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ABSTRACT

Minority workers generally have worse economic outcomes than whites, and are disproportionately impacted by many negative shocks. However, we show that Black-white employment gaps narrowed as a result of China's WTO accession because Black workers live in areas that are less exposed to imports from China and transition to non-manufacturing employment at higher rates. Hispanic populations, however, are more exposed than whites because of their industry mix and experience larger employment losses for a given level of exposure. The China shock widened Hispanic-white gaps, though this effect was short lived. The lasting negative effects were driven primarily by white workers.

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1 Introduction

Policy makers have long grappled with the fact that Black and Hispanic workers have persistently lower income, wealth, and employment outcomes relative to white workers.[1] Minorities are also disproportionately impacted by a wide range of negative income and employment shocks, including, but not limited to, the Great Recession, Covid-19, and typical month-to-month fluctuations in income.[2] Despite these overall trends, we show that Black-white employment gaps actually narrowed as a result of one important shock to U.S. labor markets: the increase in manufacturing imports following China being admitted to the WTO (a.k.a. the "China shock"). This is due to both the Black population's lower initial exposure to manufacturing imports from China and their greater propensity to transition from manufacturing to nonmanufacturing employment. We do not find evidence of a similar narrowing of Hispanic-white employment gaps as a result of the China shock. These results have important implications for policies related to both trade and racial and ethnic inequality.

The negative effects of import competition on manufacturing employment have received a great deal of attention in both the academic literature and in policy debates. Yet little attention has been paid to how import competition affects workers of different races and ethnicities, or how it impacts overall racial and ethnic inequality. These effects can vary greatly across groups, as subpopulations will be differentially exposed to import competition due to differences in where they live and work. Furthermore, for a given level of exposure, job displacement effects may vary across populations because of their mix of skills, differences in adaptability to labor market shocks, or impacts of discrimination. In this paper, we document differences in exposure to import competition across Black, white, and Hispanic populations, identify differential coefficient impacts on labor market outcomes for a given exposure, and explore mechanisms through which these differences materialize. We then provide a formal decomposition that combines the exposure and coefficient effects, and interpret our results in the context of overall racial and ethnic labor market inequality in the U.S.[3]

In their seminal work, Autor et al. (2013) show that US commuting zones (CZs) that were more exposed to the China shock in the early 2000s experienced persistent relative employment declines. They define exposure based on the initial share of employment in the CZ producing a similar mix of products to those that would increasingly be imported from China, largely in manufacturing. However, manufacturing employment is concentrated in predominantly white CZs. Figure 1 maps

[1] See, for example, Dettling et al. (2017), Bayer and Charles (2018), Casey and Hardy (2018), and McIntosh et al. (2020).

[2] See, for example, Hoynes et al. (2012), Cho and Winters (2020), Hardy and Logan (2020), and Ganong et al. (2020).

[3] In this paper, we use the terms Black and white to refer to non-Hispanic Black and non-Hispanic white individuals.

import exposure and Black and Hispanic population shares at the CZ level in 2000 and shows very different spatial distributions. In addition, prior to the China shock, Black workers were underrepresented in manufacturing employment, compared to white and Hispanic workers.

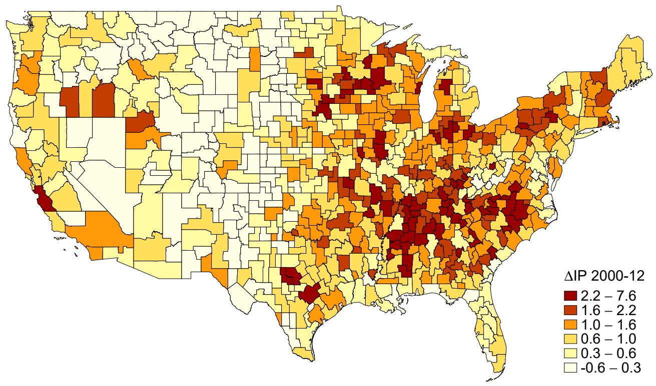
To capture direct exposure to the China shock, we define a CZ-group-level shock based on race- or ethnicity-specific employment shares across industries. Average exposure varies across groups due to baseline differences in how populations are distributed across CZs and how employment is distributed across industries. We find that the Black population is 15% *less* exposed to import competition from China, compared to the white population. This gap amounts to roughly one-quarter of the inter-quartile range of white import exposure and is due to differences in where white versus Black populations work, and, especially, where they live. In contrast, the Hispanic population is 21% *more* exposed than the white population due to their overrepresentation in the subsectors of manufacturing that would face the greatest pressures from production in China.

These differences in direct import exposure alone are but one input into the overall effect of import competition on employment rates by race and ethnicity. Minorities could be more likely than their white coworkers to lose jobs when a negative shock hits. Or, spillover effects to the local economy could have differential impacts based on race or ethnicity; some groups could suffer greater job loss due to overall negative effects on the local economy, or benefit more from a shift towards services associated with the China shock (Bloom et al., 2019). To capture the effects of import competition on exposed workers, we examine employment impacts at the CZ-race/ethnicity level over the 2005-2018 period, compared to a 2000 baseline. We explore impacts of the group-specific import exposure shock, as well as effects of the more standard CZ-level shock which allows for spillovers of shocks across race/ethnicities. When doing so, we take into account identification issues raised in the literature (e.g., Autor et al. (2013); Pierce and Schott (2016)), and most recently by Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020). The latter two papers raise important concerns about shift-share estimators in general, and applications to estimating the effect of the China Shock on local labor markets in particular. However, we present evidence that these issues are much less of a concern when estimating effects that vary by race and ethnicity.

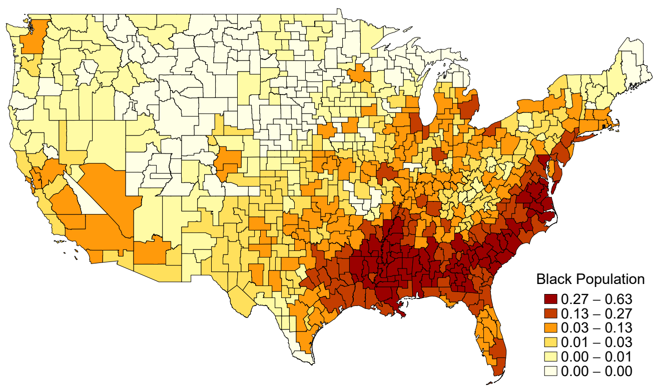
We find that increased exposure to import competition reduces manufacturing employment for Black, Hispanic, and white workers, and at similar magnitudes for a one unit change in exposure. Because the Black population is less exposed to import competition, their overall manufacturing employment losses are smaller. Our novel decomposition approach shows that Black workers experience a 2.4 percentage point (31%) smaller decline in manufacturing employment-to-population due to import exposure relative to white workers. Because the Hispanic population is more exposed

Figure 1: Maps of CZ-level Import Exposure and Population Shares

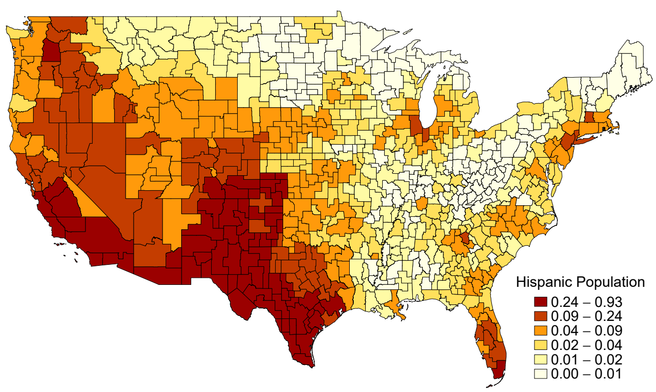
Panel A: Change in Import Exposure from China 2000-2012



Panel B: Black Population Share



Panel C: Hispanic Population Share



Notes: The map in panel A shows the change in import exposure from 2000-2012 by Commuting Zone (CZ), defined in equation 1 and in Autor et al. (2021). The map in panel B (C) shows the Black (Hispanic) population share of each CZ, obtain from the 2000 Census. Color-coding distinguishes the bottom four quintiles and the top two deciles, from lightest to darkest.

to import competition, their overall manufacturing employment losses are quite a bit larger. Hispanic workers experience a 2.8 percentage point (36%) larger decline in manufacturing employment relative to white workers.

We also find that increased import competition is associated with larger and statistically significant *increases* in non-manufacturing employment for Black workers relative to white workers. Black workers experience a 3.8 percentage point increase in non-manufacturing employment-to-population for a one unit increase in import competition, compared to no change for white workers. The Black-white differential impacts are largely stable over the time period studied and hold for both the race-specific and CZ-wide shocks. Effects do not appear to be driven by educational or occupational differences, suggesting that Black workers are not more adaptable simply because they perform lower-skilled jobs. However, baseline differences in industrial competition do play a role. Black workers likely benefit from their overrepresentation in education and health services. Further, data on job-to-job transitions show that Black workers are more likely than white workers to transition from manufacturing to non-manufacturing jobs at baseline, and perhaps benefit from their greater labor market fluidity. Finally, we see no evidence of negative relative wage effects for Black workers due to the China shock. Though average wages across manufacturing and non-manufacturing are more similar for Black workers than for white workers, suggesting that Black workers may be more likely than their white counterparts to find closer non-manufacturing substitutes to their previous manufacturing jobs.

In contrast, Hispanic workers suffer larger hits to non-manufacturing employment, compared to white workers. For a one-unit increase in exposure, the Hispanic non-manufacturing employment-to-population ratio falls by 2 percentage points, relative to no change for whites. Effects are largely driven by negative spillovers from a CZ-wide shock, rather than direct effects to Hispanic manufacturing jobs. Differences in observables, namely educational attainment and industrial composition do appear to be important. Hispanic workers are less likely to complete a high school education and are overrepresented in construction and low-skilled manufacturing, and these differences likely drive their more negative impacts. We find that effects are most negative around the time of the Great Recession, and converge to the white effect in the later years.[4]

A large body of literature has shown negative and surprisingly long-lasting relative impacts on manufacturing employment in locations exposed to import competition from China (Autor et al., 2013, 2014; Pierce and Schott, 2016; Autor et al., 2021) as well as a wide range of negative social and health consequences (Pierce and Schott, 2020; Autor et al., 2020, 2019a).[5] However, other outcomes

[4]We find no evidence that minorities differ in geographic mobility in response to import shocks, suggesting that migration within the U.S. cannot explain the differential employment outcomes.

[5]Eriksson et al. (2021) study earlier trade shocks, such as the import increase from Japan from 1975 to 1985 and

have been found to offset some of these localized negative effects. For example, Feenstra and Sasahara (2019) use the World Input-Output Database to quantify the impact on U.S. employment from both imports and exports during 1995-2011, and find that while U.S. merchandise imports from China led to reduced demand of about 2.0 million jobs, expansion in U.S. exports created even more jobs, resulting in a net increase of about 1.7 million. In addition to localized manufacturing losses, Bloom et al. (2019) find that Chinese competition reallocated employment from manufacturing to services, and from the U.S. heartland to the coasts. They discuss how offshoring production labor to China may have facilitated domestic growth in other types of jobs, product switching on the part of employers towards those with a greater comparative advantage in domestic production, or even industrial reclassification away from manufacturing and towards marketing and business services. To the extent that these changes occurred at a localized level, we should see the China shock coinciding with growth in other areas of employment such as services. However, to our knowledge ours is the first paper to look at the effects of the China shock across race and ethnic groups.[6]

As the first to study the impact of the China shock by race and ethnicity, we contribute to a large and important literature on racial and ethnic gaps in the labor market. Minority populations tend to be more vulnerable to recessionary shocks (Hoynes et al., 2012) and earn lower wages on average, which raise the concern that they will suffer disproportionately from other types of labor market shocks such as competition from a low wage country like China. For the Hispanic population, that is indeed what we find. In addition to their lower educational attainment, they may have been more prone to impacts of the housing bubble burst around the Great Recession due to their overrepresentation in construction and the relationship between manufacturing employment, the China shock, and the housing bubble.[7] However, the longstanding Hispanic-white wage and employment gaps have converged substantially in recent decades, largely due to convergence in

find no overall impacts on CZ employment rates. Hakobyan and McLaren (2016) study NAFTA and find negative effects for a small number of workers in highly affected locations and industries, but the effect on the average worker is close to zero. Papers on the effects of offshoring, as opposed to import competition, have found effects that are much smaller or even positive (Slaughter, 2000; Harrison and McMillan, 2011; Wright, 2014; Kovak et al., 2021).

[6]Previous work has explored other types of heterogeneity: Impacts on overall inequality are mixed with Autor et al. (2014) finding worse effects for low wage workers and Borusyak and Jaravel (2023) finding rising inequality only within, but not across, income deciles when considering both earnings and expenditures; Keller and Utar (2022) show that in Denmark, women exited the labor force at greater rates than men following the China shock and such exit was associated with increased fertility; Carballo and Mansfield (2022) show that unemployed and entry-level workers experienced negative impacts of the China shock due to increased competition with displaced manufacturing workers. In addition, Batistich and Bond (2021) show Black workers did face disproportionate negative consequences from the Japan trade shock due to upskilling in manufacturing, though there is little overlap between the CZs most impacted by Japan versus the China shock two decades later. Further, the China shock has much larger negative consequences to exposed populations as whole, compared to the Japan shock.

[7]Charles et al. (2016) note that the housing bubble masked a longer run decline in manufacturing due to the substitutability of labor across sectors, while Xu et al. (2019) point out that the housing bubble burst was stronger in CZs more exposed to the China shock. Together, these findings imply that the dual impacts of the China shock and the housing bubble burst may have contributed to especially large impacts on Hispanic workers who are overrepresented in construction, around the time of the Great Recession.

observables, and especially educational attainment (Trejo, 1997; Hirsch and Winters, 2013; Hull, 2017; Chetty et al., 2020; Murnane, 2013). Our results are consistent with this research in that observables appear to account for the bulk of the differential impacts on Hispanic relative to white workers. We also find that the convergence helps such that by 2018, the Hispanic population had recovered their employment losses from import competition relative to whites.

Black workers, in contrast, have experienced stagnating wage gaps with whites in recent decades.[8] Researchers have pointed out that widening income inequality exacerbates wage gaps (Juhn et al., 1993; Blau and Kahn, 1997; Bayer and Charles, 2018) and forces such as rising incarceration and technological change have served to depress labor force participation of Black relative to white workers (Neal and Rick, 2014; Hurst et al., 2021; Dicandia, 2021). In this paper, we find that trade presents a modest force pushing in the opposite direction. While Black workers exposed to import competition still faced negative impacts on manufacturing employment, they were relatively less likely to be exposed than white workers and furthermore, their greater presence in services employment meant they could take better advantage of the offsetting positive effects generated by trade at a localized level. In contrast to Hispanic workers, these results for Black workers are consistent over the 2005 to 2018 time period. Ironically, historical racial barriers to entry in manufacturing (Donohue and Heckman, 1991) combined with lower employer attachment seem to have facilitated a more rapid adjustment to the China shock for Black workers. Under most conditions, these forces tend to widen Black-white employment and wage gaps. However, we find that the Black-white employment-to-population gap narrowed by 3 percentage points (roughly 15%) due to the China shock.[9]

Our research not only sheds light on the evolution of race gaps in the U.S. but also helps interpret the literature on the impacts of import competition on local labor markets. The long-lasting impacts of the China shock on exposed locations have puzzled researchers and policy makers. The earlier conventional wisdom was that exposed populations would gradually adjust through industrial or geographic mobility (Katz and Blanchard, 1992). Results for the Black population suggest that it was possible to adjust along the job mobility side with no wage consequences. However, employment rates for white workers remain persistently depressed. Labor supply factors such as the changing nature of leisure activities or substance abuse (Aguiar et al., 2021; Case and Deaton, 2022) or a

[8] See for example the classic works of Altonji and Blank (1999); Smith and Welch (1989); Donohue and Heckman (1991); Neal and Johnson (1996), among many others.

[9] Two recent political science papers also consider the relationship between race, ethnicity, and trade, with findings that complement our results: Mutz et al. (2021) find that minorities are more supportive of trade than whites, consistent with our results on relative employment impacts; Ballard-Rosa et al. (2022) find that white workers in CZs affected by the China shock are more likely to adopt authoritarian political views if the CZ is more diverse. One possible explanation they provide is that minority workers were not as negatively effected by the China shock, increasing the perceived need by white workers to preserve their social status through authoritarianism.

better safety net could play a role. It is also possible that, commensurate with their larger wage gap across manufacturing and non-manufacturing industries, white workers were less likely to perceive service positions as substitutes for their previously-held manufacturing jobs.

This paper proceeds as follows: Section 2 describes differential import exposure across race and ethnic groups. Section 3 analyzes race and ethnicity-specific impacts on employment at the CZ-level and explores mechanisms for the differing effects. Section 4 sums up the total effects of differential exposure with a formal decomposition, and section 5 concludes.

2 Differences in Import Exposure

2.1 Data and Methods

In this section, we describe variation in import exposure across the Black, white, and Hispanic populations. We follow the previous literature, and, in particular, use measures and concepts developed by Autor et al. (2013) and updated most recently in Autor et al. (2021) (hereafter ADH) wherever possible. As such, we take as our unit of analysis the Commuting Zone (CZ) level, but disaggregate further to allow different race and ethnic groups to face different direct import exposure and experience different outcomes.

ADH measure the change in import competition for a CZ, c, in time period t, relative to a baseline time period. We choose 2000 as the baseline period, following ADH, as it falls just before the rapid acceleration in imports from China, following their World Trade Organization (WTO) accession in 2001. In equation 1, Emp_{ic} is employment in industry, i, and CZ, c, and Emp_c is overall CZ employment, both measured in 2000. ΔM_{it} is the change in US imports from China in industry i in time period t, relative to 2000. These are normalized ($Norm_i$) by domestic absorption in the industry i (gross output plus imports minus exports) measured in 2000. We denote the industry-CZ-time period shock as γ_{ict}.

$$\Delta IP_{ct} = \sum_i \frac{Emp_{ic}}{Emp_c} \frac{\Delta M_{it}}{Norm_i} = \sum_i \gamma_{ict} \tag{1}$$

In other words, ADH allocate national industry-level shocks across CZs, depending on employment shares within the CZ in the baseline time period. But different race and ethnic groups within a CZ may face different levels of exposure depending on the mix of industries they are employed in at baseline. For instance, nationally, 8.3% of the white working-age population was employed in manufacturing in 2000, compared to 7.2% of the Hispanic population and only 5.7% of the Black population. Since the vast majority of imports from China are in manufacturing, the white population may have faced more direct exposure.

We therefore define a group-specific change in Chinese import exposure for white, Black, and Hispanic groups. In equation 2, Emp_{irc} is employment of group, r, in industry, i, and CZ, c, in 2000 and Emp_{rc} is overall employment of group r in CZ c. This group-specific measure allocates national changes in imports for a given industry across CZs based on race- or ethnicity-specific employment shares in the CZ. A given shock to an industry-CZ-time period (γ_{ict}) receives more weight if the population subgroup has disproportionate employment representation in the industry compared to the CZ as a whole. If employment across industries is distributed proportionately across race and ethnic groups then the group-specific measure in equation 2 will equal the overall CZ measure.

$$\Delta IP_{rct} = \sum_i \frac{Emp_{irc}}{Emp_{rc}} \frac{\Delta M_{it}}{Norm_i} = \sum_i \gamma_{ict} \frac{Emp_{irc}}{Emp_{rc}} / \frac{Emp_{ic}}{Emp_c} \tag{2}$$

We use data from the 2000 Census to measure CZ-specific employment shares for population subgroups in three-digit NAICS industries, restricting attention to the adult (age 16-64) non-institutionalized population in non-military employment.[10] We focus on three mutually exclusive (but not exhaustive) groups: the white non-Hispanic, Black non-Hispanic, and Hispanic populations. We include in the Hispanic population anyone who self-identifies as being of Hispanic, Latino, or Spanish origin. We include in the Black population respondents to the Census who select Black as at least one of their races and restrict the white population to those who only select white and no other races.

Further data details can be found in the appendix and appendix table A.1 provides summary statistics of our key variables by race and ethnicity.

[10] ADH use the larger County Business Patterns data to measure baseline employment shares in CZs at the four-digit NAICS level, but these data do not disaggregate by race. Instead, we use 2000 Census data (from the Census Integrated Public Use Micro Samples (Ruggles et al., 2021)) to obtain race- and ethnicity-specific employment shares but must aggregate to the three-digit NAICS level. We follow ADH to align Public Use Microdata Areas (PUMAs) to CZs, restricting attention to 722 mainland Commuting Zones. We use annual import volume data from the UN Comrade Database, which provides imports from China to the U.S. for six-digit Harmonized System product codes. We then aggregate these to the three-digit NAICS industry-level using the crosswalk in Pierce and Schott (2012) to measure ΔM_i.

2.2 Results

We first document the relationship between CZ-wide import exposure (equation 1) and Black and Hispanic population shares, before turning to the group-specific measures of import exposure (equation 2). We focus on the change from 2000-12 – the focal time period in ADH – and explore a broader range of years in regression analyses below.[11]

The maps in Figure 1 provide some general intuition for which locations across the U.S. are most exposed to import competition (panel A) and which locations have the largest concentrations of Black (panel B) and Hispanic (panel C) populations. The locations experiencing the largest increases in import exposure from 2000-2012 tend to be concentrated in the rust belt – the midwest, parts of the northeast, and a handful of CZs in the west. In contrast the Black population in 2000 was heavily concentrated in the south and mid-Atlantic areas, while Hispanic populations are centered in the southwest.

Table 1 provides further detail, listing the most and least exposed CZs, along with their minority population shares, for the 50 largest CZs. Cities like Atlanta, GA, New Orleans, LA, Washington, DC, and Baltimore, MD have high Black population shares but relatively low import exposure; cities like San Jose, CA, Providence, RI, Dayton, OH, Los Angeles, CA and Grant Rapids, MI have low Black populations and a large increase in import exposure. There are some exceptions. For instance, Raleigh, NC and Chicago, IL are among the most import exposed CZs over this time period and also have high Black population shares; Detroit, MI has a high Black population share and modest import exposure (a standard deviation above the mean). However, overall, there is a strong negative correlation between import exposure and Black population share. Figure 2 provides bin scatters, relating the CZ-level change in import exposure to the CZ-level Black population share (left panel). The negative relationship is evident and strong in both magnitude and statistical significance.

The Hispanic population (panel C of figure 1) is largely located in the southwest. Many cities in this area have among the highest increases in import exposure (e.g., San Jose, CA, Austin and Dallas, TX, Los Angeles, CA), while others, (e.g., Las Vegas) have low exposure. In addition, Hispanic population centers in Florida are characterized by mid-to-low import exposure. Indeed, the bin scatter in Figure 2 (right panel) shows little correlation, except perhaps for the data points on the lower half of Hispanic population shares which do exhibit a negative relationship with import

[11] As Autor et al. (2021) show, import penetration is fairly stable after 2010. They choose 2000-12 as their focal time period because it incorporates import changes following China's joining the WTO in 2001 and ends after both the stabilization of import growth and the financial crisis of 2008.

Table 1: Import Exposure and Minority Population Shares from the 50 Most Populous CZs

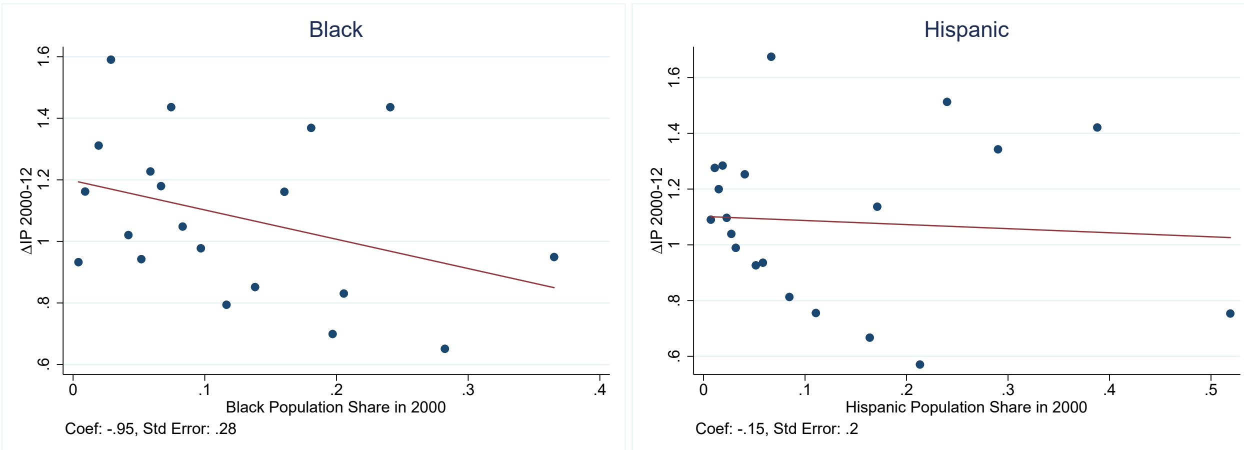
Ranking	CZ	Δ Import Penetration from China	Share of CZ that is: Black	Hispanic
1	Raleigh, NC	4.31	0.21	0.06
2	San Jose, CA	3.37	0.02	0.27
3	Austin, TX	3.08	0.07	0.24
4	Providence, RI	2.02	0.03	0.06
5	Manchester, NH	1.78	0.00	0.01
6	Dallas, TX	1.58	0.14	0.22
7	Chicago, IL	1.45	0.17	0.17
8	Dayton, OH	1.43	0.11	0.01
9	Los Angeles, CA	1.43	0.07	0.38
10	Grand Rapids, MI	1.37	0.05	0.05
⋮				
23	Detroit, MI	0.91	0.2	0.02
24	Minneapolis, MN	0.90	0.05	0.03
25	Columbus, OH	0.86	0.11	0.01
26	Cincinnati, OH	0.86	0.11	0.01
27	Miami, FL	0.85	0.19	0.41
⋮				
41	St. Louis, MO	0.60	0.18	0.01
42	New York City, NY	0.59	0.20	0.22
43	Atlanta, GA	0.56	0.29	0.07
46	Washington, DC	0.55	0.26	0.09
44	Baltimore, MD	0.49	0.26	0.02
45	Kansas City, MO	0.47	0.12	0.05
47	Jacksonville, FL	0.44	0.20	0.03
48	Orlando, FL	0.31	0.12	0.16
49	New Orleans, LA	0.24	0.35	0.04
50	Las Vegas, NV	0.15	0.07	0.19
Mean		1.03	0.13	0.16

Notes: We rank the 50 most populous commuting zones (CZs) by their change in import penetration from China 2000-12, defined in equation 1 and as in Autor et al. (2021). Population shares constructed from the 2000 U.S. Census. The bottom row reports the population-weighted average across the 50 most populous CZs in 2000.

exposure.

Turning next to the group-specific measure of import exposure, Figure 3 shows the white, Black and Hispanic distributions across CZs of the change in import penetration (IP) for 2000-2012. These distributions take into account any differential effects in trade exposure due to *industrial composition*, since we use the group-specific IP measure defined in equation 2. They also take into

Figure 2: CZ-level Import Exposure and Population Shares: Binned Scatter



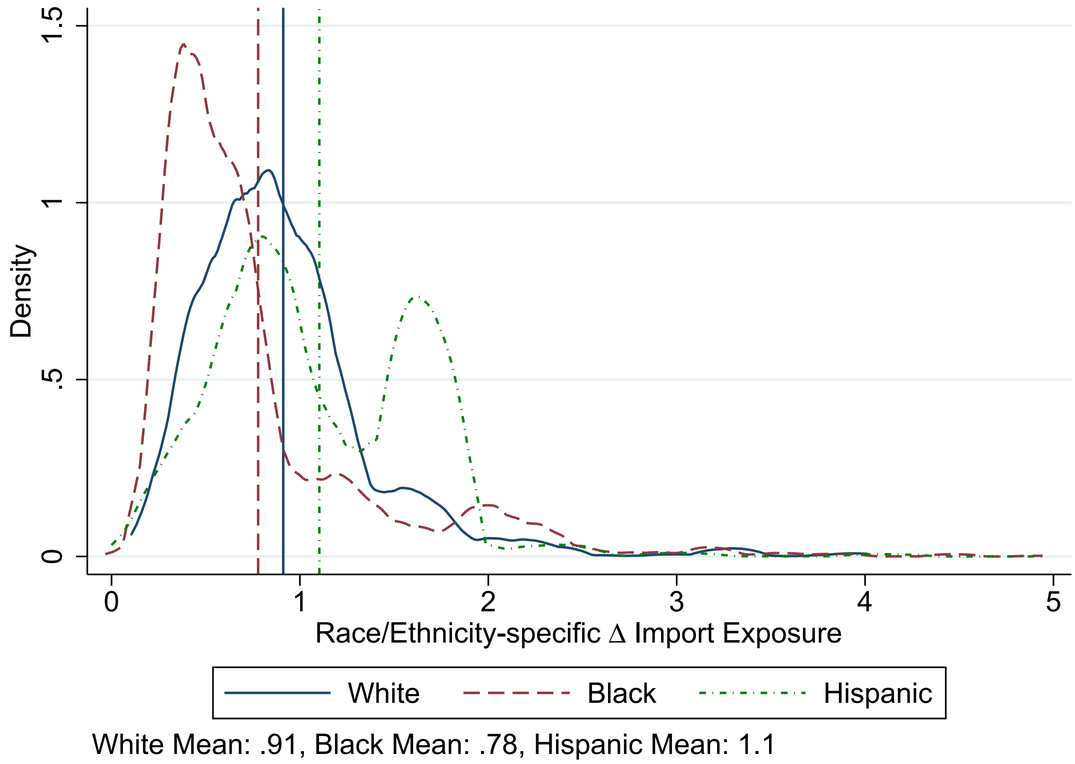
Notes: Binned scatters of Commuting Zone (CZ) level characteristics. X-axis plots the CZ-level fraction of population that was Black (left) or Hispanic (right) in the 2000 Census. Y-axis plots the CZ-level change in import exposure from China from 2000-12 defined in equation 1 and in Autor et al. (2021). CZs are grouped into 20 population-weighted bins based on Black or Hispanic population share and we plot averages within each bin as well as the best fit line.

account differences in exposure due to *population effects* since we weight CZs by their group-specific populations. The distribution for white workers (blue, solid line) is clearly shifted to the right of the Black worker distribution (red, dashed line). The mean for the Hispanic population (green dash-dot line) is larger than either the white or Black means. However, consistent with the discussion above, the distribution has two distinct modes. The Hispanic population tends to face changes in import exposure that are either extremely large, or similar to that of the white population.

To better understand the drivers of these distributions, we conduct a simple decomposition exercise, summarized in Table 2, with parallel analyses of Black-white and Hispanic-white gaps in import exposure. First, panel A summarizes these differentials by regressing the change in group-specific import exposure from 2000 to 2012 on a Black or Hispanic indicator in a stacked sample of 722 mainland Commuting Zones and two demographic groups (a white and a minority group). We weight these regressions by group-specific population in 2000 and cluster standard errors by state, as we will for our main regression analyses later. The Black population faces a 0.13 *lower* import exposure, or 15% less than the mean for the white population. The Hispanic population faces a 0.192, or a 21% *higher* import exposure than the average white person.

Next, Panel B decomposes the differentials into components attributed to population and industrial composition effects. To calculate population effects, we assign both groups the import exposure of the minority group (columns labeled 1) or import exposure of whites (columns labeled 2) and then only allow differences in population weights to generate gaps. For industrial composition effects

Figure 3: Distribution of Changes in Import Competition by Subgroup



Notes: We plot the distributions across CZs of group-specific change in import exposure from China (IP) from 2000-2012, defined in equation 2. White, Black, and Hispanic populations are mutually exclusive (but not exhaustive). Densities are weighted by race/ethnicity populations in 2000. Group-specific means are indicated with vertical lines. For clarity, the density plots (but not the mean lines) omit 2 outlier CZs with exposures greater than 9.

we do the opposite: assign both groups to have either the white population distribution (column 1) or minority population weights (column 2) and allow only differences in group-specific import exposure to generate race gaps. Within a column, population and industrial composition effects sum to the total differential.

For the Black-white differential, both population and industrial composition effects are negative, meaning they contribute to the smaller import exposure experienced by Black, compared to white, workers. However, the magnitude of the population effect is larger, accounting for the majority of the overall effect. In other words, most of the differential exposure experienced by the Black population is due to where they live, rather than where they work.

The decomposition is very different for the Hispanic population. They experience, on average, negative population effects, meaning the average Hispanic person lives in a less exposed CZ com-

Table 2: Decomposing Differential in Import Exposure

Dependent Variable:	Group-specific ΔIP 2000-12			
Panel A:	Full Differential			
	Black	-0.133*	Hispanic	0.192**
		(0.068)		(0.094)
Panel B:	Decomposition			
	(1)	(2)	(1)	(2)
Population Effects	-0.088*	-0.105***	-0.024	-0.121***
	(0.050)	(0.030)	(0.094)	(0.044)
Evaluated at	Black ΔIP	White ΔIP	Hispanic ΔIP	White ΔIP
Industrial Composition Effects	-0.046	-0.028	0.216***	0.313***
	(0.039)	(0.055)	(0.043)	(0.060)
Evaluated at	White Pop	Black Pop	White Pop	Hispanic Pop
Observations	1,444		1,444	
White ΔIP mean: 0.91				

Standard errors in parentheses clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Notes: The left two columns restrict to white and Black observations; the right two columns restrict to white and Hispanic observations. Top panel regresses race-specific IP on a Black or Hispanic indicator; CZ-race observations are weighted by race-specific population. Decomposition 1 gives the race difference attributable to population effects, evaluated at the minority group industrial composition, and the difference attributable to industrial composition effects evaluated at the white population distribution. Decomposition 2 gives the reverse.

pared to the average white person – though as we have already seen, this average masks quite a bit of heterogeneity. Outweighing the population effect, industrial composition effects are large and positive. Hispanic workers are more exposed to import competition than white workers because they are more likely to work in exposed industries. Although overall employment in manufacturing is similar, Hispanic employment within manufacturing skews towards the subsectors where China is also exporting. We list employment shares for each group in 3-digit industries along with the industry change in import exposure in appendix table A.2. Hispanic workers are overrepresented in textile-related industries (e.g., apparel, knitting, footwear, leather), as well as toys and sporting goods, and these have among the largest increases in imports from China. On the other hand, Hispanics are also overrepresented in food-related manufacturing industries (e.g., canned, frozen, and preserved fruits and vegetables) and these have among the smallest import increases. Also, white workers are overrepresented in higher technology manufacturing (e.g., computing and communications equipment and appliances) and these industries have large import shocks, as well. However, on net, Hispanic workers tend to be over represented in subsectors of manufacturing that experience larger increases in import exposure from China.

We can perform a simple back-of-the-envelope calculation to better understand the magnitude of these differences in exposure to import competition across subpopulations. The mean Black-white IP gap is 0.13 or roughly one-quarter of the inter-quartile range in IPs across CZs for the white population. Autor et al. (2021) estimate that a 75th percentile CZ experienced a 1.2 percentage point larger drop in employment-to-population ratio, compared to a CZ at the 25th percentile of exposure. We would therefore expect the Black population to experience a 0.3 percentage point (1/4 * 1.2) *smaller* decline in employment, based solely on where they live and work. The Hispanic-white gap of 0.19 is roughly one-third the size of the white inter-quartile range. So we would expect the Hispanic population to experience a 0.4 percentage point (1/3 * 1.2) *larger* magnitude decline in employment, based solely on their differential exposure.

However, as noted, it could be that for a given shock, certain groups experience a disproportionate share of layoffs or a more difficult transition to other sectors. We explore these dynamics next.

3 Import Exposure and Labor Market Outcomes, by Group

3.1 Data and Methods

We estimate the relationship between import exposure from China and employment outcomes for Black, Hispanic, and white workers at the CZ level as follows:

$$\begin{aligned} Y^s_{rct} - Y^s_{rc2000} = \beta_1 \Delta IP_{rct} + \beta_2[\Delta IP_{rct} * Black_r] + \beta_3[\Delta IP_{rct} * Hispanic_r] \\ + [\mathbf{X}_c * \mathbf{Group}_r]\beta_4 + \mathbf{I}^t * \mathbf{Group}_r + \varepsilon_{rct} \end{aligned} \tag{3}$$

Y^s_{rct} is an outcome of interest for race/ethnicity group, r, CZ, c, and year, t in sector s. Outcomes include log employment per adult population overall and within the manufacturing and nonmanufacturing sectors. As indicated in equation 3, we regress the change in these outcomes relative to 2000 on the time-varying group-specific import penetration measure (equation 2), though we also use the CZ-level measure (equation 1) in alternative specifications. As with the dependent variable, the change in import penetration is measured in the contemporaneous year relative to 2000. We allow the effect of import penetration to differ in the Black and Hispanic populations with interaction terms, $\Delta IP_{rct} * Black_r$ and $\Delta IP_{rct} * Hispanic_r$. X_c is a vector of controls, which we describe below, and all of which are interacted with race and ethnicity indicators (the vector $\mathbf{Group}_r$). Finally, I^t are year fixed effects, which are also interacted with group indicators.

We measure outcomes by race or ethnic group, CZ, and year using American Community Survey data. See appendix A.1 for variable definitions. We stack annual observations for white, Black and Hispanic populations from 2005-2018.[12] β_1 then gives the average impact of changes in import exposure over the entire time period for the white population, while β_2 and β_3 indicate whether the Black and Hispanic populations experience disproportionate responses. We also explore dynamic specifications that allow impacts to vary over time. Regressions are weighted by group-specific population in the baseline year (2000) and standard errors are clustered by state.[13]

We can estimate equation 3 using OLS. However, as in the previous literature, we are concerned that some unobservable characteristics of CZs may be driving variation in both import penetration and employment outcomes.[14] Following Autor et al. (2013) we estimate a 2SLS regression that instruments for import penetration with changes in imports by other high-income countries from China. These alternative import penetration measures are then applied to baseline employment shares from a lagged time period (1990 instead of 2000) to avoid anticipatory changes.[15]

Note that the IV strategy also helps to address measurement error in group-specific import exposure since we use one potentially noisy measure of baseline employment shares (1990) as an instrument for another (2000). In fact, the OLS estimates may suffer from correlated measurement error since the explanatory variable (group-specific import shocks) and a component of the dependent variable (baseline employment rates) are measured in the same dataset, and manufacturing employment especially could represent small samples in some CZ subgroups.[16]

In alternative specifications, we use the CZ-level import penetration measure (equation 1) as the key explanatory variable. Importantly, the CZ-wide measure could pick up spillover effects from shocks to different subpopulations. For example, the closing of a predominantly white manufacturing plant

[12] 2005 is the first year that the American Community Survey (ACS) includes the PUMA codes that we use to identify CZs and we stop our analysis in 2018 to avoid any COVID-related impacts on imports from China which would have begun in late 2019.

[13] There are many choices involved in this specification and we show below that results are robust to alternatives. Notably, our choice to stack all years of available data, rather than combining and then limiting to certain years as ADH do when using ACS data, helps with precision but does not materially change the conclusions. In addition, we use a change in logs specification, rather than levels (as some previous work as done), because populations differ in baseline employment levels and we wish to estimate the proportionality of responses.

[14] For instance, if CZs that manufacture children's toys happen to experience a negative productivity shock, we would see manufacturing employment declines associated with increases in imports of children's toys from China but causality would go in the opposite direction.

[15] Specifically, we instrument for ΔIP and its interactions with $Black_r$ and $Hispanic_r$ using $\Delta IP_{orct} = \sum_i \frac{Emp_{irc}^{1990}}{Emp_{rc}^{1990}} \frac{\Delta M_{oit}}{Norm_i}$, where ΔM_{oit} are changes in imports from China by other developed countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, Switzerland) over the same time period and employment shares are lagged (measured in 1990 instead of 2000).

[16] The correlated measurement error would not be a concern in the IV strategy which estimates the relationship between changes in employment rates from 2000 and the component of import exposure that is correlated with 1990 employment shares.

may negatively impact employees in nearby restaurants. Alternatively, companies benefiting from cheaper imports from China might expand their local employment in non-production occupations. We would expect the CZ-wide measure to produce different results than the group-specific measure due to these spillover effects, especially for non-manufacturing employment where effects of import exposure are predominantly indirect.[17]

As in the previous literature, the identifying assumption is that CZs predicted to have large versus small increases in import penetration would have been on a similar trend in employment outcomes, absent the China shock. Others have argued that, within a rich set of controls for CZ characteristics, increases in imports from China are driven by China's comparative advantage in producing those products interacted with their formally joining the WTO and are unrelated to employment trends (such as productivity changes) that would have taken place in U.S. areas producing similar product mixes. We follow Autor et al. (2021) by including a range of CZ-level controls that might be correlated with trends in manufacturing employment, and allow these to interact with indicators for Black and Hispanic.[18] In addition, we explore a range of controls, detailed in a robustness section below, to help support the identifying assumptions.

Identifying β_2 and β_3 in equation 3 requires an additional assumption: that Black-white and Hispanic-white gaps in employment outcomes would have been on similar trends across more and less import exposed CZs, but for the China shock. To address this assumption, we first directly analyze pre-period race and ethnic gaps in levels and trends as a function of import exposure. Appendix table A.3 summarizes these results. We regress Black-white and Hispanic-white employment gaps in 1980, 1990, 2000, as well as the decadal changes on the ΔIP-group interactions, using the IV specification with full controls. We conclude that our results are not driven by any evident trends in the pre-period. For the Black-white gaps, associations with import competition are both small in magnitude and insignificant, and not trending in a meaningful way. The same is true for most of the Hispanic-white gaps, as well, though the gap in 1990 is larger in magnitude (more negative) in CZs that would eventually be shocked. We find convergence so that by 2000 Hispanic-white gaps are similar across CZs, and this convergence goes in the opposite direction of our findings for the later time period.

[17] Also, CZ-level exposure is, on the one hand, measured with more precision because employment shares are based on the larger County Business Patterns data (which do not allow for disaggregation by demographic group), rather than group-specific observations in the Census. On the other hand, the CZ-wide exposure measure will be more correlated with the true shock to the majority population in the CZ – typically the white population. So we might expect a stronger correlation between the CZ-wide exposure measure and white, compared to minority, employment outcomes for that reason.

[18] Specifically, we control for year and region fixed effects, the share of the population in 2000 that was foreign born, college graduates, ages 0-17, 18-39, and 40-64, Black, Asian, Hispanic, and other races, as well as the share of employment in manufacturing, routine occupations and offshorable occupations, and the female employment share in the CZ in 2000.

Finally, a recent literature on shift-share identification methods has addressed the identifying assumptions in the China shock literature. Appendix A.2 details how we apply suggestions from Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022). We show that our conclusions are robust to the standard error correction advised in the latter and that the identification of β_2 and β_3 stands up to the specification tests of the former, even while they argue that β_1 is problematic.

3.2 Main Results

Table 3 summarizes the main regression results, estimating equation 3 for three different employment outcomes (the changes in log manufacturing, log non-manufacturing, and log overall employment per adult population). First stage regressions can be found in appendix table A.4. OLS results can be found in appendix table A.5. Panel A uses as key explanatory variables the race or ethnicity-specific change in import penetration (equation 2) and its interactions with Black and Hispanic indicators, while panel B uses the CZ-level change in import penetration as in ADH and the interaction terms.

Beginning with manufacturing in column (1), we find that manufacturing employment is negatively impacted by import exposure. Effects for the white population (main effects) are negative, significant at the 1% level, similar when using group-specific and CZ-level shocks, and commensurate with those found by other researchers when examining the population as a whole.[19] For the $\Delta IP_{rct} * Black_r$ and $\Delta IP_{rct} * Hispanic_r$ interaction terms, coefficients are small but noisily estimated.[20]

Figure 4 shows the time pattern of Black-white (blue, solid dots) and Hispanic-white (maroon, hollow dots) differential impacts of import exposure. Here, we estimate an alternative specification to equation 3 that interacts an exhaustive set of year dummies with the main ΔIP effect and its minority group interactions; the figure plots the minority group interactions using CZ-wide exposure. See appendix figure A.1 for group-specific exposure, which show very similar results for manufacturing employment.

[19] Our -0.09 estimate implies a 4.5 percentage point larger drop in the rate of change in white manufacturing employment for a 75th percentile exposed CZ, compared to a 25th. While not directly comparable to that of ADH given the functional form difference explained in section 3.1, we can multiply by the manufacturing employment rate of change at the 25th percentile (-0.2) to roughly map our result to their functional form. Our results for the white population then imply a nearly 1 percentage point larger drop in the level of manufacturing employment in the 75th versus 25th percentile CZ, which is similar to the 1.2 percentage point drop in overall manufacturing employment to population found in Autor et al. (2021).

[20] While OLS produces similar results for the most part, appendix table A.5 shows a worse -0.03 differential impact on manufacturing employment for Hispanic workers.

Table 3: Impacts of Import Exposure on Employment, IV

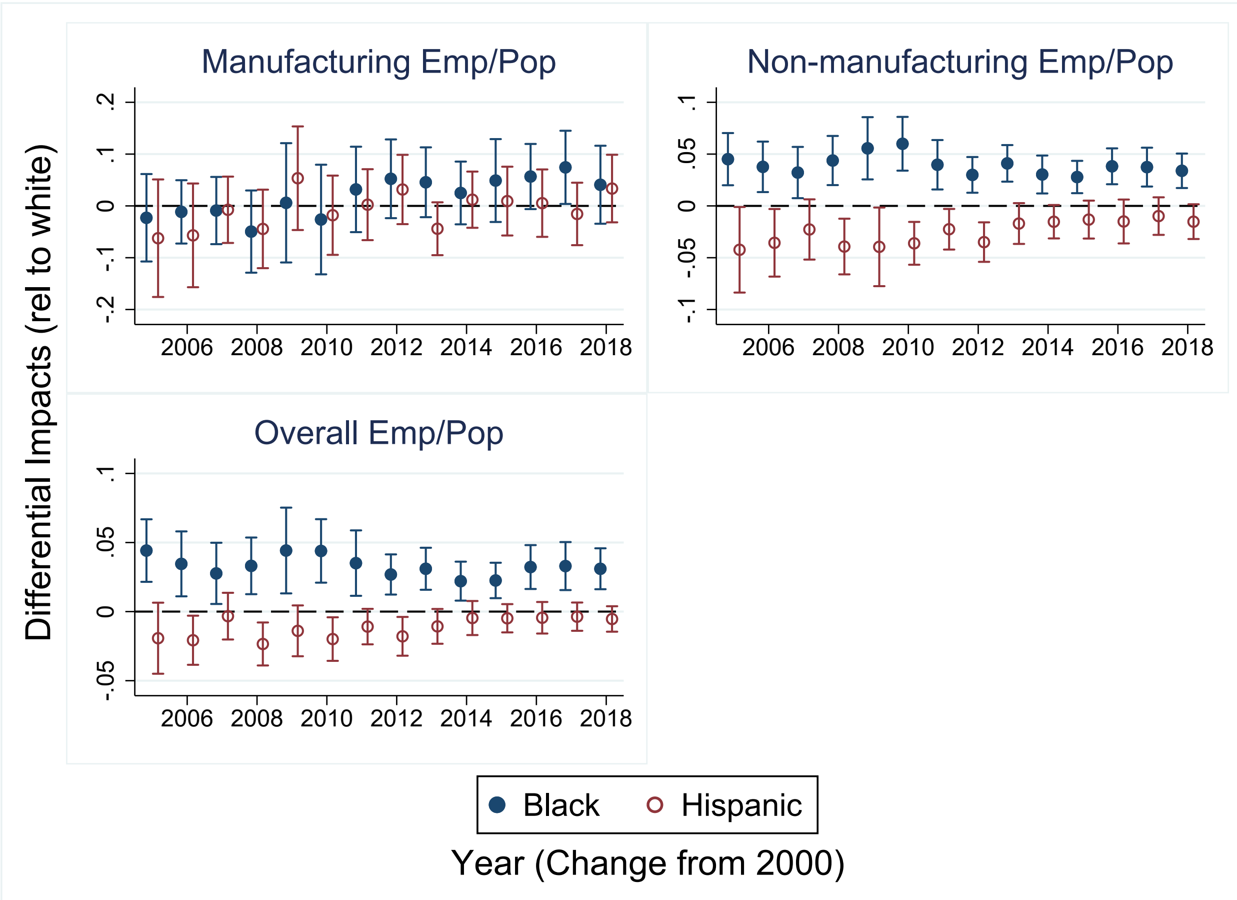
Dependent variable: Δ log employment in the sector per working age population			
Sector:	Manufacturing	Non-Manufacturing	Overall
	(1)	(2)	(3)
Panel A: Group-Specific Import Exposure			
Group-specific ΔIP	-0.093***	0.015***	-0.011*
	(0.024)	(0.006)	(0.006)
$\Delta IP * Black$	0.017	0.036***	0.023**
	(0.032)	(0.011)	(0.011)
$\Delta IP * Hispanic$	-0.011	0.033**	0.016
	(0.060)	(0.016)	(0.011)
T-stat Black overall	–2.23	3.83	0.91
T-stat Hispanic overall	–1.88	2.90	0.42
Panel B: CZ-Wide Import Exposure (ADH)			
CZ-level ΔIP (ADH)	-0.085***	0.005	-0.010**
	(0.021)	(0.004)	(0.005)
$\Delta IP * Black$	0.027	0.038***	0.030***
	(0.040)	(0.011)	(0.010)
$\Delta IP * Hispanic$	0.002	-0.021**	-0.010
	(0.033)	(0.010)	(0.007)
T-stat Black overall	–1.42	3.71	1.58
T-stat Hispanic overall	–2.82	–1.28	–2.50
Observations	26,772	30,105	30,159

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses clustered by state

Notes: 2SLS estimates of equation 3 on group-CZ-year cells using ACS data from 2005-2018, restricted to white, Black, and Hispanic observations. Dependent variables are CZ-group labor market outcomes in the year minus that in 2000. Explanatory variables are the group-specific (panel A) or CZ-wide (panel B) import exposure in the contemporaneous year minus that in 2000 and group interactions. We instrument for import exposure and its interactions using changes in imports from China for other developed countries applied to lagged employment shares and interactions. We include full controls from ADH interacted with race/ethnicity: year and region fixed effects, share of the CZ population that is foreign born, college graduates, ages 0-17, 18-39, 40-64, Black, Asian, Hispanic, and other races/ethnicities, as well as the share of employment in manufacturing, routine occupations and offshorable occupations, and the female employment share in the CZ in 2000. Standard errors are clustered on state. Models are weighted by race/ethnicity-specific CZ working-age population in 2000.

Both the Black-white and Hispanic-white differentials are negative, though insignificant, in the early time period, and especially large in magnitude for Hispanic workers. From around 2009, there is convergence, with more precisely estimated zeros on the Hispanic-white differential, and positive point estimates on the Black-white differential. The figure shows the cumulative impact of CZ-wide exposure for progressively longer time differences. Thus any short-term negative relative

Figure 4: Differential Impacts of CZ-Wide Import Exposure over Time



Notes: We expand equation 3 to include a full set of year dummies interacted with ΔIP, ΔIP*Black, and ΔIP*Hispanic. This figure plots the coefficients on the latter two and 90% confidence intervals using the CZ-wide import exposure measure and the IV specification. We include the full set of controls listed in Table 3.

impacts on minority groups are offset in the later time periods as the time difference for both manufacturing employment and trade exposure lengthens.

Taken as a whole, we conclude that there is no evidence that the Black and Hispanic populations experience *worse* impacts on manufacturing employment. There are some noisy zeros early on in the time period, but they dissipate later, such that any potentially negative relative impacts on minority populations would be short lived.

Turning to non-manufacturing employment in column 2, we see positive impacts for white workers when using the group-specific shock. This improvement is consistent with positive spillover effects from manufacturing imports leading to relatively greater non-manufacturing employment at the CZ level. Effects are attenuated when considering CZ-wide shocks (panel B); the effect for white workers is small and insignificant, which is consistent with ADH. The CZ-level shock measures the overall impact of import competition on white workers, incorporating impacts from other racial and ethnic groups that might spill over to the white population. The group-specific shock measures the direct effect of white worker import exposure on white worker outcomes.

Black workers experience strong positive effects on non-manufacturing employment relative to white workers and effects are similar across group-specific and CZ-wide shocks. The latter yields a 3.8 percentage point larger increase in the Black non-manufacturing employment rate of change, relative to the white, in a one unit more exposed CZ, significant at the 1% level.

The Hispanic interaction terms tell a different story. Hispanic workers see similar positive differentials as Black workers when using their own group-specific shock (panel A). However, the CZ-wide estimates are quite different. Hispanic workers experience a 2.1 percentage point smaller non-manufacturing employment change, compared to white workers, significant at the 5% level. On the one hand, when the jobs Hispanic workers themselves are found in experience an import shock, the Hispanic population is able to take advantage of associated growth in non-manufacturing. On the other hand, when the CZ as a whole is hit (likely driven by a larger shock to the white population), the Hispanic population suffers negative spillover effects. Such spillovers could occur if the jobs Hispanic workers perform are complementary to those of white workers. For example, if a predominantly white manufacturing plant shuts down, that could affect Hispanic workers employed as cleaners, bus drivers, or food service employees supporting those white workers, whereas Black workers may be more likely to work in unrelated service industries.[21]

Column 3 sums the manufacturing and non-manufacturing effects by examining overall employment-to-adult population ratios. The main effects indicate significant overall losses for the white population of about 1 percentage point, consistent with previous work. The Black-white differential is again positive. The combination of similar manufacturing impacts and positive impacts on non-manufacturing employment sum to relative improvements in overall employment for Black workers. The point estimate is slightly larger for the CZ-level shock. Given a 0.5 interquartile range in exposure for the white population, our estimates imply that in a 75th percentile exposed CZ, the Black-white employment-to-population gap narrows by 1.5 percentage points, relative to a 25th percentile exposed CZ. As indicated by the t-statistics in the bottom rows, the overall effect (summing

[21] Indeed, to better parse out these stories, we estimate an alternative specification for the employment outcomes that includes both the group-specific IP as well as a cross-group measure equal to the white IP shock for Black and Hispanic observations and a population-weighted average of the two minority group shocks for the white observations. Own-group and cross-group IP measures are highly correlated so this horserace-style regression is merely suggestive. However, as shown in appendix table A.6, the negative effect on non-manufacturing employment for Hispanic workers loads completely on the white shock, while they experience a same-magnitude positive effect for their own group shock. We also find that the cross-group effects matter little for the white and Black observations.

the negative effect for white workers and the positive for Black workers) is positive but insignificant; the relative improvement for Black workers comes partially at the expense of white workers who lose ground relative to their counterparts living in less exposed CZs.

The Hispanic differential for overall employment is insignificant and positive when using the group-specific shock and small, negative, and insignificant when using the CZ-level shock.

Figure 4 reveals that the Black-white differentials for non-manufacturing and overall employment are fairly stable over time. The Hispanic-white differentials show convergence, as they did for manufacturing employment. Looking at overall employment, effects towards the end of the time period are much more precisely estimated and small in magnitude. In contrast, the differentials in response to group-specific shocks (appendix figure A.1), are fairly stable positives for both the Black-white and Hispanic-white differentials.

Table 4: Impacts of Import Exposure on Wages

Dep Var:	Δ log(Hourly Wages)	
	(1)	(2)
Race-specific ΔIP	-0.009	
	(0.007)	
$\Delta IP * black$	0.011	
	(0.008)	
$\Delta IP * Hispanic$	0.034***	
	(0.009)	
CZ-level ΔIP (ADH)		-0.006
		(0.007)
$\Delta IP * black$		0.019**
		(0.009)
$\Delta IP * Hispanic$		0.014**
		(0.007)
T-stat Blacks overall	0.18	1.19
T-stat Hispanics overall	2.97	1.01
Observations	30,221	30,221
R-squared	0.751	0.749

Standard errors in parentheses clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Notes: See table 3. We include the full controls from table 3, cluster standard errors by state, and weight observations by their race or ethnicity-CZ population in 2000. Log hourly wages are defined as non-self employment annual wage and salary income divided by annual weeks worked times usual hours per week. We bottom code hourly wages to the first percentile, and topcode so that the implied full-time annual salary does not exceed topcoded income.

Finally, table 4 examines effects on wages per hour worked.[22] The Hispanic-white differential is positive and significant across both specifications, while the Black-white differential is positive and significant at the 5% level when using the CZ-wide shock. The strong positive differential wage

[22] We estimate equation 3 using the change in log hourly wages as the outcome variable. We calculate annual wage and salary income divided by annual weeks worked times usual hours per week, adjust to 2012 dollars using the PCE price index, and exclude the self-employed and those with missing earnings, weeks or hours. We topcode wages so that income for full-time, full-year work does not exceed the survey topcode for wage and salary income and bottom code to the first-percentile of non-zero values.

growth is not robust in other specifications (for example, the OLS version (not shown) and some of the additional controls in the robustness section below produce zero differential effects), but we can typically rule out differential wage *losses* beyond roughly 0.5 points with 95% confidence.

If minorities were experiencing relative employment increases but at lower wage rates, then our assessment of who was better off could be altered. However, our results show that neither group experiences wage losses relative to white workers, conditional on supplying an hour of labor.

3.3 Robustness

Our findings are robust to a range of alternate approaches. We present the results of these robustness checks in Appendix Table A.7.

We generally follow the approach of Autor et al. (2021) in determining our specifications, however there are some important differences between our approach and theirs, such as our focus on the minority-white employment differentials. Another example is that when ADH use ACS data to measure outcomes, they tend to focus on one or two focal time windows, pooling across adjacent ACS years to increase precision.[23] We face greater issues with precision than they do because our outcome measures are disaggregated by race and ethnicity so we stack all years of available data and explore dynamic specifications, rather than first pooling subsets of years. Our approach lets the data speak and, in practice, helps a bit with precision as most effects are quite stable over the time period. In Column (2), we restrict the sample to changes from 2000 to an unweighted average across 2011-13, similar to the ADH approach. These results are similar in magnitude to our main results using all available years, however a few of the coefficients are slightly less significant.

Our identification strategy requires that minority-white differentials in employment outcomes would have been on a similar trend across high and low exposed CZs, but for the China shock. Our analysis of pre-trends discussed in section 3.1 already helps to alleviate this concern (see table A.3). In addition to this pre-trend analysis, we also include specifications controlling for baseline race gaps in employment in 1980, 1990, and 2000, all interacted with race, in Column (3). The results including these controls are very similar to our main results in both magnitude and significance.

To further test our identifying assumption, as well as to control for any other important CZ-level differences not captured by our control variables, we estimate a specification similar to equation 3, but using CZ-level fixed effects. Within these fixed effects, we can identify the minority-white

[23] In Autor et al. (2013) they examine changes from 2000 to a pooled sample of 2006-08 ACS waves; in updated work (Autor et al., 2021), they primarily use administrative data but also present results for the 2000 to the pooled 2006-08 ACS waves, 2000 to pooled 2011-13 waves, and 2000 to pooled 2017-19 waves.

differential impacts, though they essentially absorb the main effect of ΔIP (i.e. the effect on white workers).[24] The results in Column (4) are qualitatively similar to what we find using our primary specification. The impacts on manufacturing employment are noisy and vary more across specifications, but they are insignificant just as they were in our primary specification. The other employment results are more stable.

Our main results use control variables that are identical to those in Autor et al. (2021). However, these controls vary only by CZ, not CZ by race or ethnicity. We explore a robustness exercise controlling for similar variables constructed at the CZ by race or ethnicity level and obtain qualitatively similar results. Black, white, and Hispanic populations vary on observables both across and within CZs, yet those measured here do not appear able to account for any of the differential impacts of import competition on employment across these groups.

Throughout this paper, we measure import exposure from China using the approach of Autor et al. (2021). For robustness, we now consider an alternative approach following Handley and Limão (2017) and Pierce and Schott (2016). They show that when the U.S. granted Permanent Normal Trade Relations (PNTR) to China, a significant amount of uncertainty surrounding tariffs on Chinese goods was resolved, leading to greater U.S. imports from China. Before PNTR, U.S. imports from China were generally subject to NTR tariff rates in practice, however, these rates had to be reapproved every year or they would revert to the higher non-NTR tariff rates assigned to nonmarket economies. Because goods for which the difference in the NTR versus non-NTR tariff rate (the NTR gap) was higher were subject to greater uncertainty, these goods experienced a stronger treatment effect as a result of PNTR. We use industry-level differences in the NTR gap to construct an instrument for import exposure, ΔIP, at the CZ-level by weighting these industry-level measures by industry employment shares within the CZ in our baseline time period. This approach produces similar results for main effects and for Black-white differentials. However, we find Hispanic-white differentials that are more positive, though not usually significant, meaning that any potential negative (though noisy) effects on non-manufacturing and overall employment experienced by Hispanics are not robust to the NTR IV strategy. Given the discussion in section 2.2, that Hispanic and white workers have different representations across manufacturing subsectors, and the fact that the NTR approach identifies off a different set of subsectors than the baseline method, it is perhaps not surprising that this result shows variability.

Appendix table A.8 shows the results of the same robustness checks described above for the specification using the change in log hourly wages as the dependent variable. The wage results are much

[24] Even though ΔIP is time-varying within a CZ-subgroup, import penetration is largely stable over our time period, so we do not use the CZ-time variation to identify the main effect β_1.

less robust then the employment results. However, all of the coefficients on the Black and Hispanic interaction terms are positive and/or insignificant. So the overall message that minority workers do not seem to experience relative hourly wage declines as a result of the China shock, and if anything may experience hourly wage gains relative to white workers, still holds.

3.4 Explaining the differences in employment outcomes

How were Black workers are able to capture large gains in non-manufacturing employment, relative to white workers, with no wage losses, while Hispanic workers experience short-lived but negative relative employment effects? In this subsection, we explore possible mechanisms.

Industrial Composition and Mobility

Black, Hispanic, and white workers tend to hold different types of jobs, which could impact how they experience spillover effects from the China shock to non-manufacturing sectors. While we lack the precision to estimate group-specific effects that are also disaggregated by industry at the CZ level, we build some intuition with figure 5. The blue bars give the share of employment across major industry categories in 2000, by group (dark, medium, and light blue for Black, Hispanic, and white workers, respectively). The maroon bar gives the impact of the China shock on industry employment per population in the CZ as a whole.[25]

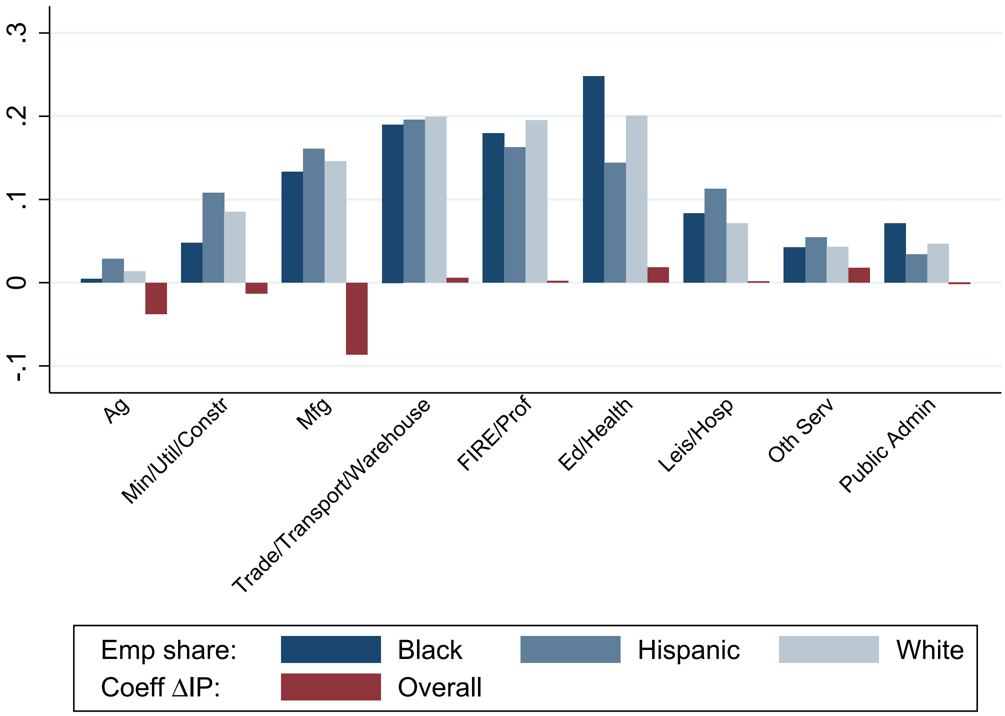
The largest employment losses are in manufacturing, but there are also negative impacts on agriculture and in mining, utilities, and construction industries. The blue bars indicate that Hispanic workers were overrepresented in both sectors in 2000. Construction is especially interesting in light of the more negative Hispanic-white employment gaps we found around the time of the Great Recession. Recent work by Xu et al. (2019) found a positive correlation between CZ-level China shock exposure and the severity of the housing bubble burst. So Hispanic workers especially may have suffered from the dual impacts of import competition and the housing bubble burst around that time and, notably, recovered thereafter.[26]

In contrast, education and health services experienced positive relative impacts on employment and

[25]Specifically, we estimate CZ-year-level regressions of the change in log employment in the indicated sector per working age population from year t to 2000 on a stacked sample of years 2005-2018. We use the same IV strategy as above. Explanatory variables are the CZ-wide ΔIP measure from t to 2000 and full controls.

[26]The housing bubble may have propped up the decline in manufacturing employment causing extra losses once the bubble burst (Charles et al., 2016). Hershbein and Kahn (2018) found that the Great Recession afforded employers an opportunity to make productivity enhancing improvements, such as reallocating productions towards labor-replacing technologies. It may also have facilitated adjustments to import competition.

Figure 5: Summary of Differential Impacts by Industry



We group workers by one-digit NAICS industry categories. The blue bars are employment shares across industries, by race in 2000. To obtain the maroon bars, we estimate CZ-year level regressions where the dependent variable is the change in log employment in the indicated industry per working age population and the explanatory variables are the CZ-level ΔIP and full controls from Table 3. The maroon bars plot coefficients on ΔIP from the IV specification.

Black workers are overrepresented in these sectors. We calculate a weighted average of coefficient effects for each group using the industry-specific employment impacts and the group-specific employment shares as weights. Doing so, we can account for some of the differential impacts found above. Specifically, we predict that Black workers should experience a roughly one-third smaller employment impact and Hispanic workers a roughly one-third larger employment impact, compared to white workers, based solely on their industrial compositions. However, the magnitudes for employment losses are much smaller than the total effects estimated above.

Another difference across groups is the extent to which workers are attached to their positions. Minority workers are generally less attached to specific employers, which could also make them less attached to their current sector of employment. This form of agility could come with disadvantages (e.g., less access to internal labor markets and lower human capital formation) but could help in weathering a localized manufacturing shock.

Table 5 explores job transitions in 2000 using the Census database. First, both Black and Hispanic workers made more job-to-job transitions overall than white workers. Second, both minority groups, but especially Hispanic workers, moved to non-employment at higher rates. Third, Hispanic workers beginning in non-manufacturing employment were slightly more likely than Black or white workers to move to manufacturing when making a job-to-job transition. Finally, Black workers were more likely to move to another sector when exiting a manufacturing job. About 76% of Black workers in manufacturing moved to non-manufacturing employment when making a job-to-job transition, compared to 68% of white and Hispanic workers. Collectively, these patterns at baseline could help explain how Black workers were able to find non-manufacturing jobs after the China shock, relative to whites, while Hispanic workers lost jobs.

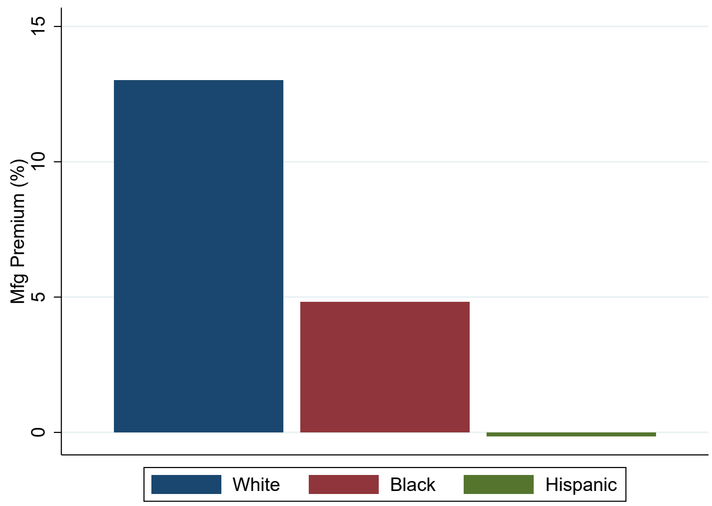
Table 5: Job Transitions

	All			Manufacturing			Non-Manufacturing		
	White	Black	Hispanic	White	Black	Hispanic	White	Black	Hispanic
J-to-J Flow Rate	5.4	8.1	12.7	3.0	4.0	8.2	5.8	8.7	13.6
Share to Mfg.	8.4	7.0	11.6	32.0	24.1	31.9	6.4	5.9	9.2
Share to Non-Mfg.	91.6	93.0	88.4	68.0	75.9	68.1	93.7	94.1	90.8
Flow to Non-emp	4.8	6.9	12.3	2.7	3.9	9.3	5.2	7.3	12.9

Notes: Constructed using the Job-to-Job Flows database from Census Longitudinal Employer-Household Dynamics for 2000. "All", reports the percent of all employment in the group that switches employers across adjacent quarters in the top row. The next rows report the percent of job switchers that move to the indicated sector. The flow to non-employment row reports the percent of employment that has no earnings in the subsequent quarter. The middle columns restrict to those in manufacturing in the starting quarter, regardless of where they move in the next quarter, and the right columns restrict to those in non-manufacturing in the starting quarter.

One reason for the greater movement away from manufacturing among the Black population could be that the manufacturing wage premium is smaller for minorities. Figure 6 shows that in 2000 the average white worker in manufacturing earned 13% more per hour than the average white worker in non-manufacturing, while this gap is only about 5% for Black workers and non-existent for Hispanic workers. These earnings premia are not causal estimates, but they can rationalize why a minority worker who was displaced from manufacturing employment could have found a non-manufacturing job at a closer wage, compared to a white worker. In fact, these premia suggest that a typical white worker would have had much further to fall were they to transition from manufacturing to non-manufacturing, and may have instead chosen to remain non-employed. Such a dynamic could account for the Black-white differential employment effects we find. Of course it could not explain the Hispanic-white differential employment effects; with no manufacturing wage premium, we would expect Hispanic workers to have an easier time finding close non-manufacturing employment substitutes compared to white workers. Instead, their much higher baseline likelihood of transitioning to non-employment may have been the driving factor.

Figure 6: Manufacturing Wage Premium by Group in 2000



Notes: We plot the ratio of average manufacturing wages to non-manufacturing wages minus 1 as a percent for each group.

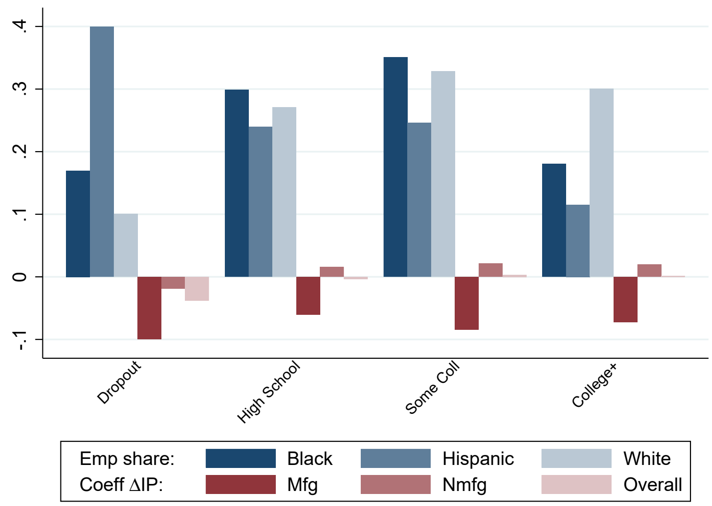
Educational Attainment and Other Observables

As is well known, race and ethnic groups differ substantially in terms of their educational attainment. We explore differential impacts across education groups in figure 7. The blue bars give the share of employment in each education level in 2000 by race or ethnicity. The maroon bars give the impacts of the China shock on manufacturing, non-manufacturing, and overall employment for each education group as a whole.

White workers are over represented among college graduates. Black workers are over represented, compared to white workers, in all education categories below college graduates. The starkest pattern from the blue bars of figure 7 is the extent to which Hispanic workers are over represented among high school dropouts. 40% of Hispanic workers did not complete high school, while 17% of Black workers, and 10% of white workers fall in that category. High school dropouts also suffer the largest employment losses in response to import competition, not only directly within manufacturing employment (dark maroon bar), but also indirectly through negative spillover effects in non-manufacturing employment (lighter maroon bars). In contrast, high school graduates and those with some college suffer smaller losses from manufacturing employment and positive gains in non-manufacturing employment.

The dynamics in figure 7 can indeed account for much of the negative relative impact on the

Figure 7: Summary of Differential Impacts by Education



Notes: The blue bars are employment shares across education groups, by race/ethnicity in 2000. To obtain the maroon bars, we estimate CZ-year level regressions where the dependent variable is the change in log employment in the indicated education group and sector per working age population in the education group and the explanatory variables are the CZ-level ΔIP and full controls from Table 3. The maroon bars plot coefficients on ΔIP from the IV specification.

Hispanic population. Using shares across education groups as weights and coefficients from figure 7, we calculate that Hispanic workers in exposed areas would experience a 1 percentage point drop in non-manufacturing employment-to-population, relative to white workers, based solely on their education levels. This estimate is about half the magnitude of the significant 2.1 percentage point coefficient on $\Delta IP * Hispanic$ in table 3, column (4), panel B. These results are thus consistent with previous research that tends to find that Hispanic-white differentials in labor market outcomes can largely be accounted for by their differing observables (Trejo, 1997). Educational attainment of the Hispanic population has been increasing over the time period studied here (Murnane, 2013; Hull, 2017) and this trend can perhaps explain why the negative relative impacts on Hispanic workers converge back to zero in recent years (figure 4).

That is not the case for the Black-white differentials. From figure 7, Black workers have substantial representation among the middle education groups, which experience similar employment impacts to those of college graduates. Since college graduates experience similar positive spillovers as well, any differences in outcomes due to educational attainment wash out. Based solely on the education distribution and education-level impacts of import exposure, we would find very similar effects across both Black and white workers.

Appendix figures A.2 and A.3 conduct similar exercises by broad occupation groups and by age groups, respectively. While there are indeed large differences across groups in their occupation and age distributions, these differences cannot account for our findings.

Geographic Mobility

If population subgroups move away from their CZ at differential rates in response to a negative shock, then the interpretation of our estimates would change. Autor et al. (2021) show that in the long run, young workers exit exposed regions at higher rates. Cadena and Kovak (2016) find that Mexican-born immigrants' location choices were responsive to Great Recession shocks. In appendix figure A.4, we summarize a specification similar to ADH, examining CZ-level population changes by group in response to the China shock. We plot coefficients and 95% confidence intervals for the Black-white and Hispanic-white differential responses to the CZ-wide shock, by year. We find no statistically significant differences across race and ethnicity groups, and the point estimates are quite stable across years. Though we lack the precision to be conclusive on this question, appendix figure A.4 provides suggestive evidence that our results cannot be accounted for by changing geographic mobility across subgroups.

4 Putting it all together

The results in Section 3 show how a given increase in import exposure affects employment outcomes. However, as shown in Section 2, Black and Hispanic workers are differentially exposed to import competition compared to the white population because of both the CZs they live in and the industries they work in. In this section we decompose the relationship between import exposure and employment differentials into the portions due to population, industrial composition, and coefficient effects in order to better understand these channels.

The differential change in log employment per population in sector s across Black (B) and white (W) workers associated with the China shock is expressed in equation 4. Here, the fitted impact for a given group and CZ (c) is the product of the group-specific ΔIP and the coefficient(s) estimated in equation 3. The coefficient for the white population β^s_W is equal to the estimated value of β_1 from the sector, s regression; the coefficient for the Black population β^s_B is equal to $\beta_1 + \beta_2$ from the same regression. We average across CZs, weighting by the share of the race group population residing in the CZ in 2000 (e.g., $\frac{pop_{Bc}}{pop_B}$). The Hispanic-white differential is analogous, where we use $\beta_1 + \beta_3$ for the impact of their ΔIP_{Hct} shock.

$$\Delta Y^s_{Bt} - \Delta Y^s_{Wt} = \sum_{c \in CZ} \frac{pop_{Bc}}{pop_B} \times \Delta IP_{Bct} \times \hat{\beta}^s_B - \sum_{c \in CZ} \frac{pop_{Wc}}{pop_W} \times \Delta IP_{Wct} \times \hat{\beta}^s_W \tag{4}$$

We can decompose the differential into: (1) Population effects, which capture differences in how the Black, Hispanic, and white populations are distributed across locations; (2) Industry composition effects, which capture differences in predicted import exposure based on industry-level employment; and (3) Coefficient effects, which capture differences in the causal impacts of a one-unit change in import exposure.

An example of such a decomposition for the Black-white differential is expressed as follows. The population effect is assessed at the Black ΔIP and coefficient; the industrial composition effect is assessed at the white population distribution and Black coefficients; the coefficient effect is assessed at the white population and ΔIP values.

$$\begin{aligned}
\Delta Y^s_{Bct} - \Delta Y^s_{Wct} = & \sum_{c \in CZ} \left(\frac{pop_{Bc}}{pop_B} - \frac{pop_{Wc}}{pop_W} \right) \times \Delta IP_{Bc} \times \hat{\beta}^s_B \text{ (Population)} \\
& + \sum_{c \in CZ} \frac{pop_{Wc}}{pop_W} \times (\Delta IP_{Bc} - \Delta IP_{Wc}) \times \hat{\beta}^s_B \text{ (Industrial Composition)} \\
& + \sum_{c \in CZ} \frac{pop_{Wc}}{pop_W} \times \Delta IP_{Wc} \times (\hat{\beta}^s_B - \hat{\beta}^s_W) \text{ (Coefficient)}
\end{aligned}$$

With three different variables contributing to the decomposition, we have six possible permutations. We report the average contribution of each component across all possible orders and bootstrapped standard errors based on 1,000 draws. Note estimates using CZ-wide import exposure measures have only two variables contributing to the decomposition, as the industrial composition is the same across groups.

Results are reported in Table 6. Panel A reports the average fitted impact on the white population. Panel B reports the Black-white differential fitted impact and decomposes these estimates into population, industrial composition, and coefficient effects. Panel C does the same for the Hispanic-white differential.

Beginning with Black-white gaps and manufacturing employment, we see that Black workers experience a 2.4 percentage point (31%, panel B, column 1) positive offset from the 7.8% drop in manufacturing employment-to-population (panel A, column 1) that white workers experience, on

Table 6: Decomposing the Minority-White Differential Impacts of Import Exposure

Dep Vars:	**Changes in log Employment-to-Population Ratios**					
	Group-specific ΔIP			**CZ-Wide ΔIP (ADH)**		
	Mfg	**Non-Mfg**	**Overall**	**Mfg**	**Non-Mfg**	**Overall**
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fitted Impact Due to Import Exposure for White Workers						
White Fitted Effect	-0.078***	0.013***	-0.0090*	-0.087***	0.0049	-0.011**
	(0.020)	(0.0050)	(0.0049)	(0.021)	(0.0043)	(0.0052)
Panel B: Black-White Differential						
Overall	0.024	0.024***	0.018**	0.033	0.035***	0.029***
	(0.025)	(0.0078)	(0.0080)	(0.038)	(0.0099)	(0.0089)
Decomposition						
Population Effect	0.0073***	-0.0028***	-0.00002	0.0062***	-0.0020***	-0.00038
	(0.0014)	(0.00056)	(0.00023)	(0.0018)	(0.00058)	(0.00029)
Industrial Composition	0.0033**	-0.0012**	0.00001		NA	
	(0.0013)	(0.00053)	(0.00011)			
Coefficient Effect	0.013	0.028***	0.018***	0.026	0.037***	0.029***
	(0.015)	(0.0045)	(0.0043)	(0.020)	(0.0061)	(0.0061)
Panel C: Hispanic-White Differential						
Overall	-0.028	0.036**	0.014	0.0071	-0.020**	-0.0089
	(0.060)	(0.016)	(0.011)	(0.033)	(0.010)	(0.0064)
Decomposition						
Population Effect	0.0088***	-0.0026***	0.00040*	0.0051*	0.00034	0.00094*
	(0.0023)	(0.00081)	(0.00023)	(0.0028)	(0.00026)	(0.00052)
Industrial Composition	-0.027***	0.0089***	-0.00065		NA	
	(0.0042)	(0.0012)	(0.00073)			
Coefficient Effect	-0.0098	0.030***	0.014***	0.0020	-0.021***	-0.0099**
	(0.023)	(0.0063)	(0.0048)	(0.020)	(0.0052)	(0.0040)

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Decompositions are based on the IV estimations in Table 3. Panel A reports the fitted employment changes for the white population ($\sum_{c \in CZ} \frac{pop_{Wc}}{pop_W} \times \Delta IP_{Wct} \times \hat{\beta^s_W}$). Panel B summarizes the overall fitted Black-white differential (eqn 4) and decomposes into Population, Industrial Composition, and Coefficient Effects, which sum to the full Black-white differential. Panel C does the same for the Hispanic-white differential. We report the average impact of each component across all possible permutations as well as standard errors based on 1000 bootstrapped samples.

average, due to group-specific import exposure. This differential itself is not statistically significant, as was the case for the coefficient effects estimated in Table 3. However, the Black population benefits from the fact that it is significantly less exposed to import competition due to both the population and industrial composition effects. Combined, these generate a 14% smaller loss in manufacturing employment than the white population (comparing 0.0073+0.0033 to -0.078). These channels do generate statistically significant differentials. In addition, the Black population experiences positive, though noisily estimated, coefficient effects. The CZ-wide ΔIP measure (column 4) produces similar results for the population and coefficient effects, though by definition shuts off the industrial composition channel.

Turning next to non-manufacturing employment outcomes, we find the Black-white differential is positive, significant, and large in magnitude. Using CZ-wide import exposure, which incorporates spillover effects both within a race group as well as across, Black workers experience a 3.5 percentage point increase in non-manufacturing employment (panel B, column 5), while white workers experience no significant change as a result of import exposure (panel A, column 5). Effects are fairly similar when using group-specific ΔIP though with that measure, the white population experiences a significant positive overall impact. The positive Black-white differential is primarily driven by the coefficient effect, while the population (and industrial composition) effects slightly, but statistically significantly, dilute the relative advantage. Because Black workers are less likely to live and work in exposed areas, they do not experience the same degree of positive effects from import exposure as they would if they lived and worked in the same areas as white workers, but these impacts are an order of magnitude smaller than the coefficient effects.

Finally, Black workers experience a significant relative advantage in overall employment as a result of import exposure: the Black-white differential is a 2-3 percentage point relative increase (panel B, columns 3 and 6), while white workers experience a 1% decline in response to either the group-specific or CZ-level shock (panel A, columns 3 and 6). The differential effect is statistically significant in both specifications. Population (and industrial composition) effects, which were positive for Black workers in manufacturing but negative for Black workers in non-manufacturing, are essentially zero for the combined sectors. Thus the coefficient effects are driving the relative advantage for Black workers in overall employment.

For the Hispanic-white gap, effects vary more across group-specific versus CZ-wide ΔIP measures. Beginning with manufacturing employment, we find a noisy -2.8 (36% of the white fitted effect) differential impact of the group-specific shock (panel C, column 1), which is driven by a large and significant industrial composition effect (-2.7 percentage points). In addition, the statistically significant population effect of a nearly 1 percentage point positive differential counterbalances a negative coefficient effect of a similar magnitude, though the latter is not significant. The CZ-wide import exposure shuts off the industrial composition effect, by definition, thus only a small, positive overall effect remains (0.7 percentage point, panel C, column 4), which itself is not statistically significant, though the population effect of 0.5 percentage point is marginally significant. Therefore, the Hispanic population experiences significantly larger losses to manufacturing employment in response to the import shock due to the fact that their baseline distribution of jobs skews towards those most exposed to import competition. This channel is partially offset by their population effects, though as we showed in section 2 Hispanic populations are clustered in both high- and low-exposure locations. Again, coefficient effects are noisily estimated so that we cannot rule out large negative or positive differentials.

For non-manufacturing employment, we find a large and positive overall differential response to the group-specific shock (column 2) but a large and negative response to the CZ-wide shock (column 5). Each estimate is primarily driven by coefficient effects, though for the former, the industrial composition effect provides an additional positive boost – the fact that the Hispanic population is more likely to be shocked due to baseline representation in exposed industries benefits them in terms of the associated spillovers to non-manufacturing employment. As discussed above, the differing signs across specifications suggest that the Hispanic population is able to respond positively to their own shock, however they are hurt disproportionately by import shocks affecting the CZ as a whole.

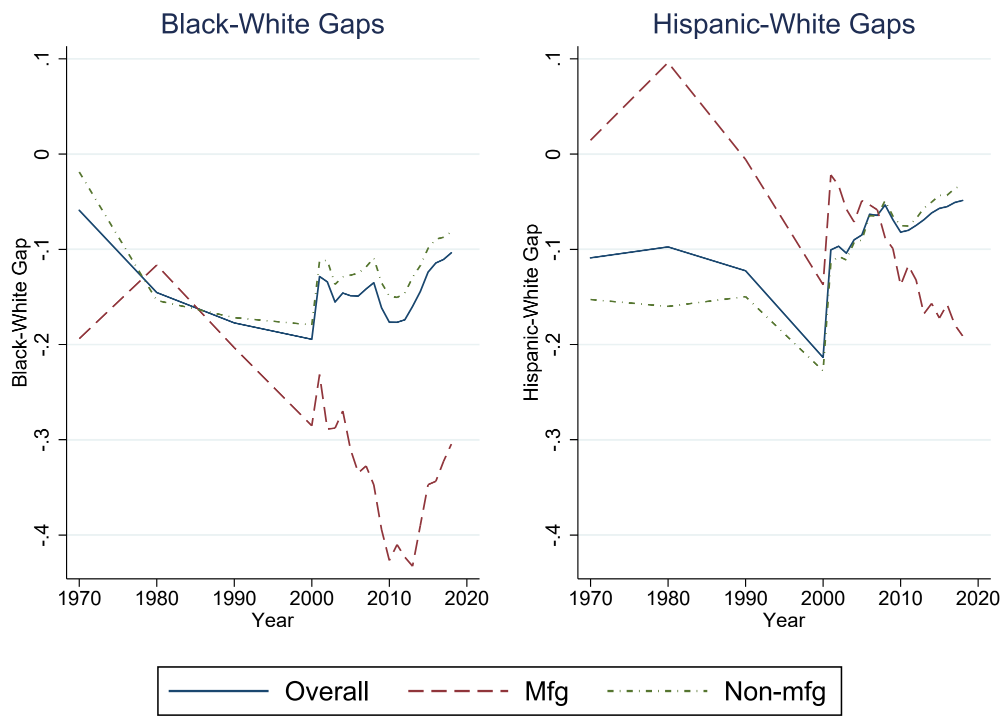
The same dynamic is present for overall employment effects, though here the industrial composition effect washes out. The CZ-wide shock is arguably the best one to focus on because it incorporates both group-specific and spillover effects. There we find that the Hispanic population experiences an additional almost 1 percentage point drop in their employment-to-population ratio, relative to the white population who themselves experience a 1 percentage point drop. The overall differential (first row of panel C) is not statistically significant because of a very small positive population effect that offsets the negative and significant coefficient effect.

In summary, we learn from the decomposition that for manufacturing employment population subgroups experience very different effects due to their average exposure to import competition. However, in terms of overall employment, coefficient effects drive the results and here we find a positive Black-white differential and a negative Hispanic-white differential as a result of the CZ-wide import shock.

We can compare these differentials attributed to the China shock to trends in employment over this time period. Figure 8 plots Black-white (left) and Hispanic-white (right) differentials in employment-to-population ratios across sectors from 1970-2018 using decennial censuses and ACS data.[27]

[27] Specifically, we plot the difference in log employment per working age population in the indicated sector across the indicated race/ethnic groups.

Figure 8: Trends in Minority-White Employment-to-Population Ratios



Notes: We plot the difference in log employment per working age population in the indicated sector using data from the 1970, 1980, 1990, and 2000 Decennial Censuses, and the 2001-2018 ACS waves.

Both minority groups have experienced declines in manufacturing employment, relative to the white population, since 1980. The Black-white gap fell sharply between about 2001 and 2012, has increased since then, but still remains slightly below 2000 levels at the end of our sample period. However, based on the results presented in this paper, it appears that the larger nationwide relative exit of Black workers from manufacturing is not associated with CZ-level import exposure. Though it's possible that this relative exit could contribute to the more muted effects on Black manufacturing employment that we find. The Hispanic-white gap has fallen steadily over most time periods from 1980. In the more recent period from 2000 to 2018, the Hispanic-white gap in manufacturing employment widened by roughly 5 log points. From table 6, this relative decline is at least partially associated with import exposure. We estimate that the group-specific China shock can account for about half of the trend (the 2.8 percentage point differential in panel C, column 1), though this estimate is noisy.

We focus next on trends in overall employment. Trends in non-manufacturing employment mirror these since the vast majority of workers are in jobs outside of manufacturing. The Black-white ratio in overall employment-to-population was close to 20 log points in 2000, experienced some cyclical movements, and was followed by convergence to about 10 log points in 2018. The 3 percentage point narrowing of the Black-white employment gap reported above (panel B, column 6) is thus equal to roughly 15% of the baseline gap and a third of the convergence over this time period.

The Hispanic-white ratio in overall employment was also around 20 log points in 2000 but exhibited substantially more convergence over the 2000s, narrowing to 5 log points in 2018. The differential impacts of the China shock move in the opposite direction of this trend. Above, we estimated a roughly 1 percentage point widening of the Hispanic-white employment gap as a result of CZ-wide import shocks (panel C, column 6). So we estimate that the national trend of convergence would have resulted in an employment gap about 20% narrower but for the China shock.

These benchmarks are important to keep in perspective when considering our results. The China shock advantaged Black workers compared to white workers in terms of employment levels. However, the Black-white employment gap is large and has exhibited little absolute convergence over the time period explored in Figure 8. Thus the China shock was a modest force moving against the many other factors contributing to increasing Black-white employment gaps. In contrast the China shock disadvantaged Hispanic workers, relative to white workers, yet the overall Hispanic-white employment gap saw considerably more convergence since 2000 than did the Black-white gap. So for Hispanic workers, the China shock was a moderate negative force undoing some of the relative employment gains that were due to other factors.

5 Conclusions

In this paper, we show that the negative effects of increased import competition from China primarily affected white and Hispanic workers, who were more likely than their Black counterparts to live and work in affected areas and industries. Black workers actually experienced relative benefits from this import competition in terms of increased employment in non-manufacturing industries. It is important to consider these results in the context of broader trends in racial and ethnic employment disparities. The Black-white employment and earnings gaps in the U.S. economy are large and have stagnated in recent decades. However, the China shock presents a modest force pushing against these trends, with a magnitude of about 30% of the 2018 Black-white employment-to-population gap. According to some metrics, the China shock widened income inequality in exposed locations (Autor et al., 2014). However, it did not result in widening Black-white employment and income gaps, which is surprising in light of the typical comovement of overall inequality and Black-white gaps (Bayer and Charles, 2018). It is also important to note that part of the reason

Black workers experienced smaller employment declines than white workers could be because their manufacturing wages were lower, and thus closer to the wages they would earn when switching to non-manufacturing employment.

The story for Hispanic workers is quite different. They fared worse in harder-hit CZs, compared to white workers, because of their lower educational attainment and overrepresentation in construction and related industries. Indeed, the combined effects of the housing bubble burst and the China shock resulted in a worse Great Recession for Hispanic workers in exposed locations. The Hispanic-white employment gap is smaller than the Black-white gap and has been narrowing in recent decades. The China shock partially offset these relative gains for Hispanic workers, with a magnitude of about 20% of the 2018 Hispanic-white employment-to-population gap. Though it is worth noting that Hispanic workers were able to recover these employment losses, relative to white workers, in the most recent decade.

Our research not only sheds light on the evolution of racial and ethnic gaps in the U.S. but also helps interpret the literature on the impacts of import competition on local labor markets. Relative to Black workers, white workers appear less willing to shift into the non-manufacturing jobs that opened following the China shock, driving the persistent negative consequences for overall employment in exposed areas. Labor supply factors may be important but it could also be that certain workers perceive the barriers to entry for high-paying non-manufacturing jobs to be too high. For instance, these jobs may require specific skill acquisition, relative to similar-paying positions in manufacturing from an earlier era. Our findings then reinforce the importance of training, especially outside of formal schooling channels, in facilitating an employment recovery for the swathe of the population most directly impacted by import competition. Though training programs have historically had pessimistic outlooks (Heckman et al., 1998; LaLonde, 1986), private-sector programs or public-private partnerships have been more successful (Card et al., 2018; Katz et al., 2022; Dillon et al., 2022). Further, Trade Adjustment Assistance training (Hyman, 2018) and wage insurance programs (Hyman et al., 2021) have been shown to be successful. Our results point to an even greater need for such programs than was previously thought, as we show that some groups did move into non-manufacturing jobs, while others did not, possibly because they did not perceive the accessible jobs to be close enough substitutes for their previously-held manufacturing positions.

This paper also points to a need for policies addressing racial and ethnic inequality. In the case of Hispanic workers, the China shock was exacerbated by relatively low education levels and employment in vulnerable industries. For Black workers, it is important to note that their relative advantage caused by the China shock comes in part from declining labor market outcomes of white workers. Further, even though Black workers were less exposed than white or Hispanic workers and were better able to shift into non-manufacturing jobs as result of the China shock, these outcomes occur against the backdrop of persistent racial inequality in the U.S. It is possible that this racial inequality played a role in the relative increase in Black non-manufacturing employment, for example if Black workers perceived a greater need to move into these new jobs due to weaker safety nets, or if they earned relatively lower wages in all sectors. So while it is reassuring to find that the China shock did not exacerbate Black-white gaps, there is still a great need for policies targeting racial inequality.

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A Appendix

A.1 Data Appendix

Census and American Community Survey Data

The primary datasets used in this paper are the 1980, 1990, and 2000 U.S. Censuses and the American Community Surveys (ACS) for 2005 through 2018. We obtain data from the Census Integrated Public Use Micro Samples (Ruggles et al., 2021). The Census and ACS samples include 5 and 1 percent of the US population, respectively. We focus on 722 mainland commuting zones (CZs), which exclude those in Alaska and Hawaii, using the crosswalk from Public Use Microdata Areas (PUMAs) to CZs provided by Autor and Dorn (2013).

We restrict attention to respondents aged 16 to 64 who do not reside in institutional group quarters. We classify observations as white if they report that they are not of Hispanic, Spanish, or Latino origin, and select "white" as their only race. We classify observations as Black if they are not Hispanic and select "Black" as any of their race choices (i.e., we categorize people who select multiple races as Black, as long as one of the races they select is). Finally, we categorize as Hispanic anyone who indicates that they are of Hispanic, Spanish, or Latino origin, regardless of race. For most of our analyses, we focus on just these three mutually exclusive (but not exhaustive) groups, but specify below instances in which we use all observations, regardless of race.

We aggregate observations to the CZ-race/ethnicity-year level using person weights. We define as employed anyone working in non-military employment. We define manufacturing jobs using the 1990 Census classification (taking values 100-392). The wage measure used in this paper is an hourly wage calculation. We replace top-coded annual wage and salary income with 1.5 times the top code value in that year. We define annual weeks worked using the categorical variable available in the Census and ACS datasets, imputing the midpoint of the category from 2000 for all years. Hourly wages are top-coded adjusted annual income divided by the annual weeks worked measure times usual hours worked per week and are missing if income, weeks, or hours are missing. We bottom-code wages to the first percentile in the national distribution and top code so that income for full-time, full-year work does not exceed the adjusted top-code value. Wages are inflation adjusted to the year 2012 using the Personal Consumption Expenditure Index (https://fred.stlouisfed.org/series/PCECA). We drop wage observations for the self-employed.

Defining Import Exposure

To calculate the CZ-wide import penetration measure (equation 1) we follow Autor et al. (2021) (hereafter ADH). We use trade data for 1997 to 2018 from the UN Comrade Database,[28] which provides bilateral imports for 6-digit Harmonised System (HS) products. We aggregate imports from China across HS codes to 4-digit Standard Industrial Classification (SIC) industries using the crosswalk provided by Autor et al. (2013). We inflate the dollar value of imports to the year 2012 using the Personal Consumption Expenditure Index. For a given 4-digit industry, we calculate the change in import exposure in year t as the change in industry imports from t compared to 2000 divided by domestic absorption. The latter is measured in 2000 and is equal to gross output plus imports minus exports. Gross output is measured by industry shipments from the NBER-CES Manufacturing Productivity Database.[29]

We apply these changes in industry imports to the CZ-year level, following equation 1 in the text, i.e., summing across all industries weighting by the fraction of employment in the CZ in that industry in 2000. We use the County Business Patterns (CBP) in 2000 from the U.S. Census Bureau to capture industry shares in the initial CZ employment.[30] CBP is an annual extension of the Census Bureau's economic censuses and provides employment in the private non-farm sector by county and 6-digit NAICS industry code. We follow ADH in mapping these cells to CZ-by-4-digit SIC industry code.

Our instrument for CZ-wide import exposure uses changes in Chinese imports from eight other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). Imports from these countries are also measured using the UN Comtrade Database. Domestic absorption is measured at a lag (1997 instead of 2000) and CZ-industry employment shares are also lagged, measured using the 1990 CBP.

The CZ-wide import measures follow ADH exactly, though we expand on the years over which changes are measured.

For group-specific import exposure (equation 2), we must use the U.S. Censuses to measure baseline employment shares by CZ, industry, and race/ethnicity (CBP data do not disaggregate by demographic group). We use the census samples as described above to calculate employment shares from the 2000 Census (or 1990 Census for the instrumented version) at the CZ-industry-race/ethnicity level. Industries can only be measured at the 3-digit Census code level. We use the crosswalk of Autor et al. (2019b) to map 6-digit HS products to the 3-digit industry level. Import exposure then

[28] https://comtrade.un.org

[29] https://www.nber.org/research/data/nber-ces-manufacturing-industry-database

[30] https://www.census.gov/programs-surveys/cbp/data.html

sums the changes in imports from China across 3-digit industries (divided by 2000 domestic absorption aggregated to the 3-digit level in the same way), weighting by the fraction of employment in the CZ and subgroup in that 3-digit industry in 2000.

The instrument uses an analogous change in imports at the 3-digit industry level for the eight other high-income countries (divided by domestic absorption measured in 1997) and employment weights from the 1990 Census.

We have also explored a version of the CZ-wide measure that uses 3-digit Census industries and employed shares from the censuses, instead of 4-digit SIC industry codes and employment shares from CBP, and obtain similar results. These findings should allay concerns that our approach for measuring group-specific import exposure (which requires the higher level of industry aggregation) introduces too much error, and are available upon request.

Main Regression Analyses

Our main analyses (equation 3 and table 3) estimate regressions on a stacked sample of 722 mainland CZ-by-race/ethnic group-by year observations from 2005-2018. Outcome variables are the change in log employment per working age population in manufacturing, non-manufacturing, or overall employment for the CZ-race/ethnic group for a given year compared to 2000. Yearly employment is measured in the ACS and baseline employment in 2000 is measured in the Census. A small number of cells are missing because no respondents were working in the sector in that year. Sample restrictions to CZ-race/ethnic groups that always have non-missing observations make little difference since regressions are weighted by the group-specific population as measured in the 2000 Census. The main specifications control for race/ethnic group-by-year fixed effects and the CZ-level controls used in Autor et al. (2021), all interacted with race/ethnic group. We take the CZ-level controls measured in 2000 directly from their replication files: region fixed effects, the share of the population that is foreign born, the share of the population that is a college graduate, population shares in ages 0-17, 18-39, 40-64, Black, Asian, Hispanic, and other, the share of employment in manufacturing, routine occupations, offshorable occupations, and the female employment share. The key explanatory variables are either the group-specific or CZ-wide change in import exposure for the contemporaneous year compared to 2000 interacted with race/ethnicity. We estimate both OLS specifications and an IV specification that instruments for the change in exposure and its interactions with race/ethnicity with the instrument described above and its interactions with race/ethnicity. Standard errors are clustered by state.

We also explore a specification that allows the impact of import exposure to vary over time (e.g., figure 4). Here the key explanatory variables are the changes in import exposure interacted with race/ethnicity and interacted with an exhaustive set of year indicators from 2005-2018. In the IV specification instruments are also interacted with year indicators.

Robustness

We explore a range of alternative specifications, summarized in appendix table A.7. Column 2, labeled "2012 only" follows an analogous approach to Autor et al. (2013). We restrict to ACS waves 2011-2013. We take an unweighted average of outcome and explanatory variables across these years, within a CZ-race/ethnicity cell. We then estimate a similar regression on this collapsed subsample.

Column 3 returns to the full sample of years and adds to the main set of controls the differences in log employment per working age population between Black and white populations and Hispanic and white populations for a given CZ in each of 1980, 1990, and 2000. These gaps are interacted with race/ethnicity indicators.

The column 4 specification includes CZ fixed effects and explicitly drops the main import exposure effect from the regressions since it has little variation within a CZ over time. The main effects of the CZ-level controls also drop out of this regression.

For column 5, we define group-specific controls for the share of the race/ethnic population that has a college degree, is in each of the age bins, is employed in manufacturing, in an offshorable occupation, or in a routine occupation, and the female employment share. We also include in this regression the year and region indicators, and the shares of the population that is foreign born, and population shares of black, asian, Hispanic, or other. All controls are interacted with race/ethnicity.

In column 6, we provide an alternative IV strategy, leveraging the Normal Trade Relations (NTR) gap approach as in Handley and Limão (2017) and Pierce and Schott (2016). We calculate CZ-level and group-level instruments as follows: We obtain the NTR gap (the difference between the NTR tariff rate and non-NTR tariff rate) at the 8-digit HS product code level from Pierce and Schott (2016). We then average this measure over products within 4-digit SIC codes or 3-digit Census industry codes, using the same crosswalks as above and weighting by product imports in 2000. We apply the industry-level NTR gap to CZ's or CZ-subgroups using employment shares as described above. We then instrument for the main measures of import exposure and its group interactions with the NTR instrument and group interactions. See appendix table A.7.

Differences in observables

We now detail how we create figures 7 and 5 and appendix figures A.2 and A.3. For the education figure, we divide the age 16-64 population into 4 mutually exclusive and exhaustive groups: dropouts are anyone without a high school diploma, including those that attended 12th grade but did not complete; high school are those with a high school diploma, GED, are alternative credential; some college are those who attended college or have an associates degree but did not complete a bachelor's; college+ completed at least a bachelor's. We plot the distribution of employed persons of the indicated race/ethnicity across these categories in 2000. To obtain the coefficients, we estimate CZ-year level regressions, similar to our main specification, where the dependent variable is the change in log employment among workers of a given education level in the indicated sector per working age population in the indicated education level. These regressions include all race/ethnic groups, and are not restricted to only Black, Hispanic, and white groups. We plot results for the IV specification with full controls (excluding any interactions with race/ethnicity terms since observations are at the CZ-year level).

For occupation and industry groups the outcomes are measured per overall working age population (since those who are not working are not necessarily associated with an occupation or industry). For occupations, we use the Level 1 categories from Autor and Dorn (2013) and define these using the code and crosswalk from Census occupation codes to occ1990dd codes they generously provided. For industries, we first map Census 1990 industry codes to NAICS codes using the 2000 Census. For ind1990 codes mapped to multiple NAICS codes, we keep the NAICS code with the largest person-weighted employment. We then use 1-digit NAICS categories.

Job-to-Job Flows

For table 5, we derive race and ethnicity-specific quarterly job-to-job flows in year 2000 from the Job-to-Job Flows (J2J) Explorer[31], which is based on Longitudinal Employer-Household Dynamics (LEHD) data. J2J provides a set of statistics on job mobility, such as the number of job-to-job transitions between 3-digit NAICS and hires and separations to and from employment. We aggregate the industry-level transitions up to the manufacturing and non-manufacturing sectors and take the average of the quarterly transitions in the third and fourth quarters of 2000 because the J2J series started in the third quarter of 2000. To calculate the job-to-job flow rates and separation rates, we divide the job-to-job transitions and separations by total employment in the

[31] https://j2jexplorer.ces.census.gov

sectors from the Quarterly Workforce Indicators (QWI)[32] for the same period. The QWI is also based on LEHD, so it should be consistent with J2J.

A.2 Appendix on shift-share identification

A recent literature has focused on identification issues surrounding shift-share methods. Notably, Borusyak et al. (2022) make an identification argument based on exogeneity of the shifters, while Goldsmith-Pinkham et al. (2020) show that identification can be achieved assuming exogeneity of the baseline shares (hereafter GSS and BHJ, respectively). Both papers use the China shock literature as a case study, offer specification tests to provide intuition for the identifying assumption, and, in the case of BHJ, offer a standard error correction.

When considering exogeneity of the shifters (i.e., industry-level import shocks), BHJ show that the China Shock passes their ancillary identification tests. They also provide a method for obtaining shift-share instrumental variable (SSIV) robust standard errors. Their argument is that the shift-share approach boils down to an industry-level regression (the level of the shock) where the data are aggregated using the CZ-level shares as weights. So the standard errors need to be adjusted for the much smaller number of observations (industry-by-group-by-year in our case).

Appendix table A.9 shows how we adapt their approach to our setting. Column 1 replicates our main results from section 3. Next, in column 2, we include the lagged manufacturing share in the CZ (from 1990). ADH include start-of-period manufacturing shares but BHJ argue that the lagged control is necessary to solve the incomplete shares issue – in this case that the sum of exposure shares varies across CZs since the vast majority of exposed industries are in manufacturing and overall manufacturing employment varies with place and time. Because our instrument uses exposure shares from 1990, BHJ argue that we should control for manufacturing shares from 1990 to address the issue. We include this control interacted with race/ethnicity. Finally, in column 3, we construct their SSIV robust standard errors (labeled, "Industry-by-Group Approach"). Reassuringly, our conclusions are robust to these changes. Point estimates on the interaction terms are similar in magnitude with the additional control and similar in statistical significance when applying the standard error correction, though some coefficients are significant at the 5%, rather than 1%, level when we use this approach. The effects of CZ-wide import exposure on overall employment for white workers are somewhat less robust to the inclusion of the lagged manufacturing control, which is highly collinear with the start-of-period manufacturing control, but these are not our primary focus.

[32] https://www.census.gov/data/developers/data-sets/qwi.html

In table A.9, we limit our attention to the CZ-level shock, rather than the race/ethnicity-specific shock. We view the CZ-level shock as the more relevant one for our analysis since it includes spillover effects across population subgroups. In addition, the race/ethnicity-specific shock is constructed using 3-digit NAICS codes which provide especially limited variation when taking the industry-level approach.

In an alternative approach, GSS show that β_1 is identified under the condition that the baseline employment shares are exogenous in the second stage equation. They show that the ADH data do not meet some of their identification tests meaning exogeneity of the shares is unlikely to hold. However, in our case, we argue that we can still achieve identification of β_2 and β_3 in their framework since identification of the interaction terms requires a somewhat milder assumption: that the baseline employment shares are uncorrelated with trends in white-minority employment differentials.

GSS emphasize that when considering identification strictly from baseline employment shares across industries, in practice, only a handful of industries contribute the vast majority of the weight in identifying the effects of interest. To be precise, they show that the second stage coefficient of interest is a weighted sum of just-identified instrumental variables estimators that each use baseline employment shares in a given industry as the instrument. The weights, which they term Rotemberg weights, then help us understand which industries are contributing the most to the overall estimate. For example, in the original Autor et al. (2013) – which leverages import changes from 1990 to 2000 and from 2000 to 2007 – the industries with the top 5 Rotemberg weights contribute 53% of the overall estimate, even though the paper uses variation in 397 industries.

To replicate their approach, we begin by showing Rotemberg weights for each population subgroup in appendix table A.10. Here we use CZ-wide baseline employment shares (rather than group-specific shares) so only variation in population shares and the impact on manufacturing employment in the just-identified equation drive differences across groups. We focus on the top 5 industries, though in fact the Rotemberg weights are even more concentrated for population subgroups: for Black and Hispanic populations, the top 3 industries contribute at least 50% of the weight, while 4 industries are required for the white population.

In what follows, for brevity, we will restrict our attention to industries contributing in the top 50% of variation for at least one population subgroup, though there is substantial overlap: Furniture and Fixtures, NEC; Radio and Television Broadcasting and Communications Equipment; Electronic Computers; Semiconductors and Related Devices; and Computer Peripheral Equiment, NEC.

First, as in GSS, we look for correlations between key CZ-level characteristics of interest and the employment shares in the prominent industries. Panel A of appendix table A.11 regresses 1990 industry shares on Black-white and Hispanic-white employment gaps in 2000 at the CZ-level, including full controls from ADH, weighting by CZ-level population, and clustering standard errors by state – all of which help to mirror our regression analysis in the paper. GSS show that industry shares are correlated with some important CZ-level characteristics, such as the share of the population with a college degree, and that is true in our analysis as well (though not shown, these control variables are included in the regressions). However, the race and ethnicity employment gaps in 2000 are not significantly related to the industry shares. The standard errors are large so that we can not rule out high-magnitude correlations. However, no clear pattern emerges from the table and none of the relationships are significant.

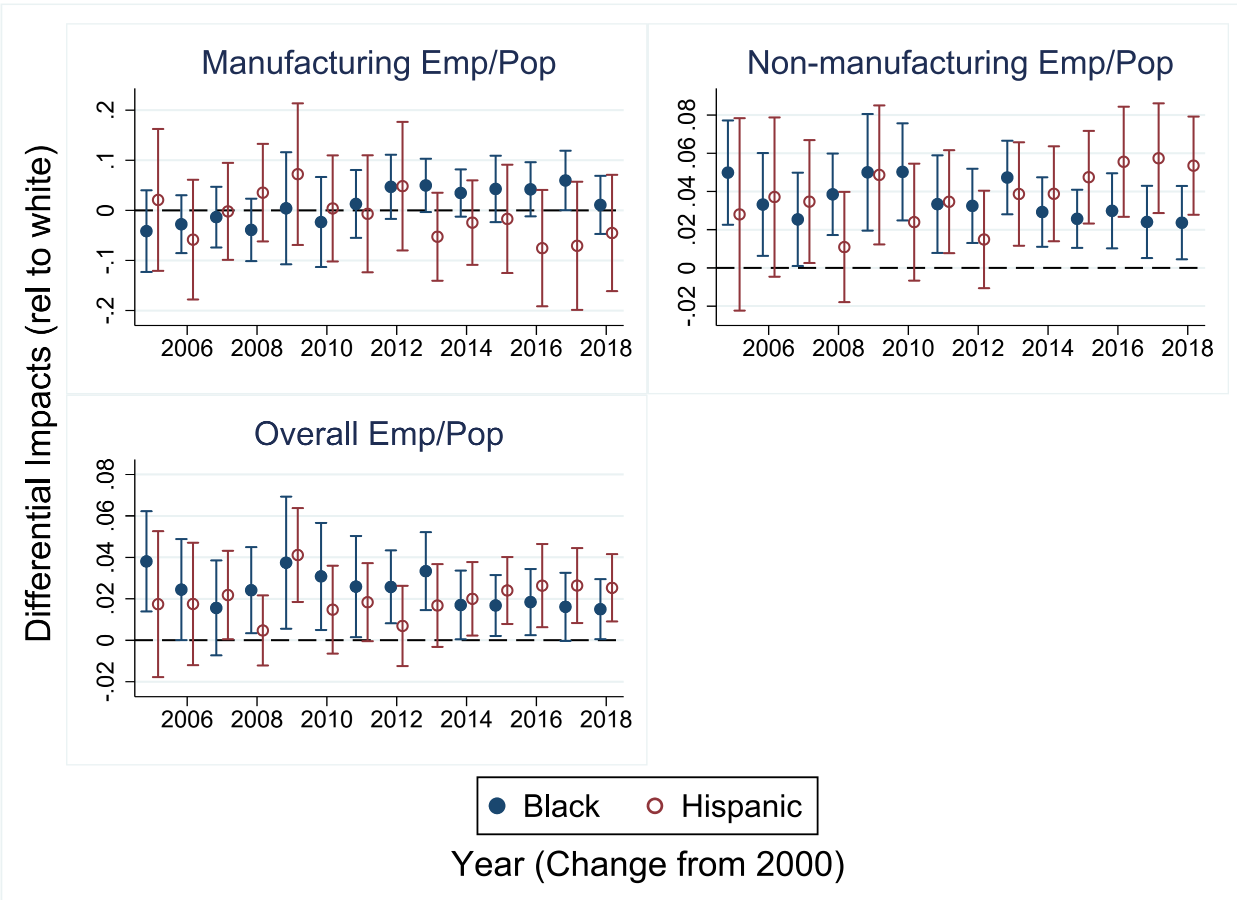
Next, following GSS, we explore pre-trends as a function of employment shares in the most important industries. Because we are focused on identifying the Black-white and Hispanic-white differential employment effects, we are most concerned about pretrends in employment gaps. Panel B thus regresses industry shares on trends in employment gaps from 1990 to 2000. Here again estimates are noisy but no coefficient is statistically significant and moreover no clear pattern emerges.

Overall, table A.11 gives us confidence that race and ethnicity gaps are not systematically related to baseline industry shares in the most important industries for identifying the effects of the China shock on employment. GSS call into question the identifying assumptions of the China shock literature for estimating β_1 – the effect of the China shock on CZ-level employment. However, when we extrapolate from their approach to our setting, we do not see red flags for the identification of the differential effects of the China shock across groups.

To summarizes, two recent papers have focused on identification issues in a shift-share setting. They take opposite approaches, one showing how identification can be achieved by assuming the shifts are exogenous and the other making a similar argument when assuming the shares are exogenous. Either one may seem like a strong assumption in this setting. However, we are reassured that when we follow the guidance in each of these approaches, our analyses holds up.

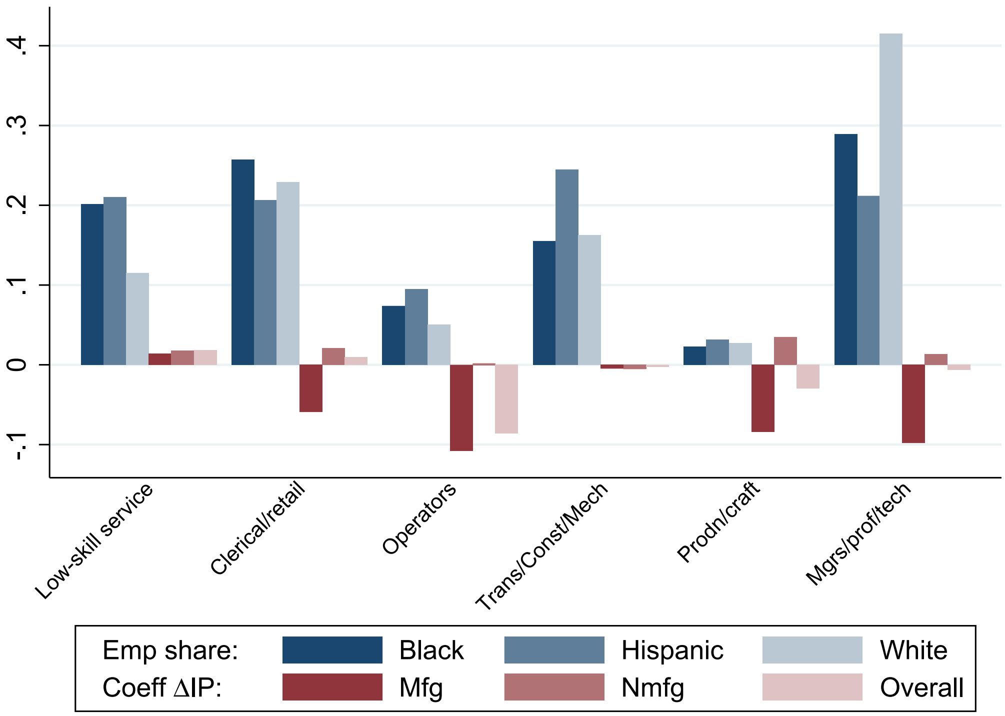
Additional Tables and Figures

Figure A.1: Differential Impacts of Group-Specific Import Exposure over Time



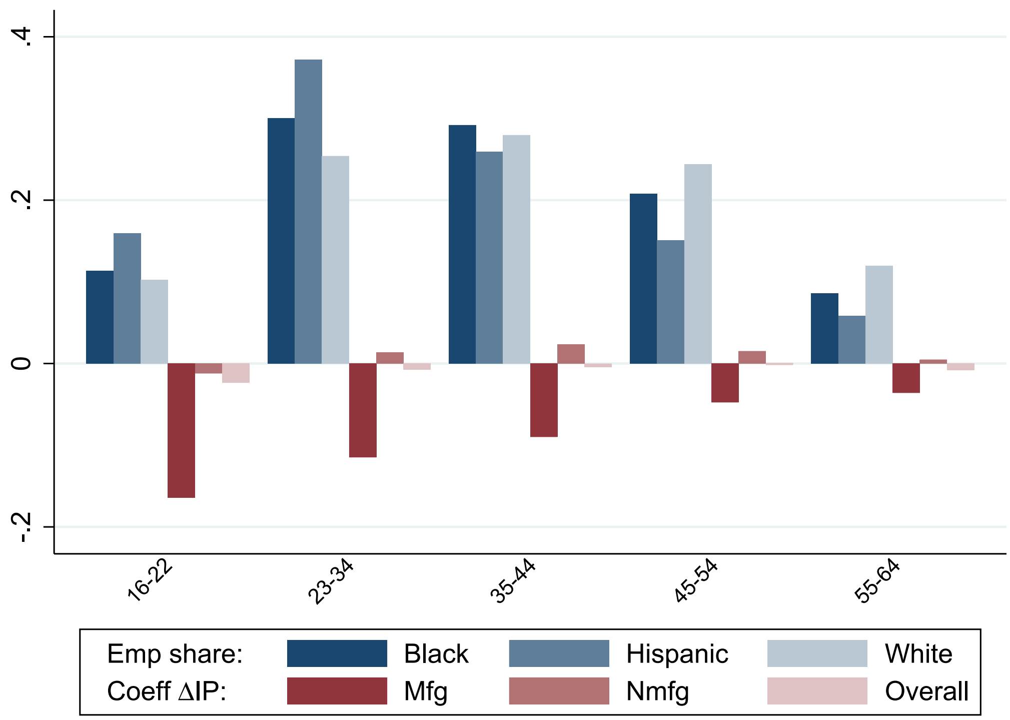
Notes: See Figure 4. This figure plots coefficients on race-or-ethnicity-specific ΔIP*Black*year and ΔIP*Hispanic*year effects (instead of CZ-wide) and their 90% confidence intervals.

Figure A.2: Summary of Differential Impacts by Occupation



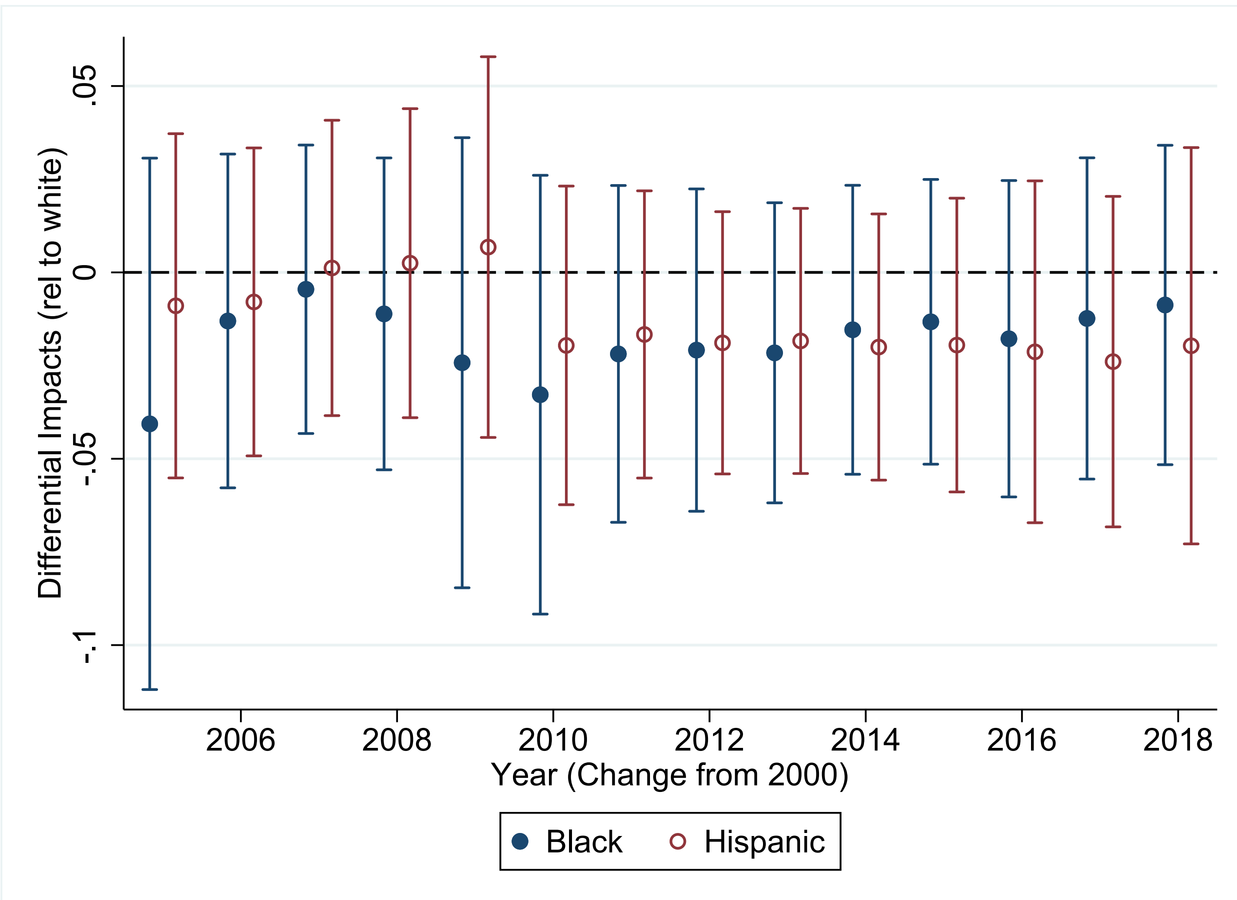
We group workers using occupational categories from Autor and Dorn (2013). The blue bars are employment shares across occupation groups, by race or ethnicity in 2000. To obtain the maroon bars, we estimate CZ-year level regressions where the dependent variable is the change in log employment in the indicated occupation group and sector per working age population and the explanatory variables are the CZ-level ΔIP and full controls from Table 3. The maroon bars plot coefficients on ΔIP from the IV specification. We find that Black, Hispanic, and white workers should experience similar employment effects in response to the China shock based solely on their occupation distributions.

Figure A.3: Summary of Differential Impacts by Age



The blue bars are employment shares across age groups, by race or ethnicity in 2000. To obtain the maroon bars, we estimate CZ-year level regressions where the dependent variable is the change in log employment in the indicated age group and sector per population in the age group and the explanatory variables are the CZ-level ΔIP and full controls from Table 3. The maroon bars plot coefficients on ΔIP from the IV specification. We find that Black, Hispanic, and white workers should experience similar employment effects in response to the China shock based solely on their age distributions.

Figure A.4: Differential Impacts on log population counts



Notes: See Figure 4. This figure plots coefficients on race-or-ethnicity-specific ΔIP*Black*year and ΔIP*Hispanic*year effects (instead of CZ-wide) and their 90% confidence intervals. The dependent variable is the change in log working age population from t to 2000 for the race or ethnic subgroup.

Table A.1: Summary Statistics

	White	Black	Hispanic
Group-specific ΔIP	0.844	0.719	1.026
	(0.483)	(0.604)	(0.570)
CZ-level ΔIP (ADH)	1.023	0.936	0.961
	(0.738)	(0.715)	(0.603)
Mfg Emp per pop, 2000	8.290	5.716	7.205
	(3.514)	(3.691)	(4.264)
Non-mfg Emp per pop, 2000	62.99	55.75	59.42
	(5.569)	(7.686)	(5.817)
Overall Emp per pop, 2000	71.28	61.47	66.63
	(4.946)	(6.118)	(4.804)
Log Hourly Wage, 2000	2.843	2.605	2.543
	(0.197)	(0.186)	(0.116)
Change in log Mfg Emp	-0.288	-0.396	-0.311
	(0.148)	(0.282)	(0.258)
Change in log Non-Mfg Emp	0.00694	0.0635	0.179
	(0.0381)	(0.0910)	(0.0918)
Change in log Overall Emp	-0.0324	0.0126	0.115
	(0.0366)	(0.0857)	(0.0707)
Change in log Hourly Wage	-0.222	-0.288	-0.242
	(0.0753)	(0.104)	(0.0776)
Obs in group-CZ-year cell	8202.6	2269.9	8422.3
	(7323.8)	(2197.9)	(10838.6)
Obs in group-CZ cell, 2000	39027.2	10845.6	32038.4
	(36536.2)	(10335.2)	(41129.2)
Group-CZ-year cells	10108	10054	10102

means; sd in parentheses

Notes: We summarize group-by-CZ-by-year cells from the 2005-2018 American Community Survey waves, weighted by population in 2000. 2000 data are from the Census. Groups are defined by their race and ethnicity and include Black, white, and Hispanic populations. Group-specific ΔIP is defined in eqn 2; CZ-level ΔIP in eqn 1. Employment variables are per adult (age 16-64) non-institutionalized group-specific population. Changes are in log employment per population from 2000. Log hourly wages are annual wage and salary income divided by annual weekly hours time usual hours per week, adjusted to 2012 dollars using the PCE price index, and exclude self-employed. All employment measures exclude military employment.

Table A.2: Industry-level ΔIP and Employment Shares by Race or Ethnicity

3-Digit Industry	Δ Imports	Share of Group-Specific Emp (%)		
		White	Black	Hispanic
Leather products, except footwear	45.17	0.03	0.02	0.07
Computers and related equipment	35.57	0.31	0.23	0.28
Radio, TV, and communication equipment	25.84	0.21	0.18	0.17
Household appliances	17.75	0.09	0.11	0.07
Footwear, except rubber and plastic	15.72	0.03	0.02	0.05
Knitting mills	15.1	0.05	0.1	0.08
Apparel and accessories, except knit	14.59	0.2	0.34	0.91
Tires and inner tubes	13.46	0.08	0.12	0.04
Cutlery, handtools, and general hardware	8.76	0.06	0.05	0.05
Furniture and fixtures	8.31	0.53	0.42	0.76
Pottery and related products	8.23	0.04	0.02	0.04
Toys, amusement, and sporting goods	7.85	0.42	0.29	0.66
Miscellaneous fabricated textile products	7.19	0.12	0.24	0.22
Other rubber products, and plastics footwear and belting	6.8	0.09	0.08	0.07
Miscellaneous fabricated metal products	6.65	0.36	0.31	0.41
Medical, dental, and optical instruments and supplies	5.93	0.34	0.2	0.35
Electrical machinery, equipment, and supplies, n.e.c.	5.77	1.04	0.79	1.11
Machinery, except electrical, n.e.c.	5.22	0.91	0.43	0.67
Metalworking machinery	5.17	0.21	0.07	0.1
Structural clay products	4.43	0.03	0.04	0.04
Glass and glass products	4.14	0.14	0.12	0.15
Ordnance	3.85	0.03	0.02	0.01
Misc. nonmetallic mineral and stone products	3.61	0.07	0.04	0.09
Construction and material handling machines	3.52	0.12	0.05	0.05
Scientific and controlling instruments	3.38	0.21	0.1	0.12
Industrial and miscellaneous chemicals	3.26	0.41	0.37	0.21
Miscellaneous plastics products	3.14	0.5	0.41	0.7
Engines and turbines	3.09	0.09	0.06	0.03
Primary aluminum industries	2.74	0.14	0.12	0.13
Miscellaneous paper and pulp products	2.63	0.12	0.11	0.12
Agricultural chemicals	1.93	0.03	0.02	0.01
Farm machinery and equipment	1.84	0.09	0.07	0.05
Sawmills, planing mills, and millwork	1.8	0.39	0.33	0.37
Canned, frozen, and preserved fruits and vegetables	1.78	0.09	0.08	0.29
Railroad locomotives and equipment	1.66	0.03	0.02	0.02
Fabricated structural metal products	1.53	0.36	0.21	0.36
Yarn, thread, and fabric mills	1.5	0.16	0.41	0.19
Soaps and cosmetics	1.34	0.08	0.11	0.13
Misc. food preparations and kindred products	1.34	0.1	0.14	0.2
Drugs	1.23	0.29	0.26	0.19
Blast furnaces, steelworks, rolling and finishing mills	1.22	0.28	0.28	0.19
Carpets and rugs	1.2	0.06	0.06	0.09
Plastics, synthetics, and resins	1.17	0.05	0.05	0.04
Metal forgings and stampings	0.84	0.1	0.07	0.09
Printing, publishing, and allied industries	0.8	1.07	0.67	0.84
Iron and steel foundries	0.79	0.15	0.13	0.14
Paperboard containers and boxes	0.76	0.12	0.14	0.15
Grain mill products	0.65	0.1	0.07	0.07
Aircraft and parts	0.48	0.37	0.25	0.25
Sugar and confectionery products	0.4	0.05	0.07	0.11
Pulp, paper, and paperboard mills	0.32	0.24	0.23	0.1
Miscellaneous petroleum and coal products	0.21	0.03	0.03	0.02
Paints, varnishes, and related products	0.15	0.06	0.05	0.07
Ship and boat building and repairing	0.14	0.14	0.21	0.1
Meat products	0.12	0.2	0.6	1
Bakery products	0.09	0.09	0.19	0.24
Wood buildings and mobile homes	0.06	0.07	0.04	0.08
Logging	0.05	0.1	0.09	0.03
Beverage industries	0.04	0.14	0.18	0.18
Motor vehicles and motor vehicle equipment	0.04	1.23	1.43	0.69
Petroleum refining	0.04	0.11	0.09	0.09
Dairy products	0.02	0.09	0.06	0.09
Tobacco manufactures	0.01	0.03	0.07	0.01
Newspaper publishing and printing	0	0.41	0.35	0.27
Guided missiles, space vehicles, and parts	0	0.19	0.09	0.14
Cycles and miscellaneous transportation equipment	-0.27	0.03	0.02	0.03
Cement, concrete, gypsum, and plaster products	-0.73	0.14	0.1	0.16

Notes: The table includes all 3-digit industries (using IND1990DD codes from Autor et al. (2013)) with non-zero import exposure changes. Industry-level import exposure changes (Δ Imports) are imports in 2012 minus those 2000, divided by domestic absorption. We also report the percentage of employment within each race or ethnicity group in the 3-digit industry.

Table A.3: Pre-Period Race and Ethnicity Gaps and Import Exposure

Dependent Variable:	Minority-white Employment-to-population Gap				
	Levels			Changes	
	1980	1990	2000	1980-90	1990-00
Panel A:	Race-specific Import Exposure				
$\Delta IP * Black$	0.0184	0.0202	0.0000832	0.00176	-0.0202
	(0.0161)	(0.0130)	(0.0147)	(0.0151)	(0.0128)
$\Delta IP * Hispanic$	0.0528**	0.0211	-0.00147	-0.0317	-0.0225
	(0.0244)	(0.0245)	(0.0162)	(0.0268)	(0.0216)
Panel B:	CZ-Wide Import Exposure (ADH)				
$\Delta IP * Black$	0.00718	0.00278	-0.000702	-0.00439	-0.00350
	(0.0144)	(0.0102)	(0.0140)	(0.0115)	(0.0110)
$\Delta IP * Hispanic$	0.00867	-0.0345**	-0.000646	-0.0432***	0.0339***
	(0.0125)	(0.0155)	(0.0118)	(0.0125)	(0.0109)
Observations	1429	1431	1444	1417	1431

Standard errors in parentheses clustered by state

*** p<0.01, ** p<0.05, * p<0.1

Notes: We stack CZ-level Black and Hispanic observations in the indicated year, obtained from the decennial censuses. We regress the indicated minority-white gap or change in gap on import exposure from 2000-2012, exhaustively interacted with minority group indicators. We include full controls, weights, and clustering as in Table 3. We summarize results for the IV specification using the race-or-ethnicity-specific ΔIP in panel A and the CZ-wide ΔIP in panel B measure from 2000-12.

Table A.4: First Stage Regressions

	(1)	(2)	(3)	(1)	(2)	(3)
Dependent Variable:	Group-specific ΔIP			CZ-level ΔIP (ADH)		
Group-specific IV	0.571***	0.408***	0.438***			
	(0.057)	(0.036)	(0.034)			
CZ-level IV (ADH)				0.441***	0.422***	0.523***
				(0.070)	(0.064)	(0.062)
White	X			X		
Black		X			X	
Hispanic			X			X
Observations	10,108	10,054	10,102	10,108	10,054	10,102
R-squared	0.804	0.795	0.718	0.668	0.665	0.799
F-stat on instrument	100	129	168	40	43	71

Standard errors in parentheses clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Notes: See Table 3. We regress the indicated import exposure measure in the contemporaneous year minus that in 2000 on the import exposure instruments, separately for white, Black, and Hispanic, including full controls. The instruments use changes in imports from China for other developed countries applied to lagged (race-specific or CZ-wide) employment shares. Standard errors are clustered on state. Models are weighted by race-specific CZ working-age population in 2000.

Table A.5: Impacts of Import Exposure on Employment, OLS

Dependent variable: Δ log employment in the sector per working age population			
Sector:	Manufacturing	Non-Manufacturing	Overall
	(1)	(2)	(3)
Panel A: Group-Specific Import Exposure			
Group-specific ΔIP	-0.060***	0.014***	-0.006
	(0.013)	(0.003)	(0.004)
$\Delta IP * Black$	-0.017	0.022***	0.008
	(0.018)	(0.008)	(0.007)
$\Delta IP * Hispanic$	-0.032	0.029***	0.009
	(0.034)	(0.009)	(0.007)
T-stat Black overall	–2.23	3.83	0.91
T-stat Hispanic overall	–1.88	2.90	0.42
Panel B: CZ-Wide Import Exposure (ADH)			
CZ-level ΔIP (ADH)	-0.024***	0.006***	0.000
	(0.008)	(0.002)	(0.002)
$\Delta IP * Black$	0.011	0.010*	0.008**
	(0.013)	(0.006)	(0.003)
$\Delta IP * Hispanic$	-0.031**	-0.003	-0.008*
	(0.015)	(0.010)	(0.005)
T-stat Black overall	–1.42	3.71	1.58
T-stat Hispanic overall	–2.82	–1.28	–2.50
Observations	26,772	30,105	30,159

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses clustered by state

Notes: We estimate equation 3 on group-CZ-year cells using ACS data from 2005-2018, restricted to white, Black, and Hispanic observations. Dependent variables are log employment in the sector per working age population in the contemporaneous year minus that in 2000. Explanatory variables are the group-specific (panel A) or CZ-wide (panel B) import exposure in the contemporaneous year minus that in 2000 and race and ethnicity interactions. All use OLS and include full controls from ADH interacted with race/ethnicity: year and region fixed effects, share of the CZ population that is foreign born, college graduates, ages 0-17, 18-39, 40-64, Black, Asian, Hispanic, and other races/ethnicities, as well as the share of employment in manufacturing, routine occupations and offshorable occupations, and the female employment share in the CZ in 2000. Standard errors are clustered on state. Models are weighted by race/ethnicity-specific CZ working-age population in 2000.

Table A.6: Cross-group versus Own-group Import Exposure

Dependent variable: Δ log employment in the sector per working age population						
Sector:	Manufacturing		Non-Manufacturing		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
Group-specific ΔIP	-0.093***	-0.050	0.015***	0.011	-0.011*	-0.017*
	(0.024)	(0.043)	(0.006)	(0.009)	(0.006)	(0.010)
$\Delta IP * Black$	0.017	-0.087	0.036***	0.040*	0.023**	0.011
	(0.032)	(0.074)	(0.011)	(0.023)	(0.011)	(0.025)
$\Delta IP * Hispanic$	-0.011	-0.064	0.033**	0.058**	0.016	0.034*
	(0.060)	(0.095)	(0.016)	(0.023)	(0.011)	(0.020)
Cross-group ΔIP		-0.041		0.004		0.006
		(0.037)		(0.008)		(0.009)
Cross $\Delta IP * Black$		0.130		-0.005		0.020
		(0.085)		(0.027)		(0.028)
Cross $\Delta IP * Hispanic$		0.070		-0.059***		-0.037**
		(0.084)		(0.019)		(0.017)
T-stat Black overall	–2.23	–1.14	3.83	3.04	0.91	1.15
T-stat Hispanic overall	–1.88	–2.23	2.90	0.91	0.42	–1.15
T-stat white overall		–3.95		2.59		–1.82
T-stat Black-white diff'l		1.09		2.53		2.09
T-stat Hispanic-white diff'l		0.15		–0.08		–0.29
Observations	26,772	26,712	30,105	30,045	30,159	30,099
R-squared	0.316	0.317	0.716	0.718	0.734	0.734

Standard errors in parentheses clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Notes: Columns 1, 3, and 5, replicate the IV results from Table 3. Columns 2, 4, and 6 additionally control for cross-group import exposure (instrumented with the cross-group instruments and interactions with race/ethnicity). Black and Hispanic observations use the white ΔIP while white observations use the population-weighted average of Black and Hispanic ΔIP as cross-group exposure.

Table A.7: Robustness: Impacts of Import Exposure on Employment

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
Panel A:	Δ log Manufacturing Employment per Population					
Group-specific ΔIP	-0.093***	-0.077***	-0.092***		-0.107***	-0.073***
	(0.024)	(0.029)	(0.024)		(0.028)	(0.028)
$\Delta IP * Black$	0.017	0.035	0.010	-0.075	0.084**	0.011
	(0.032)	(0.045)	(0.028)	(0.053)	(0.043)	(0.043)
$\Delta IP * Hispanic$	-0.011	-0.046	-0.037	0.030	0.043	0.021
	(0.060)	(0.058)	(0.060)	(0.064)	(0.060)	(0.068)
CZ-level ΔIP (ADH)	-0.085***	-0.076***	-0.085***		-0.075***	-0.133***
	(0.021)	(0.027)	(0.020)		(0.017)	(0.049)
$\Delta IP * Black$	0.027	0.064	0.020	-0.015	0.053**	0.122
	(0.040)	(0.054)	(0.036)	(0.049)	(0.026)	(0.079)
$\Delta IP * Hispanic$	0.002	0.006	-0.004	0.016	-0.002	0.042
	(0.033)	(0.037)	(0.034)	(0.037)	(0.028)	(0.058)
Observations	26,772	2,043	26,056	26,772	26,772	26,772
Panel B:	Δ log Non-Manufacturing Employment per Population					
Group-specific ΔIP	0.015***	0.011*	0.017***		0.012*	0.018**
	(0.006)	(0.007)	(0.006)		(0.007)	(0.007)
$\Delta IP * Black$	0.036***	0.035**	0.028***	0.070**	0.034**	0.026**
	(0.011)	(0.015)	(0.010)	(0.028)	(0.017)	(0.013)
$\Delta IP * Hispanic$	0.033**	0.045***	0.022*	0.059*	-0.021**	0.072***
	(0.016)	(0.016)	(0.012)	(0.032)	(0.010)	(0.014)
CZ-level ΔIP (ADH)	0.005	0.000	0.006		0.003	0.026**
	(0.004)	(0.005)	(0.004)		(0.004)	(0.012)
$\Delta IP * Black$	0.038***	0.027**	0.034***	0.035**	0.018*	0.028
	(0.011)	(0.012)	(0.011)	(0.014)	(0.010)	(0.024)
$\Delta IP * Hispanic$	-0.021**	-0.025**	-0.008	-0.016	-0.020***	0.006
	(0.010)	(0.011)	(0.009)	(0.015)	(0.006)	(0.031)
Observations	30,105	2,166	29,030	30,105	30,105	30,105
Panel C:	Δ log Overall Employment per Population					
Group-specific ΔIP	-0.011*	-0.012*	-0.009*		-0.008	-0.022***
	(0.006)	(0.007)	(0.005)		(0.007)	(0.008)
$\Delta IP * Black$	0.023**	0.026*	0.015	0.019	0.036**	0.016
	(0.011)	(0.014)	(0.010)	(0.018)	(0.015)	(0.014)
$\Delta IP * Hispanic$	0.016	0.025**	0.004	0.034	0.007	0.049***
	(0.011)	(0.012)	(0.007)	(0.021)	(0.009)	(0.009)
CZ-level ΔIP (ADH)	-0.010**	-0.012*	-0.009*		-0.008*	-0.030**
	(0.005)	(0.007)	(0.005)		(0.004)	(0.014)
$\Delta IP * Black$	0.030***	0.025**	0.026***	0.017*	0.018**	0.030
	(0.010)	(0.012)	(0.008)	(0.010)	(0.008)	(0.024)
$\Delta IP * Hispanic$	-0.010	-0.011	-0.006	0.001	-0.012**	0.027
	(0.007)	(0.008)	(0.006)	(0.010)	(0.005)	(0.018)
Observations	30,159	2,166	29,070	30,159	30,159	30,159
Original Controls	X	X	X			X
2012 only		X				
Race or Ethnicity Gaps			X			
CZ Fixed Effects				X		
Group-Specific Controls					X	
NTR IV						X

Standard errors in parentheses clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Notes: See Table 3. All results are based on the IV specifications. Column 2 restricts the sample to an unweighted average across 2011-13, most analogous to earlier ADH work. Column 3 controls for race or ethnicity gaps in log employment in 1980, 1990, and 2000, all interacted with race or ethnicity. Column 4 includes CZ fixed effects. Column 5 uses race-or-ethnicity-specific measures for controls wherever possible, also interacted with race or ethnicity. Column 6 instruments for ΔIP with the NTR gap applied to race-or-ethnicity-specific or CZ-wide employment shares, as indicated.

Table A.8: Robustness: Impacts of Import Exposure on Wages

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV
			Δ log Hourly Wage			
Group-specific ΔIP	-0.009	-0.010	-0.008		0.006	-0.033***
	(0.007)	(0.009)	(0.006)		(0.008)	(0.012)
$\Delta IP * Black$	0.011	0.017	0.009	0.012	0.013	0.018
	(0.008)	(0.014)	(0.008)	(0.015)	(0.011)	(0.016)
$\Delta IP * Hispanic$	0.034***	0.055***	0.033***	0.004	0.011	0.061***
	(0.009)	(0.012)	(0.010)	(0.022)	(0.013)	(0.013)
CZ-level ΔIP (ADH)	-0.006	-0.007	-0.005		0.003	-0.049**
	(0.007)	(0.010)	(0.007)		(0.005)	(0.021)
$\Delta IP * Black$	0.019**	0.034**	0.018**	0.009	0.013	0.026
	(0.009)	(0.014)	(0.008)	(0.011)	(0.008)	(0.025)
$\Delta IP * Hispanic$	0.014**	0.024**	0.015**	0.016	-0.004	0.068***
	(0.007)	(0.010)	(0.007)	(0.012)	(0.005)	(0.020)
Observations	30,221	2,166	29,120	30,221	30,221	30,221
Original Controls	X	X	X			X
2012 only		X				
Race or Ethnicity Gaps			X			
CZ Fixed Effects				X		
Group-Specific Controls					X	
NTR IV						X

Standard errors in parentheses clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Notes: See Table 3 and appendix table tab:robustness.

Table A.9: BHJ Standard Error Correction

	(1) IV	(2) IV	(3) IV
Panel A:	Δ log Mfg Emp per Pop		
CZ-wide ΔIP (ADH)	-0.085***	-0.056***	-0.056***
	(0.021)	(0.018)	(0.021)
$\Delta IP * Black$	0.027	0.011	0.012
	(0.040)	(0.039)	(0.026)
$\Delta IP * Hispanic$	0.002	0.006	0.006
	(0.033)	(0.033)	(0.044)
Observations	26,772	26,772	16,464
Panel B:	Δ log Non-Mfg Emp per Pop		
CZ-wide ΔIP (ADH)	0.005	0.005	0.004
	(0.004)	(0.004)	(0.005)
$\Delta IP * Black$	0.038***	0.032***	0.032**
	(0.011)	(0.011)	(0.014)
$\Delta IP * Hispanic$	-0.021**	-0.026***	-0.026*
	(0.010)	(0.010)	(0.015)
Observations	30,105	30,105	16,464
Panel C:	Δ log Overall Emp per Pop		
CZ-wide ΔIP (ADH)	-0.010**	-0.005	-0.005
	(0.005)	(0.004)	(0.004)
$\Delta IP * Black$	0.030***	0.028***	0.027**
	(0.010)	(0.010)	(0.013)
$\Delta IP * Hispanic$	-0.010	-0.016***	-0.015**
	(0.007)	(0.006)	(0.006)
Observations	30,159	30,159	16,464
Original Controls	X	X	X
BHJ Control		X	X
Industry-by-Group Approach			X

*** p<0.01, ** p<0.05, * p<0.1

Notes: See Table 3. All results are based on the IV specifications. Column 2 includes baseline manufacturing employment shares interacted with race/ethnicity. Column 3 applies the SSIV approach of Borusyak et al. (2022) to obtain robust standard errors.

Table A.10: Summary of Rotemberg Weights (GSS), by Group

White Population				
Industry Name	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	Ind Share (%)
Furniture and Fixtures, NEC	0.21	11	-0.02	0.42
Radio and Television Broadcasting and Communications Equipment	0.18	95	-0.11	0.14
Electronic Computers	0.1	37	-0.13	0.14
Semiconductors and Related Devices	0.08	20	-0.21	0.2
Computer Peripheral Equipment, NEC	0.07	21	-0.06	0.11
Black Population				
Industry Name	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	Ind Share (%)
Furniture and Fixtures, NEC	0.26	11	-0.04	0.38
Radio and Television Broadcasting and Communications Equipment	0.15	96	-0.14	0.13
Computer Peripheral Equipment, NEC	0.11	20	-0.04	0.08
Telephone and Telegraph Apparatus	0.1	25	-0.13	0.12
Electronic Computers	0.07	38	-0.2	0.09
Hispanic Population				
Industry Name	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$	Ind Share (%)
Electronic Computers	0.19	39	-0.06	0.21
Radio and Television Broadcasting and Communications Equipment	0.18	103	-0.02	0.18
Semiconductors and Related Devices	0.18	20	-0.15	0.32
Electronic Components, NEC	0.07	15	-0.36	0.23
Computer Peripheral Equipment, NEC	0.06	21	-0.12	0.1

Notes: This table reports statistics about the Rotemberg weights (see Goldsmith-Pinkham et al. (2020)) for each population subgroup and for the industries with contributing the top 5 weights. In all cases, we report statistics about the aggregated weights, where we aggregate a given industry across years. $\hat{\alpha}_k$ is the estimated Rotemberg weight, g_k is the national change in import exposure for each industry, $\hat{\beta}_k$ is the coefficient from the just-identified second-stage regression where the outcome is the change in log manufacturing employment per population, and Ind Share is the percent of employment in the industry.

Table A.11: Relationship between Industry Shares and Characteristics (GSS)

	(1) Furniture and Fixtures	(2) Semiconductors and Related	(3) Radio and Television	(4) Computer Peripheral	(5) Electronic Computers
Panel A: Gaps in Levels, 2000					
Black-white Emp Gap, 2000	-0.184	0.023	0.384	0.666	-0.624
	(0.235)	(0.113)	(0.278)	(0.469)	(0.552)
Hispanic-white Emp Gap, 2000	0.583	-0.169	0.171	0.563	-0.080
	(0.476)	(0.161)	(0.328)	(0.587)	(0.140)
Full Controls	X	X	X	X	X
Observations	722	722	722	722	722
R-squared	0.233	0.172	0.271	0.290	0.123
Panel B: Trends in Gaps 1990-2000					
Trend Black-white Emp Gap, 1990-2000	-0.010	0.007	0.154	0.060	-0.494
	(0.150)	(0.071)	(0.102)	(0.184)	(0.359)
Trend Hispanic-white Emp Gap, 1990-2000	-0.378	0.028	0.100	0.085	0.066
	(0.286)	(0.073)	(0.125)	(0.179)	(0.219)
Full Controls	X	X	X	X	X
Observations	709	709	709	709	709
R-squared	0.233	0.172	0.269	0.282	0.128

Standard errors in parentheses clustered by state
*** p<0.01, ** p<0.05, * p<0.1

Notes: We estimate CZ-level regressions with full controls from ADH, weight by CZ-wide population in 2000, and cluster standard errors by state. Dependent variables are CZ-level employment shares in the indicated industry in 1990. Industries are selected if they get among the highest group-specific Rotemberg weight contributing to at least 50% of the overall variation.