NBER WORKING PAPER SERIES

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Working Paper 30646
http://www.nber.org/papers/w30646

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2022

We disclose no additional funding sources. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 30646
November 2022
JEL No. F16,J15

ABSTRACT

We examine how the labor market effects of import competition vary across Black, Hispanic, and white populations. For a given level of exposure to imports from China, we find no evidence that minority workers are relatively more harmed than white workers in terms of their manufacturing employment. However, Hispanic workers are overrepresented in exposed industries and therefore face greater manufacturing employment losses relative to whites on net. In addition, they experienced relative losses in non-manufacturing employment, largely due to their lower educational attainment and baseline industry mix. Overall, the China shock increased the Hispanic-white employment gap by about 5%, though these effects were short lived. In contrast, Black workers are less likely to live in areas or work in industries facing import competition, resulting in less negative effects on manufacturing employment relative to whites. In addition, exposed Black workers experienced gains in non-manufacturing and overall employment with no measurable wage consequences, while white workers saw depressed employment rates due to the China shock. The lasting effects of import competition in exposed areas were driven by white workers, while the experience of Black workers suggests that movement into non-manufacturing jobs was possible. White workers did not take advantage of these opportunities, perhaps due to better safety nets or perceptions that the available jobs were poor substitutes for those lost in manufacturing. The China shock narrowed the Black-white employment gap by about 15%. While many recent labor market trends have exacerbated Black-white gaps, import competition is a modest offsetting force.

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1 Introduction

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. At the same time, racial and ethnic inequality have risen to the forefront of public discourse in the US. Yet little attention has been paid to how import competition affects workers of different races and ethnicities. 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.[1]

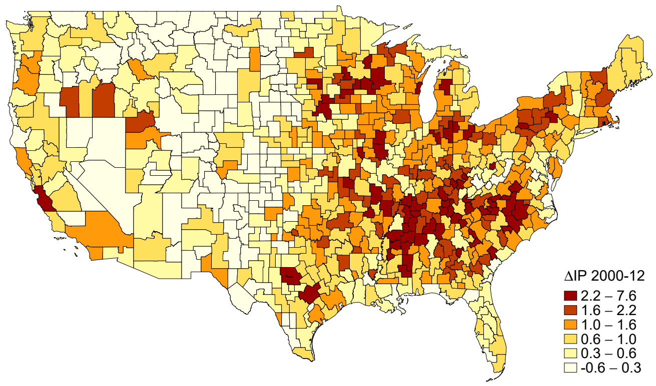
In their seminal work, Autor et al. (2013) show that US commuting zones (CZs) that were more exposed to the China Shock in the early 2000s experienced persistent relative employment declines. They define exposure based on the initial share of employment in the CZ producing a similar mix of products to those that would increasingly be imported from China, largely in manufacturing. However, manufacturing employment is concentrated in predominantly white CZs. Figure 1 maps import exposure and Black and Hispanic population shares at the CZ level 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. We find that the Black population is 15% *less* exposed to import competition from China, compared to the white population, due to baseline differences in where they work, and, especially, where they live. This gap amounts to roughly one-quarter of the inter-quartile range of white import exposure. In contrast, the Hispanic population is 21% *more* exposed than the white population due to differences in where they work. Despite the fact that Hispanic workers live in CZs that are slightly less exposed, on average, they were much more likely to be working in the subsectors of manufacturing that would face the greatest pressures from production in China.

These differences in import exposure alone are but one input into the overall effect of import competition on employment rates by race and ethnicity. It could be the case that minorities are more likely than their white coworkers to lose jobs when a negative shock hits. Or, spillover effects

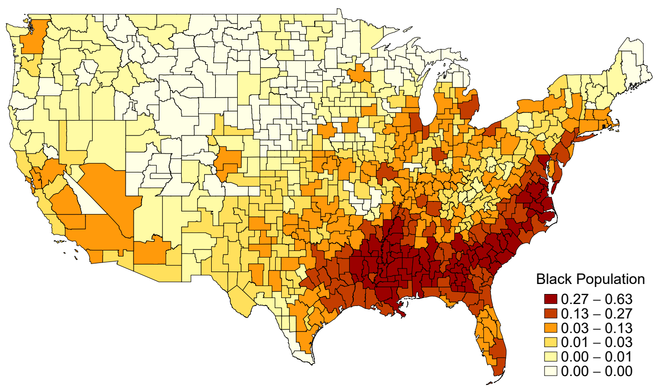
[1] In this paper, we use the terms Black and white to refer to non-Hispanic Black and non-Hispanic white individuals.

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

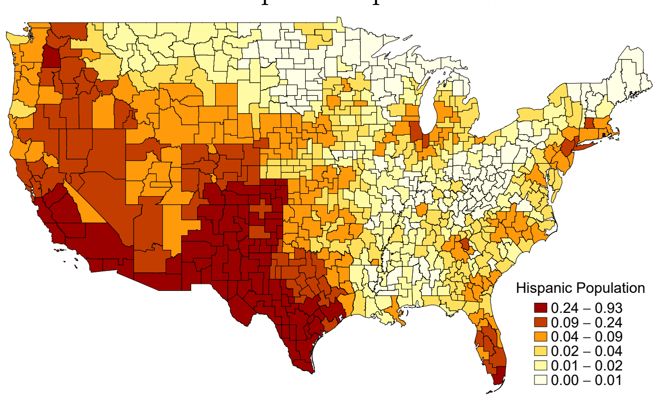
Panel A: Change in Import Exposure from China 2000-2012



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 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 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. Since 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. This overall differential is not statistically significant, however the portion due to where individuals live and work is significant and accounts for a 1 percentage point smaller decline for Black workers. Because the Hispanic population is more exposed 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. Again, this overall differential is not statistically significant, but the portion due to where individuals work is very large and significant, making up almost all of the Hispanic-white differential.

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. 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 and in public sector employment. 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.

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 in the later years.[2]

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).[3] However, other outcomes 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. However, to our knowledge ours is the first paper to look at the effects of the China shock across race and ethnic groups.[4]

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. At the end of our sample period in 2018, the employment-to-population ratio of Black workers was 10 points below that of whites, and their wage gap persisted at roughly 30 log points. Hispanic workers saw a smaller 5 point employment gap with whites but a similarly sized wage gap. Minority populations tend to be more vulnerable to recessionary shocks (Hoynes et al., 2012), which raises the concern that they will suffer disproportionately from other types of labor market shocks as well. For the

[2]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.

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

[4]Previous work has explored other types of heterogeneity: Autor et al. (2014) show that low-wage workers bore greater incidence of the China shock, thereby widening economic inequality; 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.

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.[5] Construction was especially hard hit during the Great Recession, impacting a potential non-manufacturing employment option at a time when manufacturing was negatively impacted by the China shock. However, the longstanding Hispanic-white wage and employment gaps have converged substantially in recent decades, largely due to convergence in 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 has largely recovered their relative employment losses from import competition.

Black workers, in contrast, have experienced stagnating wage gaps with whites in recent decades.[6] Researchers have pointed out that changes in the earnings structure, and in particular widening income inequality, exacerbate 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. Overall, we find the Black-white employment-to-population gap narrowed by 3 percentage points (roughly 15%) due to the China shock.

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

[5] 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.

[6] 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.

that it was possible to adjust along the job mobility side. Black workers were overrepresented in service industries at baseline and were perhaps more agile in light of their typical lower employer attachment. However, they were also able to make these adjustments with no measurable wage consequences. Our results by education and occupational categories suggest that the greater adjustment was not simply because Black workers were in lower-skilled jobs to begin with. So we would expect that white workers should have also been able to take similar advantage of this shift outward in labor demand in services accompanying the China shock. Instead, their employment rates 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 better safety net could play a role. It is also possible that 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. Section 4 sums up the total effects of differential exposure with a formal decomposition. Section 5 explores mechanisms and section 6 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 import exposure and experience different outcomes. For data sources, we follow the previous literature wherever possible. However, disaggregating CZ-level analyses by race and ethnicity presents some challenges since we must at times rely on smaller sample sizes. We discuss a range of approaches intended to limit any noise generated from these smaller samples.

ADH measure the change in import competition for a CZ, c, in time period t, relative to the baseline time period, 2000. 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.[7] We focus on three mutually exclusive

[7]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.

(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.

Appendix table A.1 provides summary statistics of our key variables by race and ethnicity.

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.[8]

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.

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.

[8]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.

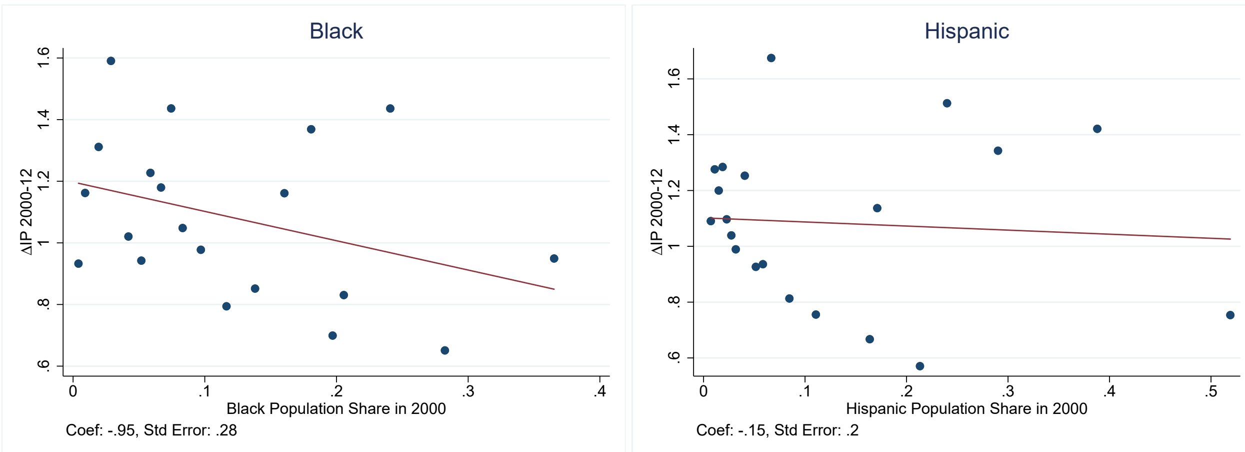
Table 1: Import Exposure and Minority Population Shares from the 50 Most Populous CZs

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.

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 exposure.

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

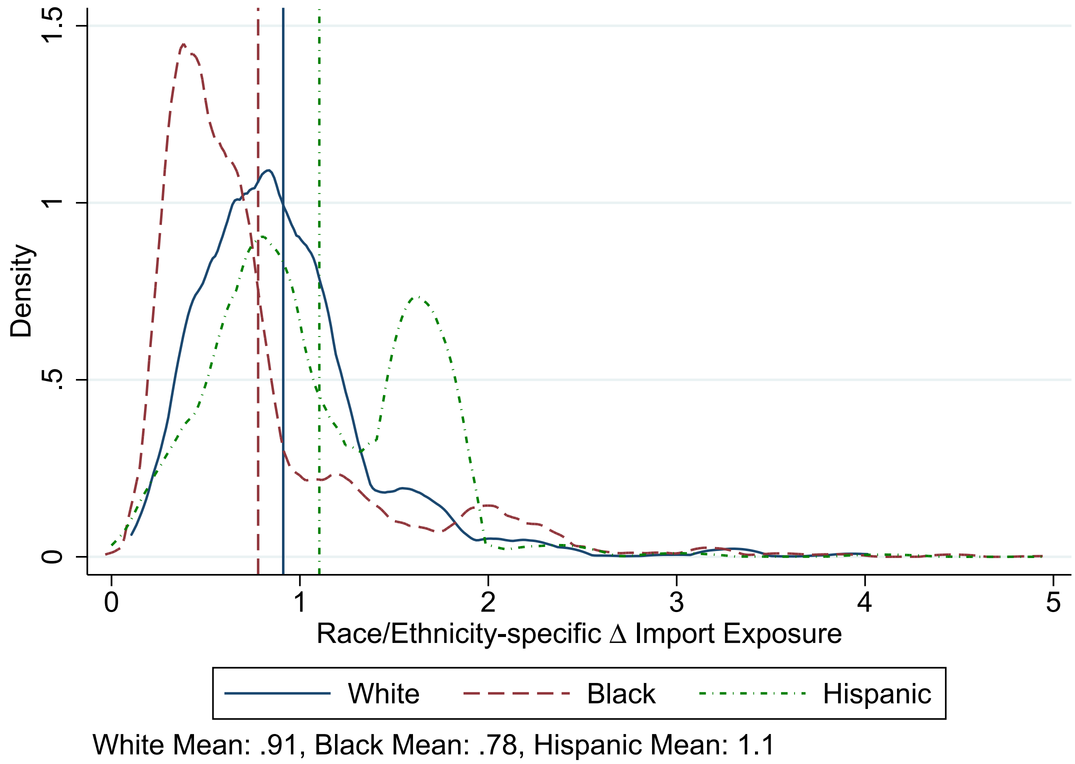


Notes: Binned scatters of Commuting Zone (CZ) level characteristics. X-axis plots the CZ-level fraction of population that was Black (left) or Hispanic (right) in the 2000 Census. Y-axis plots the CZ-level change in import exposure from China from 2000-12 defined in equation 1 and in Autor et al. (2021). 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.

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 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 quite a bit 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. We conduct parallel analyses to understand the Black-white and Hispanic-white gaps in import exposure. First, panel A summarizes these differentials by regressing the change in group-specific import exposure on a Black or Hispanic indicator in a stacked sample of 722 mainland Commuting Zones. 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

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.

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 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 compared 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. 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

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.

share of layoffs or a more difficult transition to other sectors. We explore these dynamics next.

3 Import Exposure and Labor Market Outcomes, by Race

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:

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

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 well as wages. We regress the change in these outcomes relative to 2000 on the time-varying group-specific import penetration measure (ΔIP) defined in equation 2. 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 race and ethnicity indicators (the vector $\mathbf{Group}_r$). Finally, I^t are year fixed effects, which are also interacted with race and ethnicity indicators.

We measure outcomes by race or ethnic group, CZ, and year using American Community Survey data. We stack annual observations for white, Black and Hispanic populations from 2005-2018.[9] 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 race or ethnicity-specific population in the baseline year (2000) and standard errors are clustered by state.[10]

We first 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.[11] 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 address simultaneity concerns.[12]

Note 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

[9] 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.

[10] There are many choices involved in this specification and we show below that results are robust to alternatives. When ADH use ACS data to measure outcomes, they tend to focus on one or two focal time windows, pooling across a small number of ACS years. To increase precision, we stack all years of available data, rather then first combining and then focusing on subsets of years. 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.

[11] 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.

[12] Specifically, we instrument for ΔIP and its interactions with $Black_r$ and $Hispanic_r$ using $\Delta IP_{orct} = \sum_i \frac{Emp^{1990}_{irc}}{Emp^{1990}_{rc}} \frac{\Delta M_{oit}}{Norm_i}$, 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).

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.[13] This concern is especially pronounced for the manufacturing employment outcome since it reflects the fewest observations.

In alternative specifications, we use the CZ-level import penetration measure (equation 1) as the key explanatory variable. 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 ACS. 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. Finally the CZ-wide measure could pick up spillover effects from shocks to different subpopulations. Shocks to manufacturing employment for one race or ethnic group may impact employment for another group through spillover effects. For example, the closing of a predominantly white manufacturing plant 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.

As in the previous literature, the identifying assumption is that CZs predicted to have large increases in import penetration would have been on a similar trend in employment and wage outcomes to CZs predicted to have low import penetration, 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.[14]

[13] 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.

[14] 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.

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-race and ethnicity 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.

In addition, we explore a range of controls to help support the identifying assumption. We control for race and ethnicity-specific versions of the CZ-level controls listed above, Black-white and Hispanic-white gaps in employment in the CZ for 1980, 1990, and 2000, all interacted with race/ethnicity indicators. Finally, in one specification, we include CZ fixed effects, which absorb the main effect of ΔIP but still allow us to identify the differential impacts.[15]

3.2 Main Results

Table 3 summarizes the main regression results, estimating equation 3 for three different outcomes: the changes in log manufacturing, log non-manufacturing, and log overall employment per adult population. All specifications include full controls from Autor et al. (2021), interacted with race and ethnicity. We provide both OLS (column 1) and IV (column 2) estimates. First stage regressions can be found in appendix table A.4. 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 results in the first two columns, 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

[15]Though ΔIP is in principle time-varying within a CZ, we do not use this variation to identify the main effect β_1 when including CZ fixed effects since, as noted above, import penetration is largely stable over this time period.

Table 3: Impacts of Import Exposure on Employment

Dependent variable: Δ log employment in the sector per working age population						
Sector:	Manufacturing		Non-Manufacturing		Overall	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Panel A: Group-Specific Import Exposure						
Group-specific ΔIP	-0.060***	-0.093***	0.014***	0.015***	-0.006	-0.011*
	(0.013)	(0.024)	(0.003)	(0.006)	(0.004)	(0.006)
$\Delta IP * Black$	-0.017	0.017	0.022***	0.036***	0.008	0.023**
	(0.018)	(0.032)	(0.008)	(0.011)	(0.007)	(0.011)
$\Delta IP * Hispanic$	-0.032	-0.011	0.029***	0.033**	0.009	0.016
	(0.034)	(0.060)	(0.009)	(0.016)	(0.007)	(0.011)
T-stat Black overall	–4.08	–2.23	4.61	3.83	0.26	0.91
T-stat Hispanic overall	–2.62	–1.88	4.94	2.90	0.45	0.42
Panel B: CZ-Wide Import Exposure (ADH)						
CZ-level ΔIP (ADH)	-0.024***	-0.085***	0.006***	0.005	0.000	-0.010**
	(0.008)	(0.021)	(0.002)	(0.004)	(0.002)	(0.005)
$\Delta IP * Black$	0.011	0.027	0.010*	0.038***	0.008**	0.030***
	(0.013)	(0.040)	(0.006)	(0.011)	(0.003)	(0.010)
$\Delta IP * Hispanic$	-0.031**	0.002	-0.003	-0.021**	-0.008*	-0.010
	(0.015)	(0.033)	(0.010)	(0.010)	(0.005)	(0.007)
T-stat Black overall	–1.11	–1.42	2.61	3.71	1.90	1.58
T-stat Hispanic overall	–3.66	–2.82	0.38	–1.28	–1.54	–2.50
Observations	26,772	26,772	30,105	30,105	30,159	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. Column 1 uses OLS while column 2 instruments for import exposure and its race and ethnicity interactions using changes in imports from China for other developed countries applied to lagged employment shares and race interactions. All specifications 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.

commensurate with those found by other researchers when examining the population as a whole.[16]

[16]Our IV estimate of roughly -0.09 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. (The inter-quartile range of exposure for the white population is roughly 0.5.) While not directly comparable to that of ADH given the functional

For the $\Delta IP_{rct} * Black_r$ and $\Delta IP_{rct} * Hispanic_r$ interaction terms, coefficients using the IV specification are small and insignificant. We find a point estimate of 0.017 (standard error of 0.032) for the Black interaction with group-specific exposure and a point estimate of -0.011 (0.06) for the Hispanic interaction. Each of these are only one-ninth the magnitude of the baseline effect for whites. Panel B shows very similar effects when using CZ-wide import exposure, consistent with the discussion above that we would expect manufacturing employment losses to be driven by direct shocks with little scope for spillovers from other group shocks. The coefficients on the interaction terms are not very precisely estimated and some 95% confidence intervals include relatively large negative values. In fact the OLS specification for the Hispanic interaction shows a 3 percentage point larger drop in manufacturing employment and is significant at the 5% level when using CZ-wide imports. However, as we show next, these potential negative effects are short lived.

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 coefficients on the CZ-wide $\Delta IP * Black_r$ and $\Delta IP * Hispanic_r$ interactions using the IV specification. See appendix figure A.1 for plots of the group-specific ΔIP interaction terms, which show very similar results for manufacturing employment.

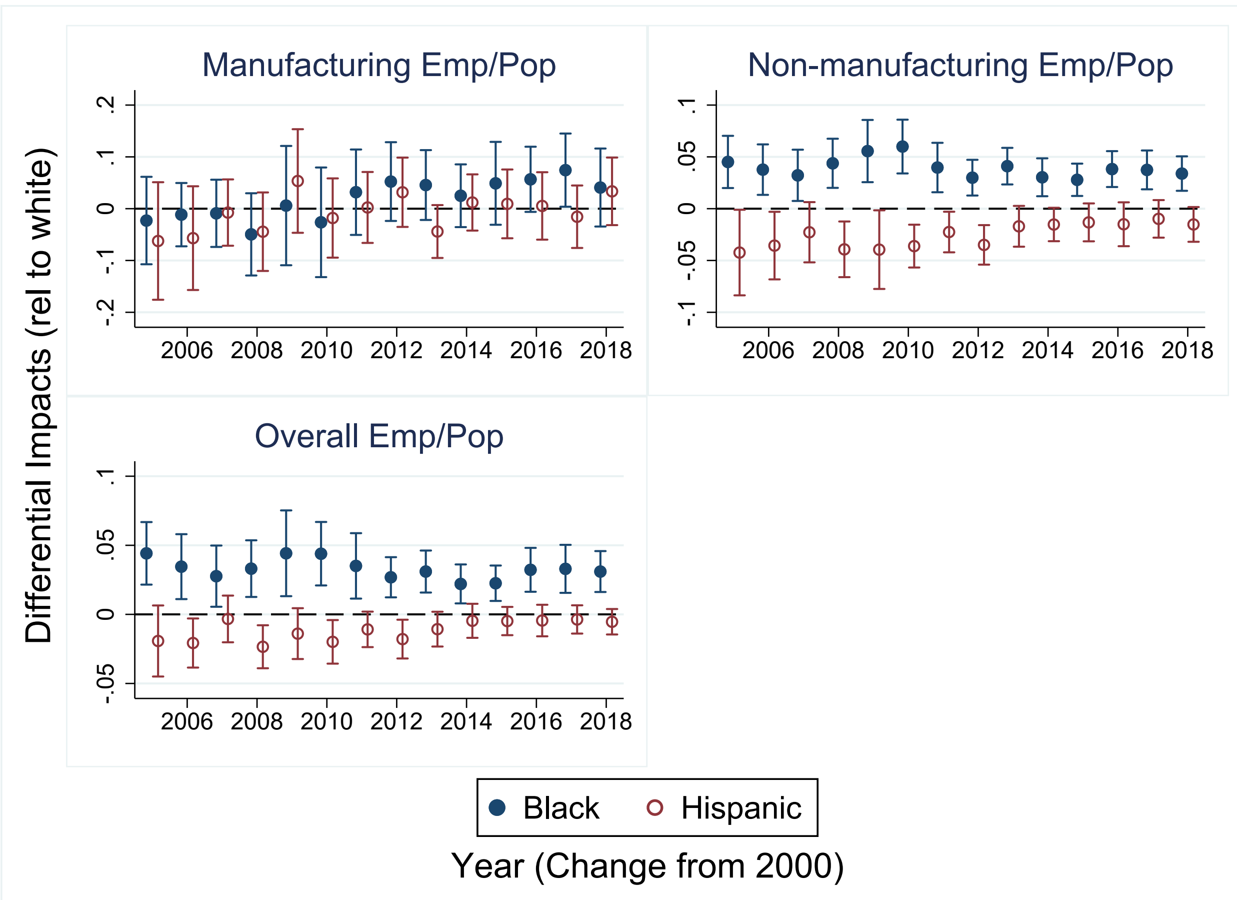
Both the Black-white and Hispanic-white differentials are negative, though insignificant, in the early time period, and especially large in magnitude for Hispanic workers. From around 2009, there is convergence, with more precisely estimated zeros on the Hispanic-white differential, and positive point 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 impacts on minority groups are offset in the later time periods as the time difference for both manufacturing employment and trade exposure lengthens.

Taking these results so far 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 the middle columns, we see generally positive impacts for white workers, especially when using the group-specific shock. This improvement is

form difference explained in section 3.1, we can multiply by the manufacturing employment rate of change at the 25th percentile (-0.2) to obtain a rough estimate. 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).

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.

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 in the IV specification, which is consistent with ADH. As discussed above, the difference in results across panels A and B is likely driven by a few factors: First, 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. Second, the group-specific shock may be a more precise estimate of the shock experienced by the white population, and therefore suffer less from attenuation bias. However, third, CZ-level import exposure is generally measured more precisely than group-specific import exposure because baseline employment shares are based on a census rather than a survey. So the results differ across panels due both to the inclusion of spillover effects in Panel B and to differences in how precisely the shock is measured, though it's not clear which measure should be more precise.

The Black interaction terms indicate that Black workers experience strong positive effects on non-manufacturing employment relative to white workers. Effects are similar using CZ-wide shocks for the IV specification (though somewhat attenuated in the OLS), which 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. Given a 0.5 interquartile range in exposure for the white population, our estimate implies that the Black-white non-manufacturing employment gap would narrow by 1.5 percentage points more in a 75th percentile CZ, compared to a 25th percentile CZ, due to the China shock.

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. The IV specification shows that 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.[17]

The right panel 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 in the IV specification, 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 IV point estimate is slightly larger for the CZ-level shock. In a 75th percentile exposed CZ, we find that 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 the negative effect for white workers and the positive for Black workers) is positive but insignificant. So we do not see robust evidence of level improvements in employment for the Black population living in more exposed, relative to less exposed, CZs. However, exposure to import competition causes a significant reduction in the Black-white employment gap. 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. These estimates are again noisy: for instance in the IV specification using the CZ-level shock, we could not rule out that the Hispanic population experiences an overall employment loss that is two-to-three times the size of the effect for whites.

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.

[17]Indeed, to better parse out these stories, we estimate an alternative specification 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.5, 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.

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.6 and describe them below.

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 ACS years to increase precision. 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. 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. In practice, our approach helps a bit with precision as effects are quite stable over the time period. In Column (2) of Table A.6, 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 differentials in employment outcomes would have been on a similar trend in CZs with both high and low import exposure, 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) of Table A.6. 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 differential impacts, though they essentially absorb the main effect of ΔIP (i.e. the effect on white workers). 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. 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 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.

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. Based on these differential exposures, we expect that the Black population as a whole will be less harmed by the negative impacts of the China shock on manufacturing employment, but also less helped by the positive spillovers to non-manufacturing employment than if they were as exposed as white workers. The Hispanic population story is different: they will be more harmed by the negative effects of their own-group shock on manufacturing employment due to their baseline industry mix, and therefore more helped in non-manufacturing employment. Also, to the extent that they experience negative coefficient effects on non-manufacturing and overall employment in response to CZ-level shocks, their geographic locations (which are, on average, slightly less exposed), will help offset these effects. 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 4. We use coefficients from the IV specifications reported in Table 3. 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 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+0.0044 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 effect.

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

Table 4: 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 ($\sum_{c \in CZ} \frac{popW_c}{popW} \times \Delta IP_{Wct} \times \hat{\beta^s_W}$). 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.

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%) 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.

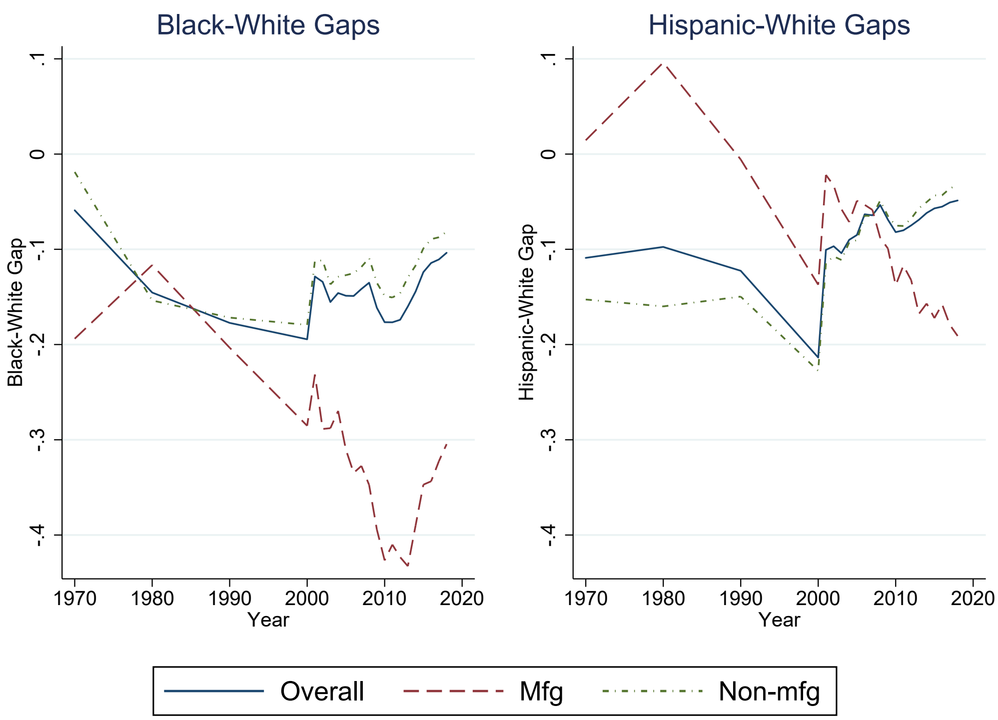
The same dynamic is present for overall employment effects, though here the industrial composition effect washes out. The CZ-wide shock is arguably the best one to focus on because it incorporates both group-specific and spillover effects. There we find that the Hispanic population experiences an additional 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 5 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.[18]

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

Figure 5: 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 of ΔIP on Black relative to white workers that we find in the manufacturing sector. 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 4, 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 5. 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.

Why does the Black population appear better able to take advantage of the increase in non-manufacturing employment in exposed locations while the Hispanic population does not? We explore a variety of factors in the next section.

5 Explaining the differences in employment outcomes

The results presented above show that Black workers experience large positive non-manufacturing employment effects relative to white workers when impacted by an increase in import exposure from China, while Hispanic workers experience negative relative employment effects. In this section, we explore four possible explanations. First, because the results so far have focused on employment, it could be the case that there are important differences in wage outcomes across workers underlying the effects. For example, if Black workers experienced relative increases in non-manufacturing employment, but at lower wage rates, then our assessment of who was relatively better or worse off could be altered. Second, Black, Hispanic, and white workers tend to differ on observables, such as educational attainment, and hold different types of jobs. Perhaps the differential response to the trade shock can be accounted for by these observables. Third, it could be the case that Black workers are generally less attached to specific jobs or specific industries, making it more likely for them to switch from manufacturing to non-manufacturing employment when hit with an import shock. Fourth, the different population groups could have different geographic mobility levels, which would then impact the interpretation of our findings.

5.1 Wages

Table 5 shows the relationship between changes in import exposure and log weekly wages. We estimate equation 3 using the change in log weekly wages as the outcome variable.[19] The Black-white differential is positive in all specifications though generally not significant, with the exception of Column (4) which shows a positive and marginally significant differential effect for Black workers. The 95% confidence intervals are narrow enough to rule out relative wage losses beyond roughly 0.5 points. These results suggest that Black workers are not experiencing relative wage declines compared to white workers as a result of import exposure, and that the Back-white differential is, if anything, positive.

Similarly, we see no evidence that Hispanic-white wage gaps are negatively impacted by import exposure. In fact, in response to the group-specific shock, Hispanics see significant and sizeable relative increases in weekly wages. These wage benefits are not evident when considering CZ-wide import shocks, though there we see no evidence of negative impacts. Thus we find that in response to group-specific shocks, Hispanic workers experience both relative employment and relative wage increases, compared to white workers. However, when the CZ as a whole experiences a negative import shock, Hispanic workers see employment losses and basically no relative wage change. Here again, the IV specification allows us to rule out 0.5 point relative wage losses with 95% confidence.

[19] We calculate annual wage and salary income divided by annual weekly hours, adjust to 2012 dollars using the PCE price index, and exclude the military, the self-employed, and those with zero earnings. We topcode weekly wages so that income for full-year work does not exceed the survey topcode for wage and salary income and bottom code weekly wages to the first-percentile of non-zero values.

Table 5: Impacts of Import Exposure on Wages

Dep Var:	Δ log(Weekly Wages)			
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Race-specific ΔIP	-0.014**	-0.013		
	(0.007)	(0.009)		
$\Delta IP * Black$	0.003	0.016		
	(0.006)	(0.010)		
$\Delta IP * Hispanic$	0.015**	0.030***		
	(0.007)	(0.010)		
CZ-level ΔIP (ADH)			-0.001	-0.013
			(0.003)	(0.009)
$\Delta IP * Black$			0.002	0.024*
			(0.003)	(0.012)
$\Delta IP * Hispanic$			-0.002	0.013
			(0.004)	(0.009)
T-stat Black overall	–1.46	0.19	0.22	0.76
T-stat Hispanic overall	0.22	1.71	–0.75	–0.00
Observations	30,221	30,221	30,221	30,221
R-squared	0.708	0.708	0.707	0.704

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 weekly wages are defined as annual wage and salary income divided by annual weeks worked. We bottom code weekly wages to the first percentile, and topcode weekly wages so that they do not exceed topcoded income divided by 50.

5.2 Observables

While we lack the precision to estimate group-specific effects that are disaggregated by observable characteristics at the CZ level, we build some intuition with figure 6. The blue bars give the share of employment in each education level in 2000 by race or ethnicity (dark blue for Black workers, medium blue for Hispanic workers, and light blue for white workers). The blue bars sum to one within a race or ethnic group across education categories. We then estimate the impact of the China shock on manufacturing, non-manufacturing, and overall employment separately for each education group. The maroon bars report coefficients on the CZ-wide ΔIP using the IV specification with full controls from table 3.[20]

As is well known, race and ethnic groups differ substantially in terms of their educational attainment. 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 6 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.

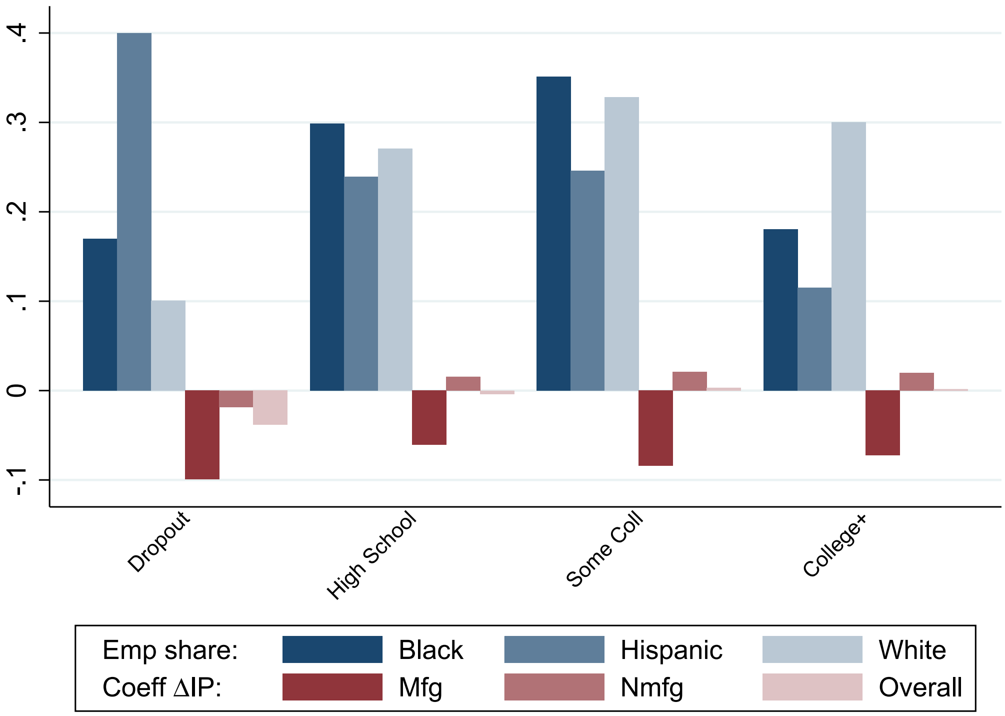
The dynamics in figure 6 can indeed account for much of the negative relative impact on the Hispanic population. Within a sector, we calculate a weighted average of coefficient effects for each subgroup, using their shares across education groups as weights and coefficients from figure 6. We find that 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.

This back-of-the-envelope estimates show that educational attainment can account for some of the differential impact we estimated above for Hispanic workers, compared to white workers. 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 6, Black workers have substantial representation among the middle education groups, which experience similar employment impacts

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

Figure 6: 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.

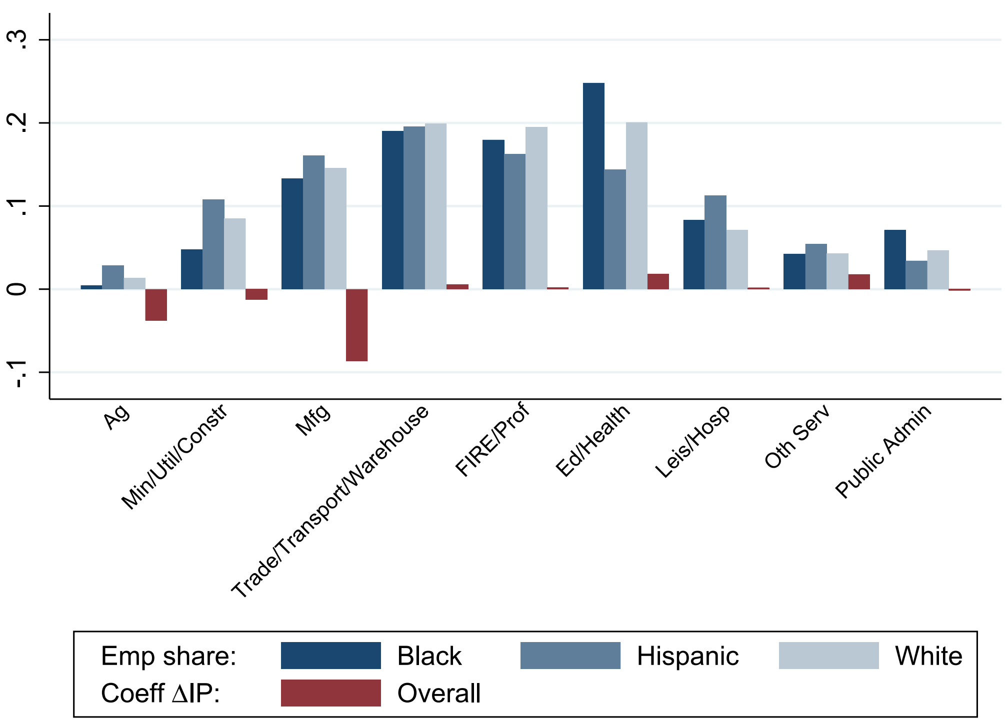
to those of college graduates. Since college graduates experience similar positive spillovers as well, any differences in outcomes due to educational attainment wash out. Based solely on the education distribution and education-level impacts of import exposure, we would find very similar effects across both Black and white workers.

Industrial composition is also an important driver of differential impacts. Figure 7 plots the employment distributions across major industry categories in 2000, by race or ethnicity (blue bars), as well as the overall impact of the China shock on industry employment per population (maroon bar).[21] The largest employment impacts are in manufacturing, but there are also negative impacts on agriculture and in mining, utilities, and construction industries. Hispanic workers are overrep-

[21]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. Explanatory variables are the CZ-wide ΔIP measure from t to 2000 and full controls.

resented in all three of these sectors. In contrast, education and health services experience among the largest positive relative impacts on employment and Black workers are overrepresented in these sectors. Using the impacts across industries, weighted by group-specific employment shares at baseline, 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 based solely on industrial competition are much smaller than the total effects estimated in section 3.

Figure 7: 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.

In appendix figure A.2, we conduct similar exercises across broad occupation groups. Here we find that the large differences across groups in their occupation distributions cannot account for differential impacts of import exposure. We also explore differences in the age distribution across groups (appendix figure A.3), since the Hispanic population is, on average, younger than the other groups, and younger workers tend to fare worse in response to economic shocks. However, when we use a weighted average of coefficient effects for each subgroup to capture the predicted effects by group based solely on their age distribution, we find that age differences cannot account for our results.

5.3 Job Transitions

Table 6 explores job transitions in 2000 using the Census database. Both Black and Hispanic workers make more transitions overall than white workers, a pattern that might make them more agile in response to shocks. 5.4% of white workers move jobs across adjacent quarters, compared to 8.1% of Black workers and 12.7% of Hispanic workers. Moreover, the middle panel shows that the vast majority of Black workers (75.9%) in manufacturing employment move to non-manufacturing when making a job-to-job transition, while Hispanic and white workers are less likely to transition to non-manufacturing when leaving manufacturing jobs (both at roughly 68%). Even before the China shock, Black workers in manufacturing were less likely to remain in manufacturing when making a job-to-job transition, and more likely to make a transition to non-manufacturing. Furthermore, while Black workers are bit more likely than white workers to transition to non-employment, Hispanic workers are substantially more likely. These patterns are true for overall employment as well as within manufacturing. These pre-existing patterns could help Black workers transition to new jobs when their factories close or when employment in non-manufacturing increases, potentially explaining the positive effects of import exposure on non-manufacturing employment for Black relative to white workers. Hispanic workers may have difficulty making similar transitions given their large propensity to exit employment and the fact that when making job-to-job transitions, they are no more likely to exit manufacturing than white workers, and, if they have been working outside of manufacturing, they are actually more likely to transition into manufacturing.

Table 6: Job Transitions

	All			Manufacturing			Non-Manufacturing		
	White	Black	Hispanic	White	Black	Hispanic	White	Black	Hispanic
Job-to-Job Flow Rate	5.38	8.13	12.68	2.98	4.01	8.20	5.79	8.73	13.56
Share of Flow Rate to Mfg.	8.42	7.04	11.56	32.03	24.13	31.88	6.35	5.89	9.16
Share of Flow Rate to Non-Mfg.	91.58	92.96	88.44	67.97	75.87	68.12	93.65	94.11	90.84
Flow Rate to Non-employment	4.79	6.86	12.34	2.72	3.87	9.29	5.15	7.29	12.93

Constructed using the Job-to-Job Flows database from Census Longitudinal Employer-Household Dynamics for 2000. The left panel, labeled "All", reports the percent of all employment in the indicated race or ethnicity 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 rate to non-employment reports the percent of employment that has no earnings in the subsequent quarter. The middle panel reports statistics restricting to the sample that workers in manufacturing in the starting quarter, regardless of where they move in the next quarter, and the right panel restricts to the sample that works in non-manufacturing in the starting quarter.

5.4 Geographic Mobility

Our results thus far pertain to employment rates per working age population in a CZ. 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 race or ethnic 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. Thus, we see no evidence of widening population effects. We lack the precision to be conclusive on this question, but we think appendix figure A.4 provides suggestive evidence that our results cannot be accounted for by changing geographic mobility across subgroups.

5.5 Discussion

The differential impact of import competition for Hispanic workers seems to be driven by their worse observables relative to both white and Black populations. The Hispanic population's educational attainment as well as their industrial composition make them more vulnerable to import competition shocks and less able to take advantage of employment shifts towards non-manufacturing. However, the negative relative impacts are concentrated around the Great Recession period when Hispanic workers suffered the dual impacts of import competition and the housing bubble burst. Indeed, previous research has found that the Great Recession afforded employers an opportunity to make productivity-enhancing improvements, such as reallocating production towards labor-replacing technologies (Hershbein and Kahn, 2018). It may also have impacted employer's adjustments in response to import competition, with Hispanic workers bearing the brunt. We find that the differential impacts on Hispanic workers around the time of the Great Recession are short-lived. In the next decade, we see no evidence of differential impacts, meaning Hispanic employment impacts caught up to white employment impacts. After the recessionary adjustment period, we see no evidence of widening Hispanic-white inequality due to the China shock.

In contrast, Black workers exhibit a greater ability to take advantage of the increased demand for non-manufacturing jobs. It could be the case that white workers are reluctant to shift into these positions. This relative movement of Black workers appears to be facilitated by both greater ex ante job mobility, the types of non-manufacturing jobs they tend to hold, and a larger exodus from manufacturing not correlated with the trade shock. One might expect Black workers to be more mobile because they perform low skilled jobs, and low skills may be more transferable across sectors, for example because they do not require specialized training. However, the results presented above suggest that ex-ante skill levels cannot explain the differential patterns across races. Another potential explanation is that because Black workers earn less overall, they are more willing to move into low-paying service positions. Our wage results suggest that Black workers do not experience wage cuts for moving into these positions. However, in 2000, manufacturing/non-manufacturing wage differentials were similar for white and Black workers. White workers earned about 5% more per week in manufacturing than in non-manufacturing, while Black workers earned about 4% more. The similarity in these gaps suggest that white workers would not have had appreciably farther to fall, were they to take non-manufacturing jobs after a manufacturing displacement. Instead, white workers may have been able to take advantage of a better social safety net or had other reasons for wanting to avoid service sector jobs that are on average lower paying (for all groups), while Black workers required the income.

6 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 overall 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. Even while the China shock widened income inequality in exposed locations (Autor et al., 2014), it did not result in widening Black-white employment and income gaps, which is surprising in light of past patterns in these gaps due to other factors (Bayer and Charles, 2018).

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. 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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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 a weekly wage calculation. Our definition follows Autor et al. (2013). 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. Weekly wages are top-coded adjusted annual income divided by the annual weeks worked measure. We bottom-code weekly wages to the first percentile in the national distribution and top code so that weekly wages times 50 do 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,[22] 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.[23]

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.[24] 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

[22] https://comtrade.un.org
[23] https://www.nber.org/research/data/nber-ces-manufacturing-industry-database
[24] 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.6. 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.6.

Differences in observables

We now detail how we create figures 6 and 7 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 6, we derive race and ethnicity-specific quarterly job-to-job flows in year 2000 from the Job-to-Job Flows (J2J) Explorer[25], 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

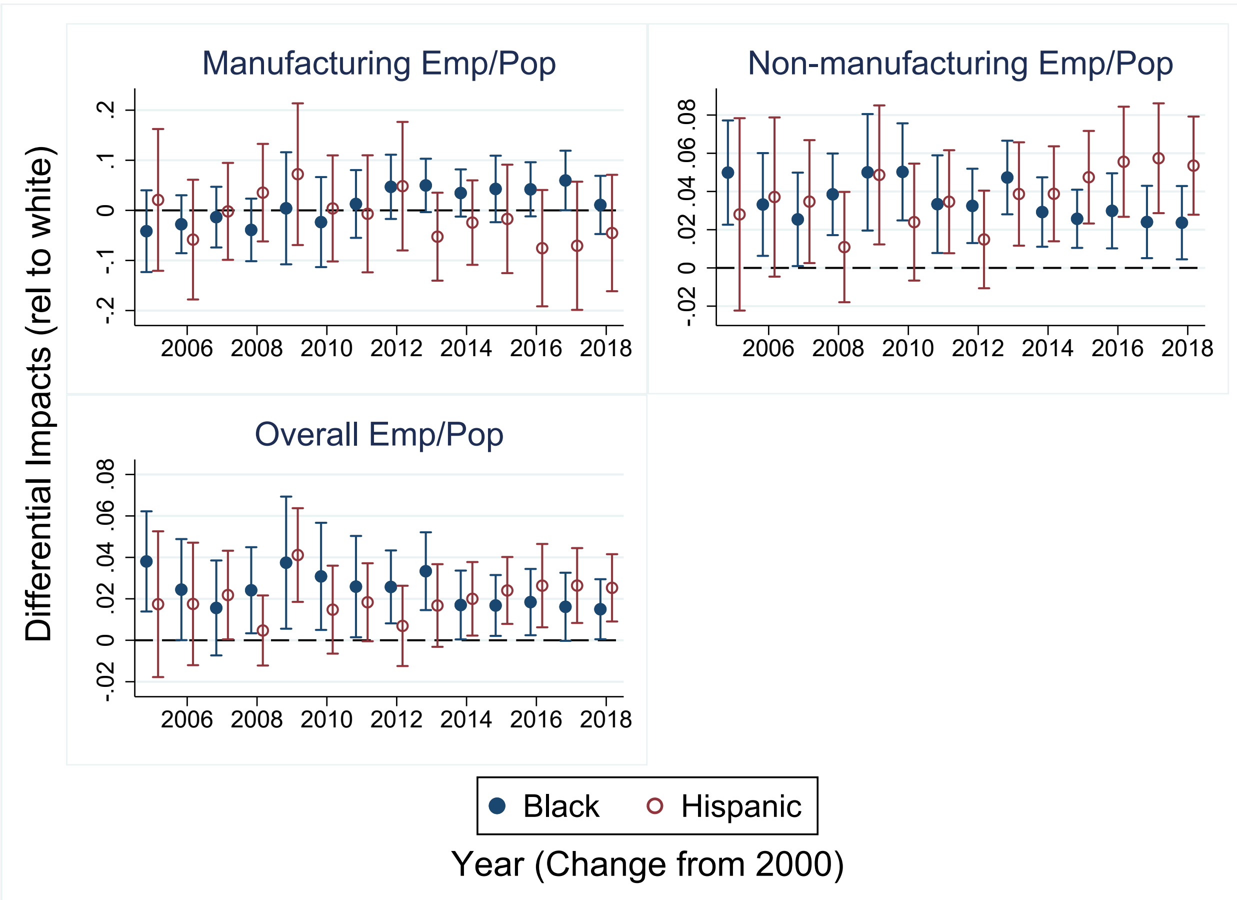
[25]https://j2jexplorer.ces.census.gov

sectors from the Quarterly Workforce Indicators (QWI)[26] for the same period. The QWI is also based on LEHD, so it should be consistent with J2J.

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

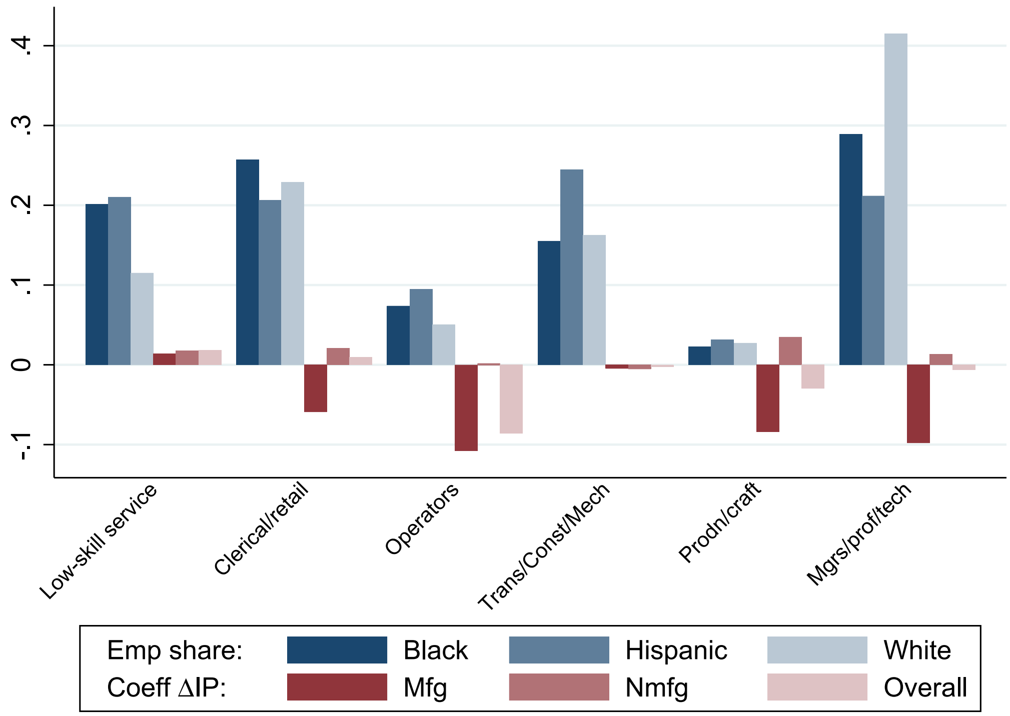
Additional Tables and Figures

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



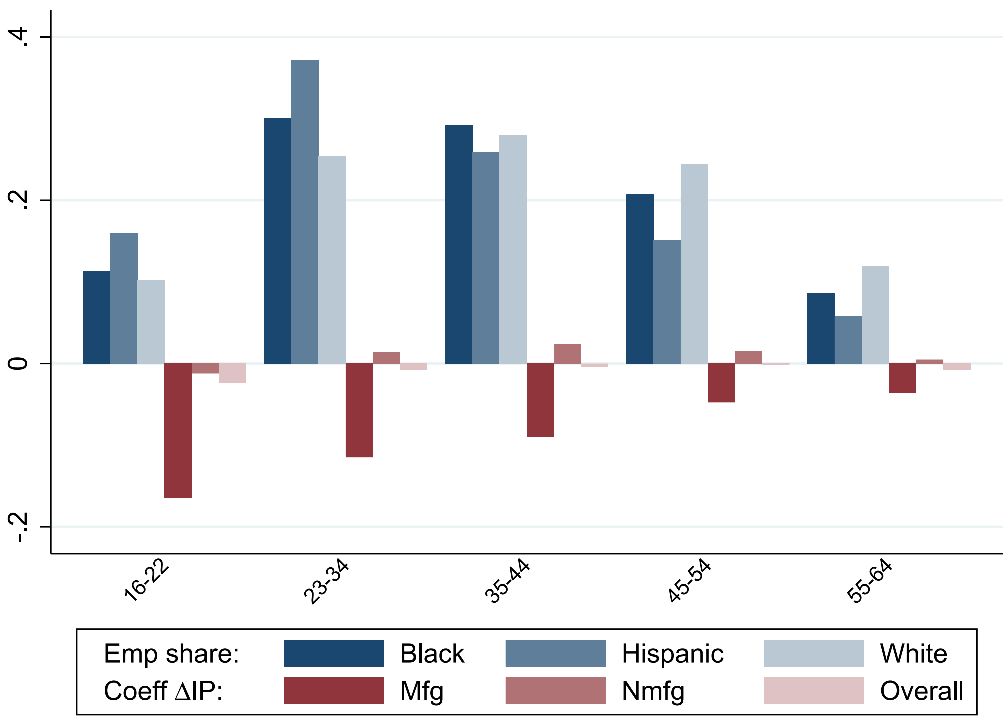
Notes: See Figure 4. This figure plots coefficients on race-or-ethnicity-specific ΔIP*Black*year and ΔIP*Hispanic*year effects (instead of CZ-wide) and their 90% confidence intervals.

Figure A.2: Summary of Differential Impacts by Occupation



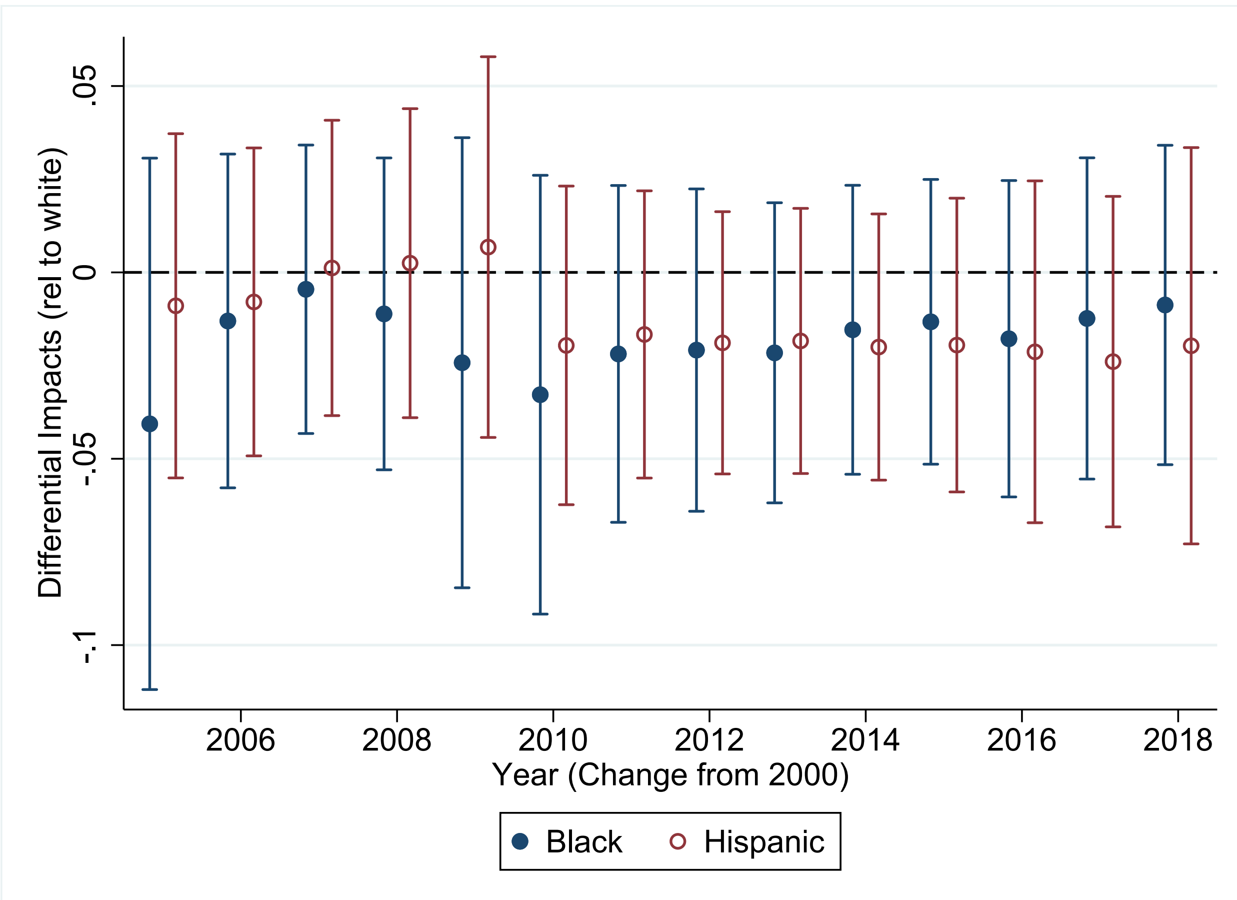
We group workers using occupational categories from Autor and Dorn (2013). The blue bars are employment shares across occupation groups, by race or ethnicity in 2000. To obtain the maroon bars, we estimate CZ-year level regressions where the dependent variable is the change in log employment in the indicated 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 Weekly Wage, 2000	6.433	6.171	6.133
	(0.208)	(0.200)	(0.124)
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 Weekly Wage	-0.244	-0.319	-0.272
	(0.0814)	(0.121)	(0.0950)
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 weekly wages are annual wage and salary income divided by annual weekly hours, adjusted to 2012 dollars using the PCE price index, and exclude self-employed. All employment and wage 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: 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.6: 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.