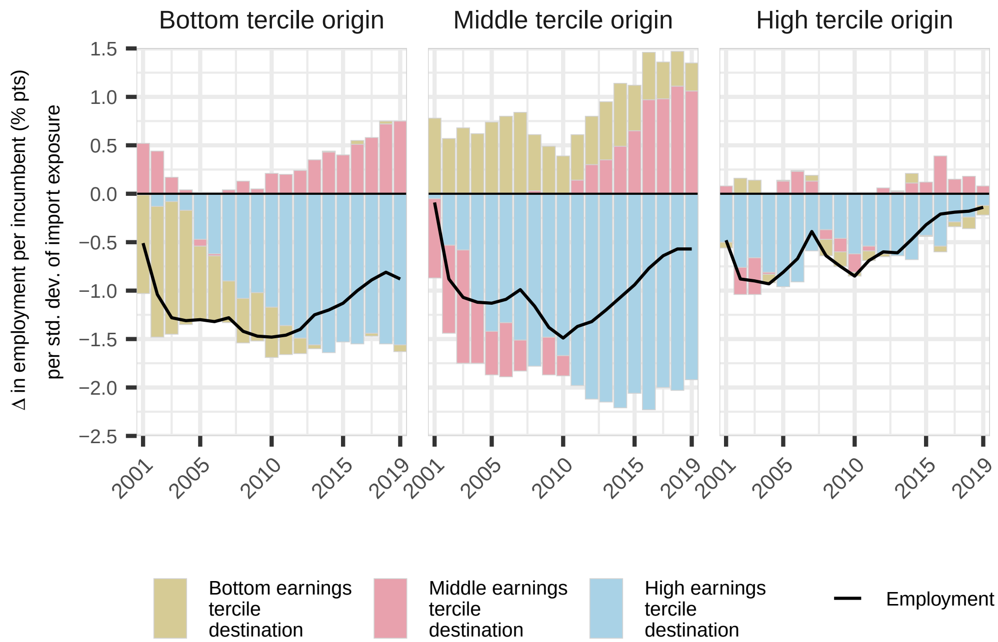
Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (7). The outcome variable is the change in employment per sector incumbent. The outcome is denominated by the initial count of incumbents, less workers that have aged out of the 18–64 bracket each year. All regressions include controls for Census division indicators and the 2000 manufacturing employment share in CZ. See Table A.16 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

the first decade reflect a loss of high-tercile jobs with no transition to middle or low-terciles jobs. When the rebound ultimately occurs, it operates through regaining high-tercile jobs.

The first panel of Figure A.3 further decomposes earnings tercile transitions into transitions among sector-CZ stayers—those who remain employed in manufacturing in the initial CZ, but may move across employers—and non-stayers. While most of the reduction in employment by earnings tercile accrues to non-stayers, there is a notable exception: most of the fall in high-tercile jobs among middle-tercile manufacturing workers is experienced by sector-CZ stayers. In plain language, trade exposure diminishes the earnings trajectories of middle-tercile manufacturing workers, even among those who remain in manufacturing.

A. Earnings tercile switching



B. Industry premium switching

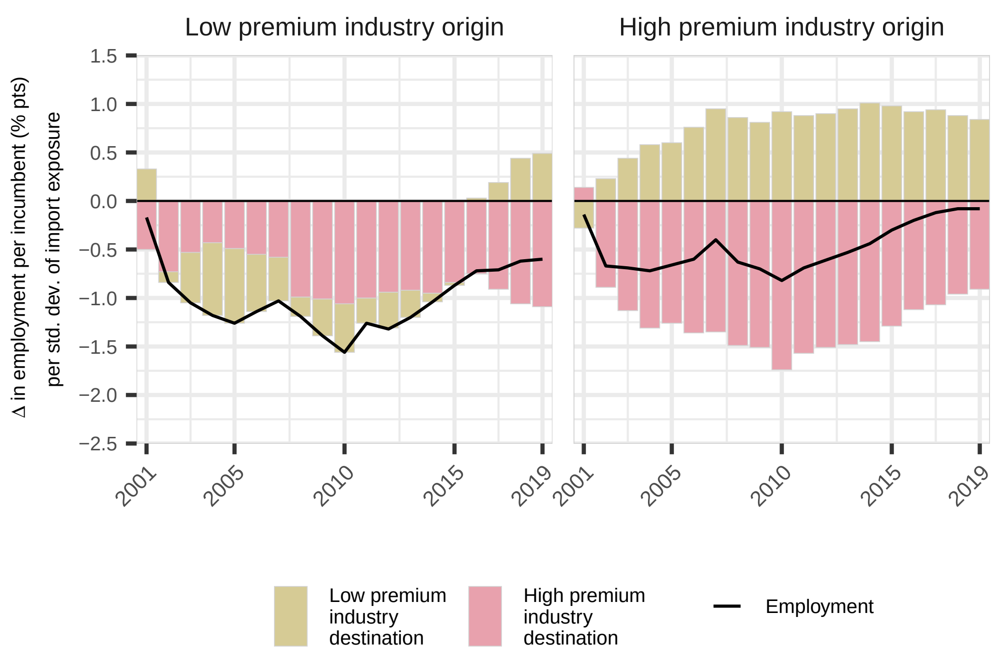


Figure 22: The Impact of CZ-Level Trade Exposure on Earnings Tercile and Industry Premium Switching of Workers Employed in Manufacturing in 2000.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). The outcome variable is the earnings tercile and industry premium flow destination, in panels A and B respectively. The outcome is denominated by the initial count of incumbents, less workers that have aged out of the 18-64 bracket each year. All regressions include controls for Census division indicators and the 2000 manufacturing employment share in CZ. See Tables A.17 and A.18 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

Panel B of Figure 22 reports estimates for the trajectory of manufacturing incumbents by industry premium in 2000. Workers beginning in low-premium manufacturing industries see a sharp drop in employment between 2000 and 2010, which attenuates by about half over the next nine years. The full net employment decline of trade-exposed low-premium manufacturing workers is accounted for by a fall in their outflow rate to high-premium industries. This adverse effect *increases* in the final four years of the outcome window, but it is partially offset by rising employment in low-premium industries. Surprisingly, trade-exposed incumbents in high-premium manufacturing also see a net employment fall in the first decade of the outcome window. This effect is only half as large as for low-premium manufacturing incumbents, and by 2019, these workers have regained all of their lost ground, measured by employment rates. The composition of their employment has differentially shifted, however, from high-premium to low-premium sectors. Thus, nearly two decades after trade exposure, employment in high-premium sectors of initially high-premium manufacturing workers remains significantly depressed.

The second panel of Figure A.3 further decomposes industry premium changes into transitions among sector-CZ stayers and non-stayers. Among manufacturing workers initially in low-premium industries, the reduction in outflows to high-premium industries is equally prevalent among those who remain in manufacturing and those who move to non-manufacturing. Among manufacturing workers initially in high-premium industries, however, the long-run shift in job composition towards low-premium industries is entirely due to workers moving from high-premium manufacturing to low-premium non-manufacturing.

Longitudinal analysis of initial manufacturing incumbent workers reinforces the narrative conveyed by the employment changes and worker flows seen in trade-exposed local labor markets. Initial manufacturing incumbents in trade-exposed CZs see permanent falls in employment and reduced transitions into—and increased transitions out of—high-wage jobs and high-premium industries. Contrary to conventional understanding, trade-exposed manufacturing workers become less, not more, likely to take employment outside their initial CZ. They are, however, more likely to transition out of manufacturing within their initial CZ.

7 Discussion

In a seminal analysis of the distributional consequences of trade, Ricardo (1815) identified the winners of England's import-restricting corn laws as the landowners whose incomes were buttressed by higher domestic food prices and the losers as the industrial workers and factory owners who endured elevated food costs and diminished demand for their services. Ricardo correctly foresaw that the repeal of the corn laws would redistribute income from the former to the latter group. In the ensuing two centuries, Ricardian comparative advantage has provided a dominant economic paradigm for analyzing the aggregate gains and distributional consequences of trade. One might therefore have expected that economists would anticipate the sharp redistributive consequences of China's spectacular rise as a manufacturing power. Such anticipation was rare, however. For nearly two decades after China's export boom began in the early 1990s, many economists and policy makers remained sanguine about how U.S. labor markets were adjusting in a new hyper-globalized era (Wood, 2018; Rodrik, 2019).

A decade of research has since established that local labor markets that were specialized in industries facing a large increase in Chinese import competition in the 1990s and 2000s experienced a differential decline in manufacturing employment. This decline was not compensated by a simultaneous, commensurate rise in non-manufacturing employment, and the consequences of this employment dislocation differed sharply across workers according to their region, sector, and education level. Ultimately, the speed, magnitude, and enduring impacts of this global event on U.S. labor markets and workers catalyzed a revised understanding and research agenda for interpreting how labor markets in industrialized countries adjust to the pressures of globalization. Motivated by empirical results on the adverse consequences of the China trade shock for exposed places (e.g., Autor et al., 2013), quantitative analysis of the labor market consequences of trade has advanced dramatically in the last decade. That work yields a diversity of assessments of the welfare consequences of China's export boom and of globalization more broadly. Yet, the literature still has not coalesced around a consistent narrative regarding how labor markets adjust to disruptive events.

This chapter enriches, disciplines, and amends that narrative by analyzing the distinct adjustment paths of U.S. labor markets and U.S. workers to increased Chinese import competition during the 2000s. The unified research design that we propose and apply identifies the causal effects of the China trade shock on outcomes in local labor markets viewed from two different perspectives: (1) *places*, meaning trade-induced net changes in the stock of jobs in a local labor market, as measured by industrial composition, demographic composition, and earnings levels; and (2) *people*, meaning trade-induced flows ("ins and outs") of workers across labor markets, sectors, employment statuses, and earnings levels that give rise to these net changes. Our time period spans two decades, from 2000, the year before China joined the World Trade Organization, to the pre-pandemic year of 2019.

Our analysis finds little evidence to support the central adjustment mechanisms considered by the literature. Conventional wisdom suggests three primary channels for labor market adjustment to localized economic shocks: geographic mobility, sectoral reallocation, and outflows to non-employment. However, our results reveal that none of these channels operates as anticipated. Geographic outflows unexpectedly *decline* in response to rising trade exposure, accompanied by a reduction in geographic inflows from other regions, with both responses attributable to native-born white workers. Reallocation of former manufacturing workers to local non-manufacturing jobs plays a minimal role. Outflows to non-employment make only a modest contribution to employment changes in trade-exposed locations in the long-run, particularly among former manufacturing workers. The long-term decline in manufacturing employment is not driven mostly by outflows of incumbent workers, either to non-manufacturing, to employment in other locations, or to non-employment. Instead, declining manufacturing employment largely reflects dwindling inflows of young, native-born, white, non-college-educated men.

Adjustment is neither slow nor stunted, however. Rather, the major margins of adjustment prove distinct from those considered by the literature. The reconstitution of employment in trade-impacted locations stems primarily from two unexpected sources: the entry of young adults who were below working age during China's WTO accession, and the influx of foreign-born workers obtaining their first U.S. jobs in trade-exposed locations. These new entrants are markedly different from incumbent workers—they are more likely to be native-born Hispanics, foreign-born Hispanics and other races, women, and the college-educated. New entrants disproportionately enter low-premium service industries. Simultaneously, the changes in mobility patterns favor low-paying jobs: initially bottom-tercile workers become less likely to out-migrate to other regions or achieve upward mobility to high-tercile jobs, while mid-tercile workers and those in high-premium industries increasingly experience downward mobility toward low-tercile and low-premium employment.

These interconnected shifts reveal a tension: although incumbent workers—particularly manufacturing workers—in trade-exposed locations face deteriorating economic prospects, trade-exposed regions have simultaneously generated new opportunities that attract a broader set of new entrants, reflected in gender, ethnicity, nationality, and educational backgrounds. While these findings testify to the long-term resilience of local labor markets, the eventual employment rebound took over a decade to materialize and the workers who participated in the recovery were not those who initially bore its costs.

Our findings call for a reexamination of the labor market adjustment mechanisms considered in the extant literature using spatial equilibrium models to evaluate the labor market consequences of the China trade shock in the U.S. context. A significant focus of this literature has been geographic employment mobility (e.g. Caliendo et al. 2019); however, we find little empirical support for this mechanism. This literature also emphasizes employment mobility across sectors (e.g. Galle et al. 2023), but we find only a small role for this mechanism. Few papers in this literature (e.g., Kim and Vogel 2021) present models in which non-employment may rise persistently, as we find to be the case. Importantly, the trade literature has yet to consider how labor markets adjust through the regional and sectoral choices of new entrants—both new generations of youth and foreign immigrants selecting their first jobs in the U.S.—which we find to be the most quantitatively important channels of labor market adjustment.[60] Moving beyond spatial equilibrium models that rely on transitory joblessness and geographically-mobile workers, while also incorporating generational change and international immigration, represents a pressing direction for future work.

The complex and, in many ways, unanticipated path of local labor market adjustment to the China trade shock poses largely unstudied questions about how regions will and should specialize in response to globalization. If the expanding industries (e.g., K-12 education, primary medical care, retail establishments) in trade-exposed places are largely non-tradable, what sources of income or transfers are offsetting the apparent rise in regional trade deficits due to declining manufacturing employment? Alternatively, if some expanding industries are tradable, which of the seemingly non-tradable sectors are successfully exporting their products to other regions? Further research is necessary to understand how regional production and income flows adapt to the retreat of local manufacturing employment in the face of advancing globalization.

While our focus has been on the labor market, parallel questions about the long-run impacts of exposure to import competition on non-labor outcomes remain unanswered. What are the lasting effects of import competition on the resilience of places in the realms of public services, criminality, poverty, and political extremism? Does the connection between the erosion of labor market opportunities and adverse health outcomes, increased risky behavior, and higher mortality in trade-exposed places persist? And what are the consequences of these adverse outcomes for the human capital formation of children who are raised in trade-exposed places? More work is needed to understand the long-term and intergenerational consequences of trade adjustment on non-labor outcomes.

The persistence of economic distress among non-college-educated, formerly-manufacturing workers has precipitated interest in the application of place-based policies in declining industrial regions (Austin et al., 2016). Our results on the differential adjustment of places versus people to the China trade shock suggest that place-based policies, long a concern

[60] Dix-Carneiro (2014) and Guren et al. (2015) present overlapping generations models that emphasize the importance of young generations in labor market adjustment to trade shocks. Cadena and Kovak (2016) and Autor et al. (2025) provide reduced-form evidence on the role of foreign-born immigrants in regional adjustment to the Great Recession and to the China trade shock, respectively.

among economists (Glaeser and Gottlieb, 2008), are likely to have complex targeting effects. Targeting trade-exposed places may benefit both new generations of entering youths and foreign-born immigrants—whose location choices appear relatively elastic to changing conditions—and also initial incumbents in these locations, whose geographic mobility sharply declines in response to these same conditions.

Although the focal China trade shock studied in this chapter sharply decelerated after 2007, the adjustment process that followed is ongoing. It took more than a decade after China's WTO accession for trade-exposed locations to regain their initial employment levels, and the bulk of the rapid differential employment increase in these locations occurred after 2014. Though our outcome window concludes at the onset of the Covid pandemic, the trends depicted by our data suggest that trade-exposed locations were, as of 2019, still in the midst of rapid demographic and industrial transitions. Assessing what role policy has played—and could play—in shaping the path of these transitions remains a crucial task for research.

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A Additional Tables and Figures

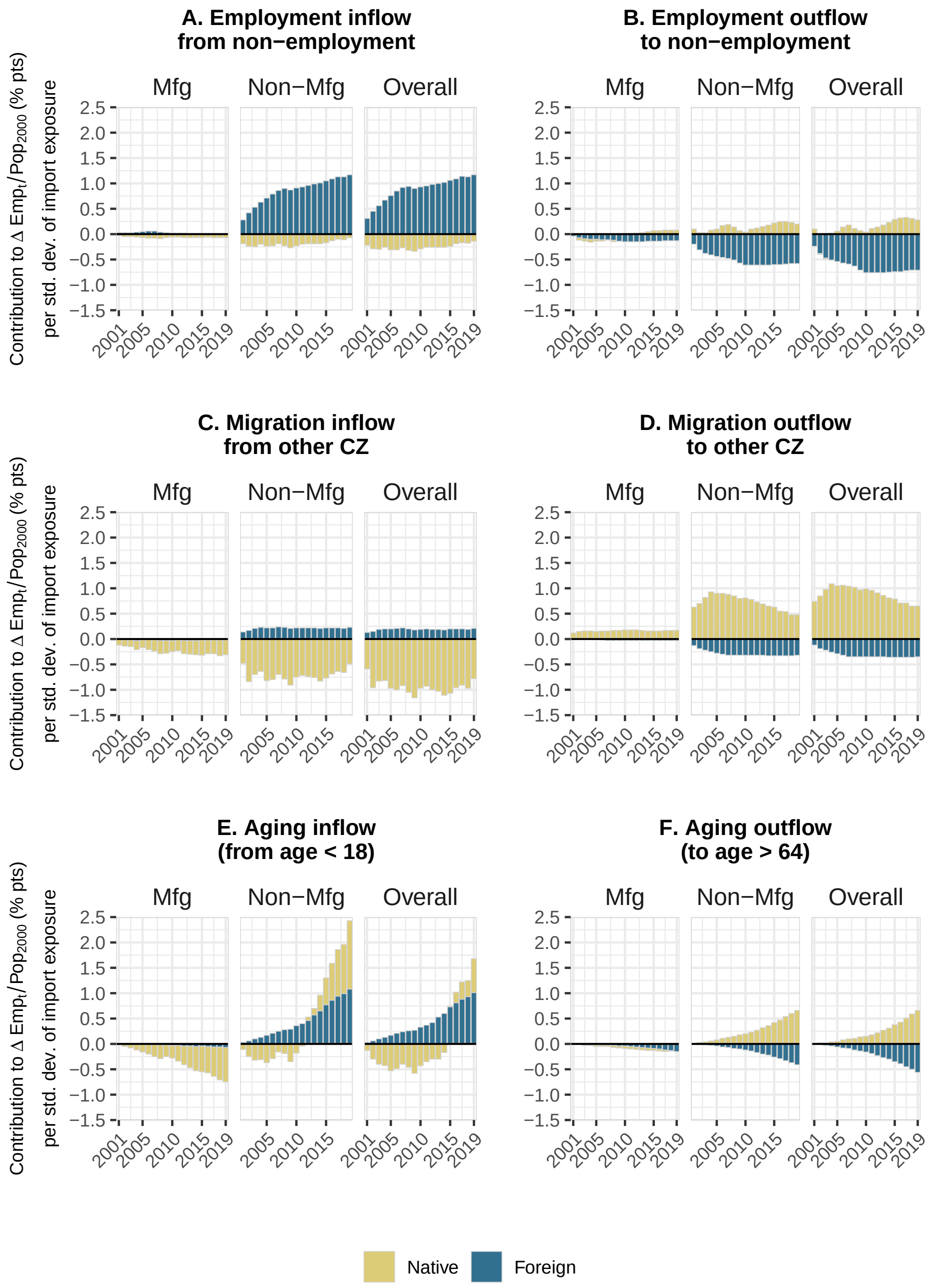


Figure A.1: The Impact of CZ-Level Trade Exposure on Gross CZ Employment Flows by Nativity.

Notes: See note to Figure 10. Estimates are shown by worker nativity: native and foreign-born. Greater inflows of workers which raise CZ employment are indicated with positive bars in panels A, C and E. Greater outflows of workers which reduce CZ employment are indicated with negative bars in panels B, D and F. See Table A.13 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

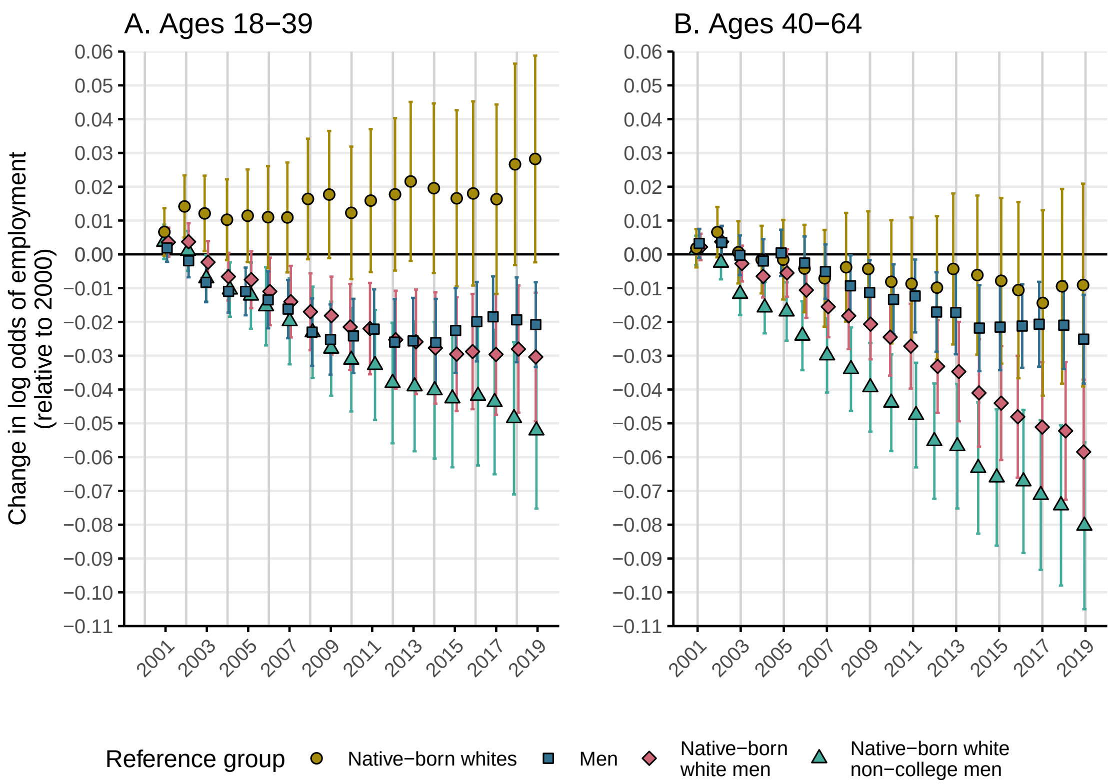
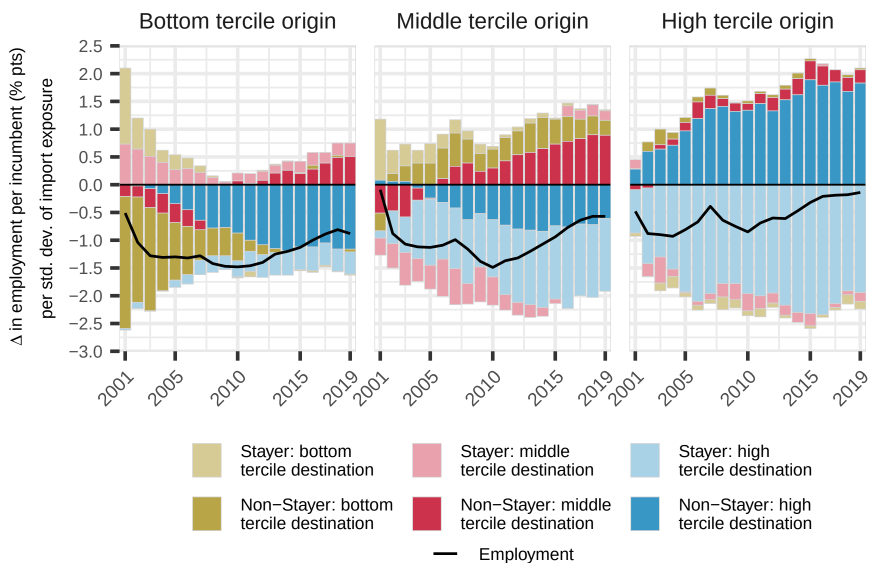


Figure A.2: The Impact of CZ-Level Trade Exposure on the Prevalence of Specific Demographic Groups in Employment by Age Bracket.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). The outcome variable is the change in log odds of employment relative to 2000 levels for each reference group compared to all others, e.g. native-born whites compared to native-born non-whites and foreign-born individuals. Vertical bars display ±1.96 standard errors. All regressions include controls for Census division indicators and the 2000 manufacturing employment share in CZ. See Table A.14 for 2010 and 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

A. Earnings tercile switching



B. Industry premium switching

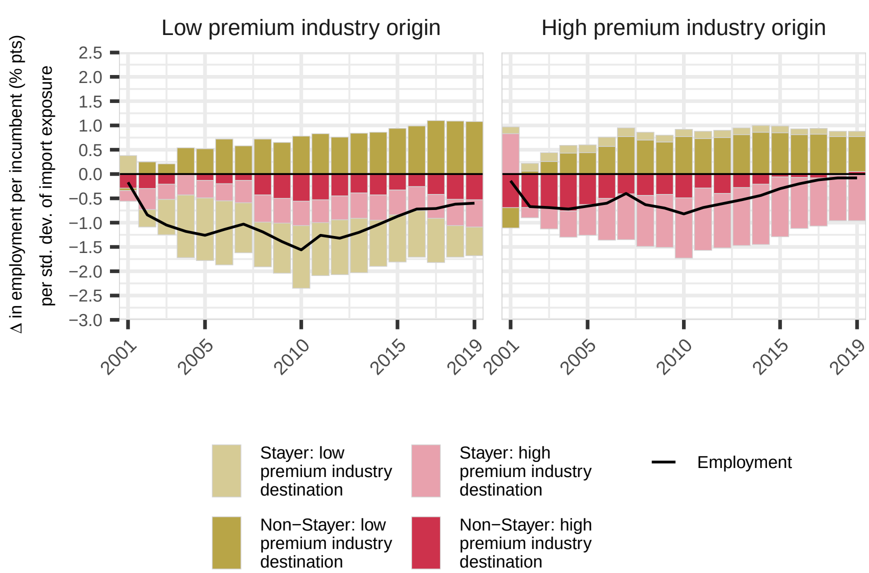


Figure A.3: The Impact of CZ-Level Trade Exposure on Earnings Tercile and Industry Premium Switching of Workers Employed in Manufacturing in 2000 by Sector-CZ Staying.

Notes: This figure displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). The outcome variable is the earnings tercile and industry premium flow destination decomposed by sector-CZ staying. Stayers are defined as individuals remaining employed in the original CZ and sector. Non-Stayers are defined as individuals who exited the original CZ, switched sectors, or exited to non-employment. The outcome is denominated by the initial count of incumbents, less workers that have aged out of the 18-64 bracket each year. All regressions include controls for Census division indicators and the 2000 manufacturing employment share in CZ. See Tables A.17 and A.18 for 2019 point estimates with standard errors.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

Supersector	2000	2019
Mining & resource	1.33	1.37
Information tech.	2.96	2.15
Other services	3.07	2.97
Government	4.15	3.76
Construction	5.86	5.61
Finance & real est.	6.16	5.91
Leisure & hosp.	8.66	11.33
Business & prof.	13.42	14.66
Manufacturing	14.20	9.16
Health & education	19.44	23.42
Trade & transport	20.75	19.68

Table A.1: The Share of National Employment by Industry, 2000 and 2019.

Notes: This figure reports the share of U.S. private sector payroll employment by major industry in 2000 and 2019 among the 42 states included in our LEHD sample. These states comprise approximately 92.2% of U.S. private sector payroll employment in 2000 and 90.5% in 2019.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

	Manufacturing		Non-Manufacturing	
	2000	2019	2000	2019
Earnings Tercile				
Bottom earnings tercile	18.04	13.43	35.86	30.41
Middle earnings tercile	36.32	32.45	32.85	31.48
High earnings tercile	45.64	54.11	31.30	38.11
Earnings tercile (Less than college)				
Bottom earnings tercile	19.44	15.27	39.41	35.50
Middle earnings tercile	41.05	38.12	37.25	36.63
High earnings tercile	39.51	46.62	23.34	27.87
Earnings tercile (College or more)				
Bottom earnings tercile	12.74	7.72	28.84	20.71
Middle earnings tercile	18.50	14.80	24.13	21.65
High earnings tercile	68.75	77.49	47.03	57.64
Industry premium				
Low premium industries	15.79	10.76	61.27	62.98
High premium industries	84.21	89.24	38.73	37.02
Industry premium (Less than college)				
Low premium industries	16.96	11.61	63.34	66.72
High premium industries	83.04	88.39	36.66	33.28
Industry premium (College or more)				
Low premium industries	11.62	8.44	57.28	56.52
High premium industries	88.38	91.56	42.72	43.48

Table A.2: The Share of Manufacturing and Non-Manufacturing Employment by Earnings Tercile and Industry Premium, 2000 and 2019.

Notes: This table reports the share of employment for manufacturing and non-manufacturing workers by demographic, earnings tercile, and industry premium in 2000 and 2019. Earnings tercile thresholds are defined such that they divide workers into three earnings bins, each comprising one third of earners, in 2000. In subsequent years, those thresholds are fixed in real terms using the Personal Consumption Expenditure deflator. Employment is classified as high-premium if the wage premium reported by Card et al. (2024) for the worker's industry of employment exceeds the employment-weighted average premium for the U.S. economy. See the text for additional details.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

	Manufacturing		Non-Manufacturing	
	2000	2019	2000	2019
Full sample				
Employment (millions)	17.09	12.22	103.20	121.20
Employment share	14.20	9.20	85.80	90.80
Sex				
Male	68.01	71.29	48.71	48.38
Female	31.99	28.71	51.29	51.62
Age				
$18-24$	10.25	9.48	17.95	16.75
$25-39$	37.55	33.45	37.72	36.46
$40-54$	40.11	34.36	34.10	29.74
$55-64$	12.09	22.71	10.24	17.06
Race/Ethnicity				
White	69.43	62.09	68.66	57.92
Black	9.20	9.69	11.39	12.31
Hispanic	11.81	13.70	10.54	15.15
Other race	9.55	14.52	9.41	14.62
Nativity				
Native	87.61	83.76	90.71	86.08
Foreign	12.39	16.24	9.29	13.92
Race and Nativity				
Native white/Black	76.45	69.51	77.56	67.49
Foreign white/Black	2.18	2.27	2.50	2.75
Native Hispanic/Other	11.15	14.25	13.15	18.60
Foreign Hispanic/other	10.22	13.97	6.79	11.17
Education				
Less than college	78.03	73.33	65.43	62.73
College or more	21.97	26.67	34.57	37.27

Table A.3: The Share of Manufacturing and Non-Manufacturing Employment by Demographic, 2000 and 2019.

Notes: This table reports the share of employment for manufacturing and non-manufacturing workers by demographic in 2000 and 2019. See the text for additional details.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		Manufacturing	Non-Manufacturing
Overall		0.36	-0.06
Age	18 - 39	0.39	-0.06
	40 - 64	0.34	-0.07
Sex	Male	0.33	-0.07
	Female	0.44	-0.05
Education	Less than college	0.38	-0.05
	College or more	0.29	-0.08
Race/ethnicity	White	0.40	-0.04
	Black	0.33	-0.15
	Hispanic	0.18	-0.09
	Other race/ethnicity	0.32	-0.07
Nativity	Native	0.38	-0.06
	Foreign	0.23	-0.10
Race/ethnicity and nativity	Native white/Black	0.40	-0.05
	Foreign white/Black	0.13	-0.23
	Native Hispanic/other	0.24	-0.10
	Foreign Hispanic/other	0.25	-0.05
Earnings tercile	Low earnings tercile	0.34	-0.05
	Middle earnings tercile	0.45	-0.05
	High premium industries	0.30	-0.08
Earnings tercile (Less than college)	Low earnings tercile	0.36	-0.04
	Middle earnings tercile	0.47	-0.04
	High earnings tercile	0.30	-0.08
Earnings tercile (College or more)	Low earnings tercile	0.24	-0.07
	Middle earnings tercile	0.29	-0.07
	High earnings tercile	0.30	-0.08
Industry premium	Low premium industries	0.54	-0.05
	High premium industries	0.33	-0.07
Industry premium (Less than college)	Low premium industries	0.59	-0.05
	High premium industries	0.34	-0.05
Industry premium (College or more)	Low premium industries	0.29	-0.06
	High premium industries	0.29	-0.10

Table A.4: Trade Exposure of Workers Employed in Manufacturing and Non-Manufacturing, 2000.

Notes: This figure reports the average of CZ-level import penetration exposure, $\Delta IP_{i,00-07}$, as defined in equation (1), by demographic, industry, and job characteristics of the worker in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		Manufacturing	Non-Manufacturing	Overall
Age	18-39	-0.68	1.13	0.44
		(0.10)	(0.55)	(0.56)
	40-64	-0.70	2.37	1.67
		(0.12)	(0.48)	(0.51)
Sex	Male	-0.70	1.28	0.57
		(0.14)	(0.53)	(0.57)
	Female	-0.68	2.21	1.54
		(0.08)	(0.50)	(0.51)
Education	Less than college	-1.16	1.35	0.19
		(0.17)	(0.67)	(0.71)
	College or more	-0.22	2.14	1.92
		(0.05)	(0.42)	(0.43)
Race/ethnicity	White	-0.43	0.42	-0.01
		(0.13)	(0.59)	(0.61)
	Black	-0.25	0.12	-0.13
		(0.05)	(0.24)	(0.24)
	Hispanic	-0.43	1.66	1.23
		(0.07)	(0.31)	(0.30)
	Other race	-0.27	1.29	1.02
		(0.05)	(0.30)	(0.31)
Nativity	Native	-0.89	2.24	1.35
		(0.17)	(0.85)	(0.88)
	Foreign	-0.49	1.25	0.76
		(0.07)	(0.30)	(0.31)
Race/ethnicity	Native white/Black	-0.61	0.49	-0.13
and nativity		(0.16)	(0.70)	(0.72)
	Foreign white/Black	-0.06	0.05	-0.01
		(0.01)	(0.04)	(0.04)
	Native Hispanic/other	-0.28	1.75	1.47
		(0.04)	(0.33)	(0.33)
	Foreign Hispanic/other	-0.42	1.20	0.78
		(0.06)	(0.28)	(0.29)

Table A.5: The Impact of CZ-Level Trade Exposure on CZ Employment by Age, Sex, Education, Race/Ethnicity, and Nativity, 2019.

Notes: Standard errors are in parentheses. This table displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). Estimates are shown by age, sex, education, race/ethnicity, nativity, and race/ethnicity × nativity. The outcome variable is the change in employment in the CZ between 2000 and 2019, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

Supersector	2019
Mining & resource	-0.15
	(0.13)
Information tech.	-0.11
	(0.09)
Other services	0.08
	(0.04)
Government	0.18
	(0.12)
Construction	-0.06
	(0.10)
Finance & real estate	0.35
	(0.12)
Leisure & hospitality	0.54
	(0.18)
Business & prof.	0.26
	(0.34)
Manufacturing	-1.36
	(0.20)
Health & education	1.59
	(0.27)
Trade & transport	0.63
	(0.33)

Table A.6: The Impact of CZ-Level Trade Exposure on CZ Employment by Sector.

Notes: Standard errors are in parentheses. This table displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). The outcome variable is the change in employment in the CZ between 2000 and 2019, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

	Industry	Male	Female	All
Manufacturing	Mfg: highly exposed	-0.63	-0.61	-1.24
		(0.06)	(0.05)	(0.11)
	Mfg: other subsectors	-0.08	-0.06	-0.14
		(0.12)	(0.06)	(0.17)
Trade & transport	Retail: grocery & supercenters	0.20	0.39	0.60
		(0.10)	(0.13)	(0.22)
	Retail: other subsectors	0.04	0.19	0.23
		(0.07)	(0.07)	(0.13)
	Not retail	-0.12	-0.02	-0.14
		(0.11)	(0.06)	(0.16)
Health & education	Health: hospitals & nursing homes	0.10	0.22	0.32
		(0.03)	(0.11)	(0.14)
	Health: phys. offices, pharm., etc.	0.17	0.48	0.65
		(0.03)	(0.10)	(0.13)
	Education: K-12	0.11	0.25	0.37
		(0.02)	(0.06)	(0.07)
	Education: other subsectors	0.14	0.14	0.28
		(0.03)	(0.04)	(0.07)
Leisure & hosp.	Leisure: food & restaurants	0.15	0.25	0.40
		(0.06)	(0.07)	(0.13)
	Leisure: other subsectors	0.08	0.08	0.16
		(0.04)	(0.04)	(0.09)

Table A.7: The Impact of CZ-Level Trade Exposure on CZ Employment by Subsector and Sex.

Notes: Standard errors are in parentheses. This table displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). The outcome variable is the change in employment in the CZ between 2000 and 2019, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		Manufacturing	Non-Manufacturing	Overall
Native white	Less than college	-0.24	-0.05	-0.29
		(0.11)	(0.39)	(0.41)
	College or more	-0.15	0.42	0.27
		(0.04)	(0.25)	(0.25)
Foreign white	Less than college	-0.03	0.01	-0.02
		(0.00)	(0.01)	(0.01)
	College or more	-0.01	0.04	0.03
		(0.00)	(0.01)	(0.01)
Native Black	Less than college	-0.21	0.01	-0.20
		(0.04)	(0.17)	(0.17)
	College or more	-0.01	0.11	0.09
		(0.00)	(0.06)	(0.06)
Foreign Black	Less than college	-0.02	0.00	-0.02
		(0.00)	(0.02)	(0.02)
	College or more	0.00	0.00	0.00
		(0.00)	(0.01)	(0.01)
Native Hispanic	Less than college	-0.17	1.02	0.85
		(0.03)	(0.22)	(0.22)
	College or more	-0.01	0.51	0.50
		(0.00)	(0.06)	(0.06)
Foreign Hispanic	Less than college	-0.24	0.05	-0.18
		(0.04)	(0.04)	(0.06)
	College or more	-0.01	0.08	0.07
		(0.00)	(0.02)	(0.02)
Native other race	Less than college	-0.08	0.04	-0.04
		(0.01)	(0.07)	(0.07)
	College or more	-0.02	0.19	0.17
		(0.00)	(0.04)	(0.04)
Foreign other race	Less than college	-0.19	0.27	0.08
		(0.03)	(0.11)	(0.12)
	College or more	0.01	0.81	0.82
		(0.02)	(0.15)	(0.16)

Table A.8: The Impact of CZ-Level Trade Exposure on CZ Employment by Education, Race/Ethnicity, and Nativity, 2019.

Notes: Standard errors are in parentheses. This table displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). Estimates are shown by race/ethnicity × nativity × education. See Section 2.2 for definitions of race/ethnicity categories. The outcome variable is the change in employment in the CZ between 2000 and 2019, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		Manufacturing	Non-Manufacturing	Overall
Earnings tercile	Bottom earnings tercile	-0.23	1.54	1.31
		(0.04)	(0.36)	(0.36)
	Middle earnings tercile	-0.57	1.25	0.68
		(0.08)	(0.34)	(0.36)
	High earnings tercile	-0.58	0.70	0.12
		(0.14)	(0.46)	(0.50)
Earnings tercile	Bottom earnings tercile	-0.24	1.01	0.77
(Less than college)		(0.04)	(0.30)	(0.30)
	Middle earnings tercile	-0.50	0.94	0.44
		(0.08)	(0.27)	(0.29)
	High earnings tercile	-0.44	-0.35	-0.79
		(0.10)	(0.26)	(0.30)
Earnings tercile	Bottom earnings tercile	0.01	0.53	0.54
(College or more)		(0.01)	(0.09)	(0.09)
	Middle earnings tercile	-0.07	0.31	0.24
		(0.01)	(0.08)	(0.08)
	High earnings tercile	-0.14	1.06	0.92
		(0.04)	(0.27)	(0.28)
Industry premium	Low premium industries	-0.58	2.70	2.12
		(0.07)	(0.70)	(0.71)
	High premium industries	-0.80	0.79	-0.01
		(0.20)	(0.45)	(0.51)
Industry premium	Low premium industries	-0.51	1.35	0.84
(Less than college)		(0.06)	(0.50)	(0.51)
	High premium industries	-0.65	0.06	-0.59
		(0.16)	(0.30)	(0.36)
Industry premium	Low premium industries	-0.07	1.35	1.28
(College or more)		(0.01)	(0.24)	(0.24)
	High premium industries	-0.15	0.73	0.58
		(0.05)	(0.21)	(0.23)

Table A.9: The Impact of CZ-Level Trade Exposure on CZ Employment by Earnings Tercile and Industry Premium, 2019.

Notes: Standard errors are in parentheses. This table displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). Estimates are shown by earnings tercile, industry premium, and education. The outcome variable is the change in employment in the CZ between 2000 and 2019, divided by the population size of the CZ in 2000, as defined in equation (2). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		2000 - 2010		2000 - 2019	
		Estimate	Std. Err.	Estimate	Std. Err.
*Emp-Pop ratio**		-1.36	(0.55)	-0.98	(0.59)
Sector	All	-0.32	(0.62)	2.11	(1.04)
	Manufacturing	-0.84	(0.17)	-1.38	(0.21)
	Non-Manufacturing	0.52	(0.57)	3.49	(1.00)
Age	18 - 39	-0.67	(0.37)	0.44	(0.56)
	40 - 64	0.35	(0.29)	1.67	(0.51)
Sex	Male	-0.51	(0.35)	0.57	(0.57)
	Female	0.19	(0.29)	1.54	(0.51)
Education	Less than college	-0.85	(0.47)	0.19	(0.71)
	College or more	0.53	(0.19)	1.92	(0.43)
Race/ethnicity	White	-0.41	(0.43)	-0.01	(0.61)
	Black	-0.34	(0.12)	-0.13	(0.24)
	Hispanic	0.42	(0.15)	1.23	(0.30)
	Other race	0.01	(0.09)	1.02	(0.31)
Nativity	Native	-0.50	(0.57)	1.35	(0.88)
	Foreign	0.18	(0.13)	0.76	(0.31)
Race/ethnicity and nativity	Native white/Black	-0.79	(0.50)	-0.13	(0.72)
	Foreign white/Black	0.04	(0.03)	-0.01	(0.04)
	Native Hispanic/other	0.28	(0.14)	1.47	(0.33)
	Foreign Hispanic/other	0.15	(0.11)	0.78	(0.29)
Earnings tercile	Bottom earnings tercile	0.47	(0.25)	1.31	(0.36)
	Middle earnings tercile	-0.19	(0.22)	0.68	(0.36)
	High earnings tercile	-0.59	(0.27)	0.12	(0.50)
Earnings tercile (Less than college)	Bottom earnings tercile	0.16	(0.21)	0.77	(0.30)
	Middle earnings tercile	-0.28	(0.19)	0.44	(0.29)
	High earnings tercile	-0.69	(0.19)	-0.79	(0.30)
Earnings tercile (College or more)	Bottom earnings tercile	0.31	(0.06)	0.54	(0.09)
	Middle earnings tercile	0.09	(0.05)	0.24	(0.08)
	High earnings tercile	0.10	(0.12)	0.92	(0.28)
Industry premium	Low premium industries	0.36	(0.45)	2.12	(0.71)
	High premium industries	-0.68	(0.32)	-0.01	(0.51)
Industry premium (Less than college)	Low premium industries	-0.20	(0.35)	0.84	(0.51)
	High premium industries	-0.64	(0.25)	-0.59	(0.36)
Industry premium (College or more)	Low premium industries	0.56	(0.13)	1.28	(0.24)
	High premium industries	-0.04	(0.11)	0.58	(0.23)

Table A.10: The Impact of CZ-Level Trade Exposure on Net CZ Employment.

Notes: This table displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). The outcome variable is the change in employment in the CZ between 2000 and the column header year divided by the CZ population in 2000, as defined in equation (2). equation (3) defines the employment to population ratio. All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		Net sectoral reall-ocation	Gross aging inflow	Gross aging outflow	Gross migration inflow	Gross migration outflow	Gross non-emp. inflow	Gross non-emp. outflow
Overall	Mfg	-0.20	-0.75	-0.15	-0.31	0.14	-0.07	-0.04
			(0.11)	(0.09)	(0.07)	(0.06)	(0.04)	(0.05)
	Non-Mfg	0.20	2.43	0.25	-0.27	0.15	1.11	-0.38
			(0.90)	(0.33)	(0.49)	(0.32)	(0.26)	(0.27)
	Overall	–	1.68	0.10	-0.58	0.29	1.04	-0.42
Male	Mfg	-0.10	-0.59	0.08	-0.25	0.15	-0.05	0.05
			(0.08)	(0.07)	(0.05)	(0.04)	(0.02)	(0.03)
	Non-Mfg	0.10	1.16	-0.04	-0.11	-0.03	0.50	-0.31
			(0.46)	(0.17)	(0.25)	(0.17)	(0.13)	(0.14)
	Overall	–	0.57	0.04	-0.36	0.12	0.45	-0.26
Female	Mfg	-0.10	-0.16	-0.23	-0.06	-0.02	-0.02	-0.09
			(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
	Non-Mfg	0.10	1.28	0.29	-0.16	0.18	0.61	-0.07
			(0.45)	(0.17)	(0.25)	(0.16)	(0.14)	(0.13)
	Overall	–	1.12	0.06	-0.22	0.16	0.59	-0.16
Education (Less than college)	Mfg	-0.14	-0.79	0.01	-0.35	0.20	-0.14	0.07
			(0.09)	(0.07)	(0.06)	(0.05)	(0.03)	(0.04)
	Non-Mfg	0.15	-0.01	0.60	-0.73	0.56	0.36	0.27
			(0.58)	(0.23)	(0.33)	(0.23)	(0.16)	(0.21)
	Overall	–	-0.80	0.61	-1.08	0.76	0.22	0.34
Education (College or more)	Mfg	-0.05	0.05	-0.16	0.04	-0.06	0.07	-0.11
			(0.04)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)
	Non-Mfg	0.05	2.44	-0.35	0.47	-0.40	0.74	-0.65
			(0.47)	(0.14)	(0.20)	(0.14)	(0.13)	(0.13)
	Overall	–	2.49	-0.51	0.51	-0.46	0.81	-0.76

Table A.11: The Impact of CZ-Level Trade Exposure on Gross CZ Employment Overall, by Sex, and by Education, 2019.

Notes: Standard errors are in parentheses. This table displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). The outcome variable is the specified worker flow in the commuting zone between 2000 and 2019, divided by the population size of the CZ in 2000, as defined in equation (4). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		Net sectoral reall-ocation	Gross aging inflow	Gross aging outflow	Gross migration inflow	Gross migration outflow	Gross non-emp. inflow	Gross non-emp. outflow
Native white/ Black	Mfg	-0.07	-0.61	0.12	-0.26	0.16	-0.06	0.10
			(0.08)	(0.10)	(0.06)	(0.05)	(0.01)	(0.04)
	Non-Mfg	0.07	-0.95	1.04	-0.73	0.75	-0.23	0.55
			(0.76)	(0.35)	(0.43)	(0.30)	(0.12)	(0.27)
	Overall	–	-1.56	1.16	-0.99	0.91	-0.29	0.65
Foreign white/ Black	Mfg	-0.01	0.00	-0.03	0.00	-0.01	0.00	-0.02
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	Non-Mfg	0.01	0.12	-0.10	0.05	-0.07	0.16	-0.12
			(0.03)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)
	Overall	–	0.12	-0.13	0.05	-0.08	0.16	-0.14
Native Hispanic/ other	Mfg	-0.04	-0.07	-0.12	-0.03	0.01	-0.01	-0.02
			(0.03)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)
	Non-Mfg	0.04	2.30	-0.37	0.24	-0.27	0.17	-0.35
			(0.40)	(0.09)	(0.10)	(0.09)	(0.05)	(0.09)
	Overall	–	2.23	-0.49	0.21	-0.26	0.16	-0.37
Foreign Hispanic/ other	Mfg	-0.08	-0.07	-0.12	-0.02	-0.02	0.00	-0.11
			(0.03)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)
	Non-Mfg	0.08	0.96	-0.31	0.18	-0.25	1.01	-0.45
			(0.19)	(0.06)	(0.05)	(0.05)	(0.20)	(0.08)
	Overall	–	0.89	-0.43	0.16	-0.27	1.01	-0.56

Table A.12: The Impact of CZ-Level Trade Exposure on Gross CZ Employment Flows by Race/Ethnicity × Nativity, 2019.

Notes: Standard errors are in parentheses. This table displays estimates of the overall effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). The outcome variable is the specified worker flow in the commuting zone between 2000 and 2019, divided by the population size of the CZ in 2000, as defined in equation (4). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		Net sectoral reall-ocation	Gross aging inflow	Gross aging outflow	Gross migration inflow	Gross migration outflow	Gross non-emp. inflow	Gross non-emp. outflow
White	Mfg	-0.04	-0.59	0.19	-0.27	0.21	-0.05	0.13
			(0.08)	(0.09)	(0.06)	(0.06)	(0.01)	(0.04)
	Non-Mfg	0.04	-1.25	1.14	-0.85	0.87	-0.11	0.57
			(0.65)	(0.34)	(0.38)	(0.28)	(0.10)	(0.23)
	Overall	–	-1.84	1.33	-1.12	1.08	-0.16	0.70
Black	Mfg	-0.02	-0.02	-0.10	0.01	-0.06	-0.01	-0.05
			(0.03)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
	Non-Mfg	0.02	0.43	-0.21	0.17	-0.19	0.04	-0.15
			(0.28)	(0.10)	(0.11)	(0.08)	(0.05)	(0.10)
	Overall	–	0.41	-0.31	0.18	-0.25	0.03	-0.20
Hispanic	Mfg	-0.10	-0.05	-0.16	-0.05	0.01	0.01	-0.09
			(0.03)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)
	Non-Mfg	0.10	2.19	-0.48	0.32	-0.37	0.49	-0.58
			(0.40)	(0.12)	(0.12)	(0.11)	(0.11)	(0.12)
	Overall	–	2.14	-0.64	0.27	-0.36	0.50	-0.67
Other race	Mfg	-0.02	-0.09	-0.07	0.00	-0.02	-0.02	-0.04
			(0.03)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
	Non-Mfg	0.02	1.07	-0.20	0.10	-0.16	0.69	-0.22
			(0.23)	(0.05)	(0.05)	(0.04)	(0.14)	(0.06)
	Overall	–	0.98	-0.27	0.10	-0.18	0.67	-0.26
Native	Mfg	-0.11	-0.68	0.00	-0.29	0.17	-0.07	0.08
			(0.09)	(0.09)	(0.07)	(0.06)	(0.02)	(0.04)
	Non-Mfg	0.11	1.35	0.66	-0.49	0.48	-0.07	0.20
			(0.82)	(0.34)	(0.46)	(0.31)	(0.12)	(0.26)
	Overall	–	0.67	0.66	-0.78	0.65	-0.14	0.28
Foreign	Mfg	-0.09	-0.07	-0.15	-0.02	-0.03	0.00	-0.13
			(0.03)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)
	Non-Mfg	0.09	1.08	-0.41	0.23	-0.32	1.17	-0.58
			(0.22)	(0.08)	(0.07)	(0.06)	(0.24)	(0.10)
	Overall	–	1.01	-0.56	0.21	-0.35	1.17	-0.71

Table A.13: The Impact of CZ-Level Trade Exposure on Gross CZ Employment Flows by Race/Ethnicity and Nativity, 2019.

Notes: Standard errors are in parentheses. This table displays estimates of the overall effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). The outcome variable is the specified worker flow in the commuting zone between 2000 and 2019, divided by the population size of the CZ in 2000, as defined in equation (4). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

	Change in log odds of employment	
	2000–2010	2000–2019
All ages		
Native-born whites	0.005	0.014
	(0.009)	(0.014)
Men	-0.018	-0.023
	(0.005)	(0.006)
Native-born white men	-0.020	-0.042
	(0.005)	(0.009)
Native-born white non-college men	-0.032	-0.059
	(0.007)	(0.011)
Ages 18-39		
Native-born whites	0.012	0.028
	(0.010)	(0.016)
Men	-0.024	-0.021
	(0.006)	(0.006)
Native-born white men	-0.021	-0.030
	(0.006)	(0.010)
Native-born white non-college men	-0.031	-0.052
	(0.008)	(0.012)
Ages 40-64		
Native-born whites	-0.008	-0.009
	(0.009)	(0.015)
Men	-0.013	-0.025
	(0.005)	(0.007)
Native-born white men	-0.024	-0.059
	(0.006)	(0.011)
Native-born white non-college men	-0.044	-0.080
	(0.007)	(0.013)

Table A.14: The Impact of CZ-Level Trade Exposure on Change in Log Odds of Employment from 2000, 2010 and 2019.

Notes: Standard errors are in parentheses. This table displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of equation (5). The outcome variable is the change in log odds of employment in 2019 relative to 2000 levels for each reference group compared to its complement, e.g. native whites compared to foreigners and native non-whites. All regressions include controls for Census division indicators and the 2000 manufacturing employment share in CZ.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		Net sectoral reallo-cation	Gross aging inflow	Gross aging outflow	Gross migration inflow	Gross migration outflow	Gross non-emp. inflow	Gross non-emp. outflow
Bottom earnings tercile	Mfg	-0.03	-0.18	-0.05	-0.04	0.08	-0.01	0.00
			(0.03)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
	Non-Mfg	0.05	0.52	0.35	-0.27	0.55	0.22	0.23
			(0.40)	(0.08)	(0.10)	(0.16)	(0.07)	(0.14)
	Overall	0.02	0.34	0.30	-0.31	0.63	0.21	0.23
Middle earnings tercile	Mfg	-0.08	-0.30	-0.14	-0.12	0.07	-0.04	-0.01
			(0.04)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
	Non-Mfg	0.08	0.77	0.37	-0.24	0.08	0.39	-0.09
			(0.31)	(0.12)	(0.16)	(0.12)	(0.11)	(0.08)
	Overall	0.00	0.47	0.23	-0.36	0.15	0.35	-0.10
High earnings tercile	Mfg	-0.09	-0.27	0.05	-0.15	-0.01	-0.01	-0.03
			(0.05)	(0.08)	(0.05)	(0.03)	(0.02)	(0.03)
	Non-Mfg	0.07	1.14	-0.47	0.25	-0.48	0.51	-0.52
			(0.31)	(0.22)	(0.28)	(0.11)	(0.12)	(0.11)
	Overall	-0.02	0.87	-0.42	0.10	-0.49	0.50	-0.55
Low premium industries	Mfg	-0.08	0.00	-0.27	0.00	-0.10	0.03	-0.17
			(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
	Non-Mfg	0.13	1.35	0.51	-0.38	0.43	0.67	0.03
			(0.65)	(0.21)	(0.29)	(0.24)	(0.19)	(0.20)
	Overall	0.05	1.35	0.24	-0.38	0.33	0.70	-0.14
High premium industries	Mfg	-0.12	-0.75	0.12	-0.32	0.24	-0.10	0.13
			(0.10)	(0.09)	(0.07)	(0.06)	(0.04)	(0.05)
	Non-Mfg	0.06	1.08	-0.26	0.12	-0.27	0.44	-0.41
			(0.34)	(0.21)	(0.25)	(0.14)	(0.10)	(0.12)
	Overall	-0.06	0.33	-0.14	-0.20	-0.03	0.34	-0.28

Table A.15: The Impact of CZ-Level Trade Exposure on Gross CZ Employment Flows by Earnings Tercile and Industry Premium, 2019.

Notes: Standard errors are in parentheses. This table displays estimates of the overall effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). The outcome variable is the specified worker flow in the commuting zone between 2000 and 2019, divided by the population size of the CZ in 2000, as defined in equation (4). All regressions are weighted by employment in the CZ in 2000. All regressions control for Census division fixed-effects and CZ share of employment in manufacturing in 2000.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

Migration outflow to other CZ	Sectoral outflow within CZ	Employ-ment	Staying in initial CZ and sector
-1.63	2.49	-0.33	-1.19
(0.64)	(0.42)	(0.28)	(0.50)

Table A.16: The Impact of CZ-Level Trade Exposure on Employment, Sectoral Mobility, and Geographic Mobility of Workers Employed in Manufacturing in 2000, 2019.

Notes: Standard errors are in parentheses. This table displays estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). The outcome variable is the change in employment change in employment per sector incumbent, as defined in equation (10).

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		Destination			
Origin	Staying	Bottom earnings tercile	Middle earnings tercile	High earnings tercile	Employment
Bottom earnings tercile	Non-Stayers	-0.05	0.51	-1.16	-0.88
		(0.14)	(0.20)	(0.33)	(0.30)
	Stayers	-0.02	0.24	-0.40	
		(0.05)	(0.09)	(0.13)	
	All	-0.07	0.75	-1.56	-0.88
		(0.16)	(0.21)	(0.40)	(0.14)
Middle earnings tercile	Non-Stayers	0.27	0.89	-0.61	-0.57
		(0.11)	(0.24)	(0.28)	(0.26)
	Stayers	0.02	0.17	-1.31	
		(0.03)	(0.19)	(0.31)	
	All	0.29	1.06	-1.92	-0.57
		(0.11)	(0.29)	(0.40)	(0.26)
High earnings tercile	Non-Stayers	0.03	0.24	1.83	-0.14
		(0.09)	(0.19)	(0.51)	(0.29)
	Stayers	-0.14	-0.16	-1.94	
		(0.03)	(0.12)	(0.63)	
	All	-0.10	0.08	-0.12	-0.14
		(0.09)	(0.24)	(0.39)	(0.29)

Table A.17: The Impact of CZ-Level Trade Exposure on Earnings Tercile Switching of Workers Employed in Manufacturing in 2000, 2019.

Notes: Standard errors are in parentheses. This figure reports estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). The outcome variable is the worker earnings tercile flow in 2019 decomposed by sector-CZ staying. Stayers are defined as individuals remaining employed in the original CZ and sector. Non-Stayers are defined as individuals who exited the original CZ, switched sectors, or exited to non-employment.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

		Destination		
Origin	Staying	Low premium industries	High premium industries	Employment
Low premium industries	Non-Stayers	1.08	-0.53	-0.60
		(0.34)	(0.31)	(0.38)
	Stayers	-0.59	-0.56	
		(0.36)	(0.21)	
	All	0.49	-1.09	-0.60
		(0.32)	(0.37)	(0.38)
High premium industries	Non-Stayers	0.72	0.05	-0.08
		(0.28)	(0.36)	(0.28)
	Stayers	0.11	-0.96	
		(0.04)	(0.50)	
	All	0.84	-0.91	-0.08
		(0.29)	(0.45)	(0.28)

Table A.18: The Impact of CZ-Level Trade Exposure on Industry Premium Switching of Workers Employed in Manufacturing in 2000, 2019.

Notes: Standard errors are in parentheses. This figure reports estimates of the effect of one standard deviation of exposure to import competition using 2SLS estimation of the regression specification in equation (5). The outcome variable is the worker industry premium flow in 2019 decomposed by sector-CZ staying. Stayers are defined as individuals remaining employed in the original CZ and sector. Non-Stayers are defined as individuals who exited the original CZ, switched sectors, or exited to non-employment. Note that stayers have no employment change by definition, so their effects on employment are blank in this table.

Source: LEHD 2000–2019, Opportunity Databank 2000–2019, and ACS 2005–2019.

B Measuring the Trajectories of Manufacturing Incumbents

We aim to estimate the impacts of the China trade shock on the trajectories of manufacturing incumbents, who were employed in manufacturing in year 2000. For consistency with our other regression analyses, we define manufacturing workers' exposure to the China shock based on their 2000 CZ's average employment-weighted trade exposure across all industries, while controlling for the CZ's manufacturing employment share. This design captures whether the average manufacturing worker in a CZ was employed in an industry that became strongly exposed to Chinese import competition.[61]

Our aim is to track the flows of trade-exposed manufacturing incumbents across sectors, locations, and non-employment.

To define the outcomes of interest, we utilize the variables defined in Table 1. To avoid conflating movements into retirement with movements into non-employment, we consider only incumbents who remain in the 18–64 age bracket in any given outcome year. Specifically, we adjust the number of manufacturing incumbents in 2000 as,

$$\text{incumbents}_{\text{mfg in cz, 00:19}} \quad \equiv \quad \text{emp}^{00}_{\text{mfg in } cz} \quad - \quad \text{outflow}^{\text{aging}}_{\text{mfg in cz, 00-19}}, \tag{8}$$

where the second term on the right of equation (8) is the flow of a CZ's manufacturing incumbents who exit working-age (becoming age 65+) between 2000 and 2019. We apply a similar adjustment to the other outcome years. Given these definitions, a CZ's year 2000 manufacturing incumbents can be classified into four mutually exclusive groups in the 2019 outcome year:

$$\begin{aligned}\text{incumbents}_{\text{mfg in cz, 00:19}} = \text{stayers}_{\text{mfg in cz, 00-19}} + \text{outflow}^{\text{sectoral}}_{\text{mfg in cz, 00-19}} \\ + \text{outflow}^{\text{geographic}}_{\text{mfg in cz, 00-19}} + \text{outflow}^{\text{non-employment}}_{\text{mfg in cz, 00-19}}.\end{aligned} \tag{9}$$

As defined in equation (9), manufacturing incumbents in 2000 may as of 2019 remain in

[61] In unreported results, we further examine trade impacts on incumbent workers initially employed in non-manufacturing. These effects are generally imprecisely estimated, so we do not focus on them. Related work by Autor et al. (2014) and Pierce et al. (2024) studies the exposure of manufacturing workers to the China shock both based on their initial location and initial industry of employment, as well as the exposure of non-manufacturing workers based on location. While, for consistency with the other analyses, we focus on CZ-level exposure, we note that Autor et al. (2014) show that controlling for industry-level trade exposure has little impact on estimated worker-level effects of CZ-level trade exposure.

their sector and CZ (stayers), stay in their CZ and transition to a job in non-manufacturing (sectoral outflow), take a job in another CZ (geographic outflow), or transition to being without a job (outflow to non-employment).

To form the outcomes of interest, we normalize the terms in equation (9) by the number of manufacturing incumbents who are of working age in the relevant year (defined in equation 8) and then rearrange terms to obtain the following expression for changes in the employment rate of working-age incumbents:

$$\underbrace{\frac{\text{outflow}^{\text{non-employment}}_{\text{mfg in cz, 00-19}}}{\text{incumbents}_{\text{mfg in cz, 00:19}}}}_{\substack{\textbf{non-employment}\\ \text{of mfg incumbents}}} = \underbrace{1 - \frac{\text{stayers}_{\text{mfg in cz, 00-19}}}{\text{incumbents}_{\text{mfg in cz, 00:19}}}}_{\substack{\textbf{total non-staying:}\\ \text{exit mfg in CZ}}} - \underbrace{\frac{\text{outflow}^{\text{geographic}}_{\text{mfg in cz, 00-19}}}{\text{incumbents}_{\text{mfg in cz, 00:19}}}}_{\substack{\textbf{geographic recovery:}\\ \text{gain job in other CZ}}} - \underbrace{\frac{\text{outflow}^{\text{sectoral}}_{\text{mfg in cz, 00-19}}}{\text{incumbents}_{\text{mfg in cz, 00:19}}}}_{\substack{\textbf{sectoral recovery:}\\ \text{gain job in local non-mfg}}}. \tag{10}$$

The first term term on the right side of equation (10) represents incumbents who exit manufacturing employment in a CZ. These mobile workers may transition to employment in another CZ, as captured by the second term on the right of equation (10); to employment in non-manufacturing in the initial CZ, as captured by the third term on the right side of equation (10); or to non-employment, as shown by the term on the left side of equation (10). By using outflows to non-employment as the net outcome in equation (10), we highlight that non-employment captures the set of incumbents who exit manufacturing but do not transition to employment in another sector or local labor market.

In the empirical analysis, we estimate the impact of trade exposure on each element of equation (10), and further separate these impacts according to worker characteristics. We examine these effects for each time interval from 2000-2001 to 2000-2019 to reveal variation in the timing of these transitions.