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ABSTRACT

Minority workers generally have worse economic outcomes than whites, and are disproportionately impacted by many negative shocks. However, we show that Black-white employment gaps narrowed as a result of China's WTO accession because Black workers transitioned to nonmanufacturing employment at higher rates. They also lived in less exposed areas of the country and were less reliant on manufacturing employment at baseline. Hispanic populations in contrast were overrepresented in exposed manufacturing industries and experienced larger overall employment losses. The China shock thus widened Hispanic-white gaps, though this effect was short lived. The lasting negative effects were driven primarily by white workers.

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1 Introduction

Policy makers have long grappled with the fact that Black and Hispanic workers face persistently lower income, wealth, and employment outcomes relative to white workers.[1] Minorities are also disproportionately impacted by a wide range of negative income and employment shocks, including, but not limited to, the Great Recession, Covid-19, and typical month-to-month fluctuations in income.[2] We study one important shock to U.S. labor markets: the increase in manufacturing imports following China's accession to the WTO in 2001. Despite the attention that has been paid to Chinese imports in both the academic literature and in policy debates, little is known about impacts of the "China shock" on racial and ethnic inequality.

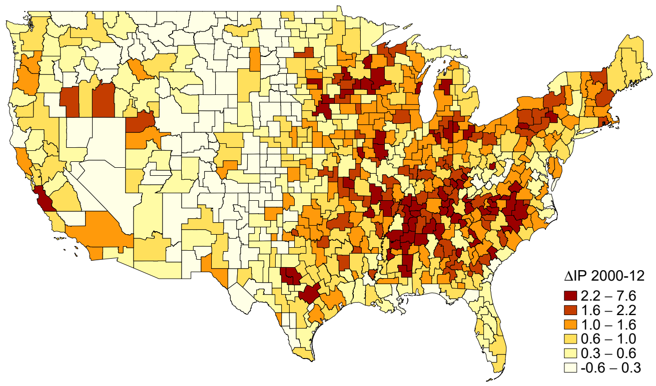
Effects of import competition can vary greatly across groups. In their seminal work, Autor et al. (2013) show that US commuting zones (CZs) producing goods that would increasingly be imported from China experienced persistent relative employment declines. However, exposed CZs are predominantly white (see figure 1), and Black workers are underrepresented in manufacturing employment compared to white and Hispanic workers, suggesting that they may be relatively insulated from the negative effects of the China shock. On the other hand, within a CZ, displacement effects will depend on differences in skill mixes, effects of discrimination, and differences in adaptability post displacement. The earlier literature on sensitivity to other types of shocks may imply worse impacts on minority workers due to these channels. Even non-manufacturing workers could be negatively impacted if their jobs are complementary to those most exposed to import competition – e.g., workers at nearby restaurants. However, the China shock may generate reallocation towards other areas of the economy – for instance, wholesale and retail trade and services. These spillover effects could benefit minority workers if they are better poised to transition into these jobs, compared to white workers.

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.[3] We find that at baseline both minority groups are less exposed to the China shock due to where they live and that Black workers are also underrepresented in exposed manufacturing jobs compared to whites, while Hispanic workers are overrepresented in these industries. Within a CZ, import competition reduces manufacturing employment at similar rates for Black, Hispanic, and white workers, and at similar magnitudes for a one unit change in CZ-level exposure. But because minority populations are less

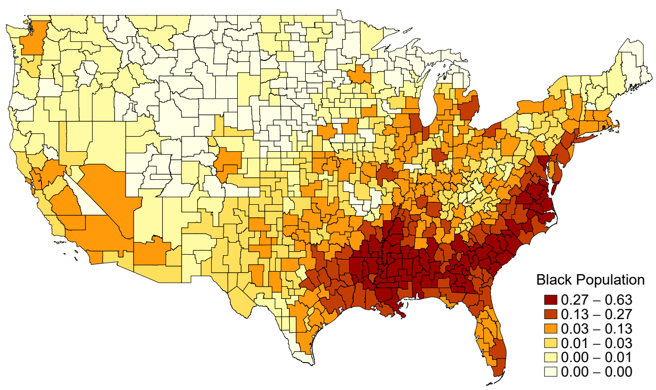
[1] See, e.g., Dettling et al. (2017), Bayer and Charles (2018), Casey and Hardy (2018), and McIntosh et al. (2020).
[2] See, e.g., Hoynes et al. (2012), Cho and Winters (2020), Hardy and Logan (2020), and Ganong et al. (2020).
[3] In this paper, we use the terms Black and white to refer to non-Hispanic Black and non-Hispanic white individuals.

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

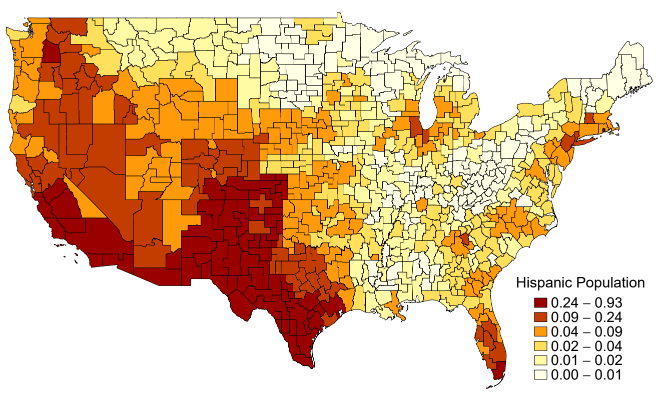
Panel A: Change in Import Exposure from China 2000-2012



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.

likely to be living in exposed CZs, their overall manufacturing employment losses are smaller.

We also find that increased import competition generates statistically significant *increases* in non-manufacturing employment for Black workers relative to white workers in exposed locations. We do not find evidence that Black workers in more exposed locations fare better than Black workers in less exposed locations. However, we find robust evidence that Black-white employment-to-population gaps narrow in more, compared to less, exposed CZs. Further, we see no evidence that wage gaps widen. The Black-white differential employment impacts are largely stable over the time period and do not appear to be driven by educational, demographic or occupational differences across groups. We find that the disproportionate relative employment gains for Black workers manifest primarily in wholesale and retail trade and professional services sectors, which are areas that have been shown to expand when manufacturing employment declines (Bloom et al. (2019), Fort et al. (2018)).

In contrast, Hispanic workers suffer larger hits to non-manufacturing employment as a result of the China shock, compared to white workers. Effects are largely driven by negative spillovers from a CZ-wide shock, rather than direct effects to Hispanic manufacturing jobs.[4] Differences in observables, namely educational attainment and industrial composition, appear to be important. Hispanic workers are less likely to complete a high school education and are overrepresented in construction and low-skilled manufacturing, and these differences likely drive their more negative impacts. We find that effects are most negative around the time of the Great Recession, and converge to the white effect in later years. Hispanic workers may have been more prone to impacts of the housing bubble burst due to their overrepresentation in construction and the relationship between manufacturing employment, the China shock, and the housing bubble.[5]

To our knowledge, ours is the first paper to look at the effects of the China shock across race and ethnic groups.[6] A large body of literature has shown negative and surprisingly long-lasting relative impacts on manufacturing employment in locations exposed to import competition from

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

[5]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. (2023) point out that the housing bubble burst was stronger in CZs more exposed to the China shock – likely due to depressed local demand caused by the China shock (Feler and Senses, 2017). 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]Previous work has explored other types of heterogeneity: Impacts on overall inequality are mixed with Autor et al. (2014) finding worse effects for low wage workers and Borusyak and Jaravel (2023) finding rising inequality only within, but not across, income deciles when considering both earnings and expenditures; Keller and Utar (2022) show that in Denmark, women exited the labor force at greater rates than men following the China shock and such exit was associated with increased fertility; Carballo and Mansfield (2022) show that unemployed and entry-level workers experienced negative impacts of the China shock due to increased competition with displaced manufacturing workers.

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).[7] However, other recent research suggests that Chinese competition was a reallocation shock, facilitating a rise in export production (Feenstra and Sasahara, 2019) and a reallocation across geographies and sectors (Bloom et al., 2019). Fort et al. (2018) find that most of the decline in manufacturing employment from 1977 to 2012 was due to within-firm reallocation from manufacturing to non-manufacturing endeavors. About one-third of the overall growth in non-manufacturing employment of manufacturing firms was in retail, about one-third was in professional services, and the remaining third was in other non-manufacturing industries. More broadly, the idea that a large shock can result in sectoral shifts is a central concept in economics (Schumpeter, 1939; Blanchard and Diamond, 1990; Davis and Haltiwanger, 1992; Hershbein and Kahn, 2018). To the extent that these changes occurred at a localized level, we should see the China shock coinciding with growth in other areas of employment such as retail or wholesale trade and professional services. Indeed, these are the industries that drive the relative employment gains of Black workers.

What facilitated Black workers' relative success at weathering the China shock? A small, recent literature finds that Black workers were disproportionately harmed by manufacturing declines during the 1980s.[8] Indeed, we show that by 2000, Black workers had been exiting manufacturing at faster rates than white workers, had seen relative declines in their manufacturing wage premium, and seen a relative reduction in unionization rates. These trends combined suggest manufacturing rents diminished for Black, relative to white, workers. Black workers therefore had closer non-manufacturing employment substitutes, which likely explains their more successful reallocation. White workers may have faced greater losses because they still retained high rents in manufacturing. Ironically, historical impacts from previous manufacturing declines facilitated a more rapid adjustment to the China shock for Black workers. Documenting this changing landscape is an important contribution of this paper. As policy makers grapple with the potential effects of current and future shocks on racial inequality, it will be crucial to take into account current levels of manufacturing importance and attachment.

We also contribute to a large and important literature on racial and ethnic gaps in the labor market.

[7] 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).

[8] Batistich and Bond (2023) show Black workers faced disproportionate negative consequences from the Japan trade shock, which Enriquez and Kurtulus (2023) largely attribute to an overrepresentation in production occupations. Dicandia (2021) shows Black workers were negatively impacted by automation shocks around the same time period and Gould (2021) shows Black workers faced disproportionate employment declines coincident with secular manufacturing declines at the MSA-level.

Minority populations tend to be more vulnerable to recessionary shocks (Hoynes et al., 2012) and earn lower wages on average, which raise the concern that they will suffer disproportionately from other types of labor market shocks such as competition from a low wage country like China. For the Hispanic population, that is indeed what we find. 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 had recovered their employment losses from import competition relative to whites.

Black workers, in contrast, have experienced stagnating wage gaps with whites in recent decades.[9] Researchers have pointed out that widening income inequality exacerbates wage gaps (Juhn et al., 1993; Blau and Kahn, 1997; Bayer and Charles, 2018) and forces such as rising incarceration and technological change have served to depress labor force participation of Black relative to white workers (Neal and Rick, 2014; Hurst et al., 2021; Dicandia, 2021). In this paper, we find that trade presents a modest force pushing in the opposite direction. While Black workers exposed to import competition still faced negative impacts on manufacturing employment, they were relatively less likely to be exposed than white workers and furthermore, they were less attached to manufacturing employment. As a result, they could take better advantage of the offsetting positive effects generated by trade at a localized level. We find that the Black-white employment-to-population gap narrowed by 3 percentage points (roughly 15%) due to the China shock.[10]

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

[9]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.

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

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

This paper proceeds as follows: Section 2 describes differential import exposure across race and ethnic groups. Section 3 analyzes race and ethnicity-specific impacts on employment at the CZ-level and explores mechanisms for the differing effects. Section 4 sums up the total impact of differential exposure and differential coefficient effects, and discusses our results in the context of the historical position of minority workers in manufacturing. Section 5 concludes.

2 Differences in Import Exposure

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 we also disaggregate further to understand whether, within a CZ, different race and ethnic groups face different direct exposures.

2.1 Data and Methods

ADH measure the change in import competition for a CZ, c, in time period t, relative to a baseline time period. We use 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. We use this CZ-wide measure and follow exactly the methods and data sources outlined in Autor et al. (2021) (see appendix A.1). 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 also define a group-specific change in Chinese import exposure, which allows the CZ-level shock to vary across white, Black, and Hispanic groups based on their employment shares. 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. For this meaure, 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, restricting attention to the adult (age 16-64) non-institutionalized population in non-military employment.[11] We focus on three mutually exclusive (but not exhaustive) groups: the white non-Hispanic, Black non-Hispanic, and Hispanic populations. We include in the Hispanic population anyone who self-identifies as being of Hispanic, Latino, or Spanish origin. We include in the Black population respondents to the Census who select Black as at least one of their races and restrict the white population to those who only select white and no other races.

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

[11] ADH use the larger County Business Patterns data to measure baseline employment shares in CZs at the four-digit SIC level, but these data do not disaggregate by race. Instead, for equation 2, we use 2000 Census data (from the Integrated Public Use Micro Samples (Ruggles et al., 2021)) to obtain group-specific employment shares but must aggregate to a three-digit level – we use ind1990DD codes (Autor et al., 2013), a variant of the Census Bureau Industrial classification system. 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 ind1990DD industry-level using the crosswalk in Pierce and Schott (2012) to measure ΔM_i.

2.2 Results

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

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

Table 1 provides further detail, listing the most and least exposed CZs – among the 50 largest, along with their minority population shares. 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 Grand 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. However, overall, there is a strong negative correlation between import exposure and Black population share. Figure 2 provides bin scatters, relating the CZ-level change in import exposure to the CZ-level Black population share (left panel). The negative relationship is evident and strong in both magnitude and statistical significance.

The Hispanic population (panel C of figure 1) is largely located in the southwest. Many cities in this area have among the highest increases in import exposure (e.g., San Jose and Los Angeles, CA, and Austin and Dallas, TX), while others (e.g., Las Vegas, NV) 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 a negative correlation for most CZs in the data (those with 0.2 Hispanic population share or less) but the four rightmost datapoints (comprising 20% of the Hispanic population) have very high Hispanic population shares and also high import exposure.

[12] 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.

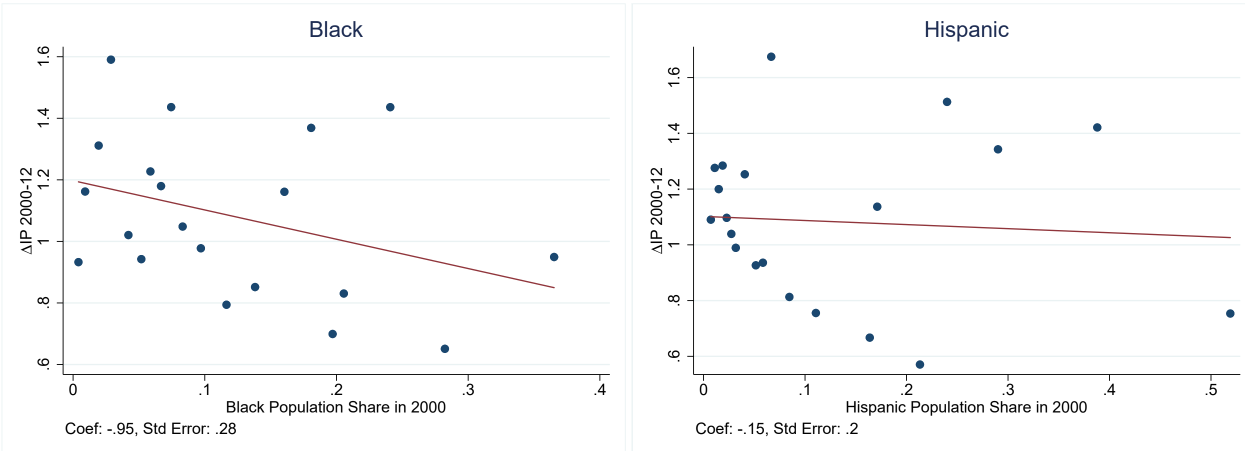
Table 1: Import Exposure and Minority Population Shares from the 50 Most Populous CZs

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.

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 due to *industrial composition*, since we use the group-specific ΔIP measure defined in equation 2. They also take into account the *population effects* documented above 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

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



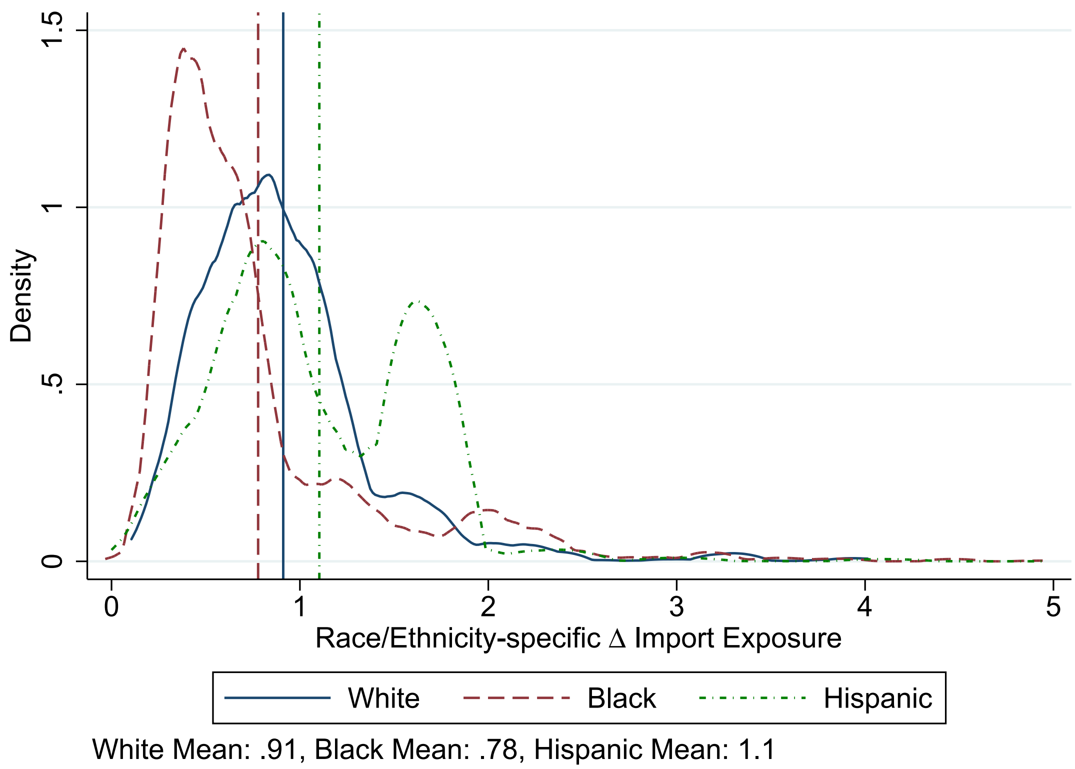
Notes: Binned scatters of Commuting Zone (CZ) level characteristics. X-axis plots the CZ-level fraction of population that was Black (left) or Hispanic (right) in the 2000 Census. Y-axis plots the CZ-level change in import exposure from China from 2000-12 defined in equation 1 and in Autor et al. (2021).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

(red, dashed line). The mean for the Hispanic population (green dash-dot line) is larger than either the white or Black means. However, consistent with the discussion above, the distribution has two distinct modes. The Hispanic population tends to face changes in import exposure that are either extremely large, or similar to that of the white population.

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

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

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.

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 some heterogeneity. The column 2 population effect shows that on average, Hispanic workers are much less likely

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.

to live in exposed areas when applying the white ΔIP to Hispanic population weights. Because white workers represent the majority population in almost every CZ, this specification is highly relevant for thinking about how Hispanic populations may be impacted or sheltered. The population effects, however, are outweighed by large and positive industrial composition effects. 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.[13]

To sum up, table 2 shows that both Black and Hispanic workers are less likely than white workers to live in communities that are impacted by a trade shock – population effects amount to about a 0.1 offset in terms of the white ΔIP. The industrial composition effects tell us whether, within a community, we should expect a population to be more or less directly impacted. While we find Black workers are marginally less directly exposed due to their industrial composition, Hispanic

[13]Appendix table A.2 lists employment shares and exposure for 3-digit industries and shows that Hispanic workers are indeed overrepresented in many highly exposed sectors, such as textiles, toys, and sporting good – even though they also have a high presence in food-related manufacturing industries that do not experience much of an import shock and they are underrepresented in some of the high tech sectors that do.

workers are substantially more directly exposed. We will next examine employment impacts across white, Black, and Hispanic workers for a given sized CZ-level shock. The population and industrial composition effects may lead us to expect employment of Black workers to respond less negatively than that of white workers, and Hispanic employment to respond more negatively. However, even with these differential exposures, it could be that for a given shock, certain groups experience a disproportionate share of layoffs or a more difficult transition to other sectors. We explore these dynamics next.

3 Import Exposure and Labor Market Outcomes, by Group

3.1 Data and Methods

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

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

Y^s_{rct} is an outcome of interest for race/ethnicity group, r, CZ, c, and year, t in sector s. Outcomes include log employment per adult population overall and within the manufacturing and non-manufacturing sectors, as well as log hourly wages.[14] We regress the change in these outcomes relative to 2000 on the time-varying CZ-level import penetration measure (equation 1), though we also explore effects using the group-specific shocks (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, $\Delta IP_{ct} * Black_r$ and $\Delta IP_{ct} * Hispanic_r$. X_c is a vector of controls, which we describe below, and all of which are interacted with race and ethnicity indicators (the vector $\mathbf{Group}_r$). Finally, I^t are year fixed effects, which are also interacted with group indicators.

We measure outcomes by race or ethnic group, CZ, and year using American Community Survey data. See appendix A.1 for variable definitions. We stack annual observations for white, Black and Hispanic populations from 2005-2018.[15] β_1 then gives the average impact of changes in import

[14] 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.

[15] 2005 is the first year that the American Community Survey (ACS) includes the PUMA codes that we use to

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. For these, we collect ACS waves into 2- or 3-year groupings, aggregate within a grouping by taking unweighted averages across years, and then estimate equation 3 separately for each year group.[16] Regressions are weighted by group-specific population in the baseline year (2000) and standard errors are clustered either by state or, as we will discuss later, by 3-digit SIC industry. While precision is a potential concern and some group-CZ-year cells comprise a small number of survey respondents, these cells carry very little weight given the population weighting, and so results are extremely robust to dropping small cells.

We can estimate equation 3 using OLS. However, as in the previous literature, we are concerned that some unobservable characteristics of CZs may be driving variation in both import penetration and employment outcomes.[17] Following Autor et al. (2013) we estimate a 2SLS regression that instruments for import penetration with changes in imports by other high-income countries from China. These alternative import penetration measures are then applied to baseline employment shares from a lagged time period (1990 instead of 2000) to avoid anticipatory changes.[18] First stage regressions can be found in appendix table A.3 for the main specification, as well as for other IV strategies detailed below.

We focus on the CZ-level import penetration measure (equation 1) as the key explanatory variable. Importantly, the CZ-wide measure could pick up spillover effects from shocks to different subpopulations. For example, the closing of a predominantly white manufacturing plant may negatively impact employees in nearby restaurants. Alternatively, companies benefiting from cheaper labor inputs from China might expand their local employment in non-production occupations. More broadly, China shock-induced reallocation may impact the population as a whole, regardless of the direct exposure of a particular subgroup. We would expect the CZ-wide measure to produce different results than the group-specific measure due to these spillovers, especially for non-manufacturing

identify CZs and we stop our analysis after 2018 to avoid any COVID-related impacts on imports from China which would have begun in late 2019.

[16] While our main specification stacks all years of data for precision, the latter approach that first combines and then estimates effects on a snapshot set of years is more standard in the literature: in Autor et al. (2013) they examine changes from 2000 to an average 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 2006-08 ACS waves, 2000 to pooled 2011-13 waves, and 2000 to pooled 2017-19 waves.

[17] 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.

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

employment where effects of import exposure are predominantly indirect. Because we are interested in the full effects of being located in an exposed CZ on race and ethnic groups, the CZ-wide measure is preferred. However, responses to the CZ-wide measure could differ across group due to the differences in industrial composition documented above. A group with less employment in manufacturing, even in an exposed location, will face smaller direct impacts of the shock, and group-specific import exposure more precisely measures their direct exposure. As such, we also explore group-specific measures in alternative specifications.[19]

As in the previous literature, the identifying assumption for β_1 is that CZs predicted to have large versus small increases in import penetration would have been on a similar trend in employment outcomes, absent the China shock. 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.[20] In addition, Borusyak et al. (2022), hereafter BHJ, address the identifying assumptions of shift-share methods and show that identification can be achieved assuming exogeneity of the shifters – in this case industry-level import shocks. Researchers have argued that changes in imports 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. BHJ provide a range of tests supporting this assumption for the China shock.[21] In their framework, the shift share approach boils down to an industry-level regression (the level of the shock) where the data are aggregated using the CZ-level shares as weights. So the standard errors need to be adjusted for the much smaller number of observations.[22] We provide results that follow their approach: using SSIV robust standard errors, clustering by three-digit SIC industry as suggested, and controlling for the manufacturing employment share in 1990 instead of that in 2000 to address the issue of incomplete shares in the year the instrument is measured.[23]

[19] CZ-level exposure is measured with more precision because employment shares are based on the larger County Business Patterns data (which do not allow for disaggregation by demographic group), rather than group-specific observations in the Census. Our IV strategy helps to address measurement error in the group-specific import exposure since we use one potentially noisy measure of baseline employment shares (1990) as an instrument for another (2000).

[20] 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.

[21] An alternative approach by Goldsmith-Pinkham et al. (2020) takes the opposite view, showing how identification can be achieved assuming exogeneity of the shares, rather than the shifters. However, they show that this assumption is not apt for the China shock.

[22] This framing is another reason to focus on the CZ-level shock over the group-specific shock. As mentioned above, for the group-specific shock, we must rely on three-digit industry codes for data reasons, which limits variation when viewed through the BHJ lens.

[23] BHJ build on the work of Adao et al. (2019), who first raised the issue of adjusting standard errors in shift share regressions to address the possibility of correlated residuals across regions with similar sectoral shares.

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.4 summarizes these results. We regress Black-white and Hispanic-white employment gaps in 1980, 1990, 2000, as well as the decadal changes on the ΔIP-group interactions, using the IV specification with full controls. We conclude that our results are not driven by any evident trends in the pre-period. For the Black-white gaps, associations with import competition are both small in magnitude and insignificant, and not trending in a meaningful way. The same is true for most of the Hispanic-white gaps, as well, though the gap in 1990 is larger in magnitude (more negative) in CZs that would eventually be shocked. We find convergence so that by 2000 Hispanic-white gaps are similar across CZs, and this convergence goes in the opposite direction of our findings for the later time period.

In addition to the methods outlined here, we explore a range of alternative approaches and controls, detailed below.

3.2 Main Results

Table 3 summarizes regression results for employment and wage outcomes. We estimate equation 3 for the changes in log manufacturing (panel A), log non-manufacturing (panel B), and log overall (panel C) employment per adult population, as well as changes in log hourly wages (panel D).[24]

Beginning with panel A, column 1 of table 3, 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, and commensurate with those found by other researchers when examining the population as a whole.[25] For the $\Delta IP_{ct} * Black_r$ and $\Delta IP_{ct} * Hispanic_r$ interaction terms, coefficients are small and positive but noisily estimated.

Figure 4 shows the time pattern of Black-white (blue, solid dots) and Hispanic-white (maroon,

[24]Sample sizes differ across columns and panels in table 3 for two reasons. First, the BHJ approach (columns labeled 3) has race/ethnicity by 4-digit SIC industries by year as observations, rather than group by CZ-year. Second, there are some cells with no observations due to small samples – particularly for manufacturing employment. As mentioned, since we weight by population, CZs based on few observations have little influence and results are robust to restricting to a balanced set of CZ-year observations.

[25]Our -0.09 estimate implies a 4.5 percentage point larger drop in the rate of change in white manufacturing employment for a 75th percentile exposed CZ, compared to a 25th. We can can multiply by the 25th percentile baseline (-0.2) to roughly map our result to ADH, given the differences in function form. Our results for the white population then imply a nearly 1 percentage point larger drop in manufacturing employment for the 75th-25th percentile comparison, which is similar to the 1.2 point drop overall found in Autor et al. (2021).

Table 3: The Impact of Import Exposure on Employment and Wages

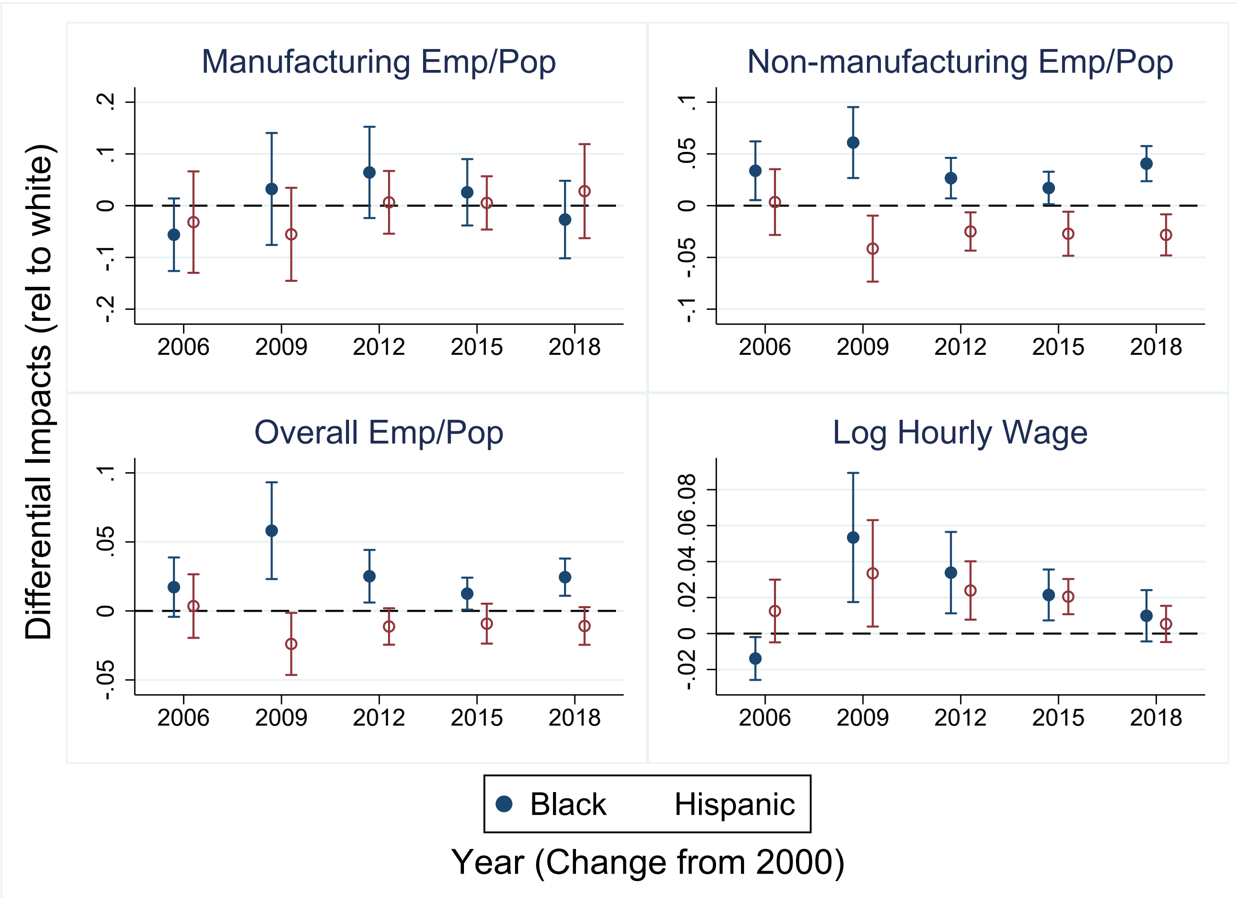
	(1)	(2)	(3)	(1)	(2)	(3)
	Panel A			Panel B		
Dependent Variable:	Δ log Mfg Emp Rate			Δ log Non-Mfg Emp Rate		
CZ-wide ΔIP (ADH)	-0.085***		-0.060***	0.005		0.004
	(0.021)		(0.023)	(0.004)		(0.005)
$\Delta IP * Black$	0.027	0.003	0.015	0.038***	0.026**	0.033**
	(0.040)	(0.042)	(0.025)	(0.011)	(0.010)	(0.017)
$\Delta IP * Hispanic$	0.002	0.014	0.008	-0.021**	-0.027**	-0.027
	(0.033)	(0.032)	(0.044)	(0.010)	(0.012)	(0.017)
T-stat Black overall	–1.42		–1.41	3.71		2.18
T-stat Hispanic overall	–2.82		–1.48	–1.28		–1.30
Observations	26,772	26,298	16,464	30,105	30,105	16,464
	Panel C			Panel D		
Dependent Variable:	Δ log Overall Emp Rate			Δ log Hourly Wages		
CZ-wide ΔIP (ADH)	-0.010**		-0.005	-0.006		-0.052*
	(0.005)		(0.005)	(0.007)		(0.028)
$\Delta IP * Black$	0.030***	0.016**	0.028*	0.019**	0.009	0.002
	(0.010)	(0.007)	(0.015)	(0.009)	(0.007)	(0.031)
$\Delta IP * Hispanic$	-0.010	-0.012*	-0.015*	0.014**	0.024***	0.050
	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.046)
T-stat Black overall	1.58		1.35	1.22		–1.20
T-stat Hispanic overall	–2.50		–2.07	1.02		–0.04
Observations	30,159	30,159	16,464	30,221	30,221	16,464
Main controls	X	X		X	X	
CZ-year FEs		X			X	
BHJ Approach			X			X

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

Notes: 2SLS estimates of equation 3 on group-CZ-year cells using ACS data from 2005-2018, restricted to white, Black, and Hispanic observations. Dependent variables are the change in log employment in the sector (or overall) per adult population and the change in log hourly wages. We instrument for import exposure (equation 1) and its interactions using changes in imports from China for other developed countries applied to lagged employment shares and interactions. Main controls are listed in footnote 20. Column 2 includes CZ-by-year fixed effects. Columns 1 and 2 cluster standard errors by state. Column 3 follows the Borusyak et al. (2022) approach: observations are at the group-year-4-digit SIC level; we replace the baseline manufacturing employment share control with that in 1990 – and otherwise include all controls, use their SSIV specification and cluster standard errors by 3-digit SIC industry.

hollow dots) differential impacts of import exposure, along with 90% confidence intervals. Here, we estimate separate regressions for each year grouping after averaging annual outcomes within a

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



Notes: See column 1 in table 3. Here we first aggregate annual observations into 2- or 3-year groupings by taking averages over the following intervals: 2005-7, 2008-10, 2011-13, 2014-16, and 2017-18. Next we estimate separate regressions for each year group. This figure plots the coefficients on ΔIP*Black and ΔIP*Hispanic and 90% confidence intervals. See appendix figure A.1 for main effects.

grouping.[26]

In the upper left panel, we see that both the Black-white and Hispanic-white differentials in manufacturing are insignificant. The early time periods show negative point estimates and wide confidence intervals – we cannot rule out a -0.1 differential impact for either group. However, there is convergence over time, with more precisely estimated zeros on the Hispanic-white differential, and positive point estimates on the Black-white differential in most of the later years. 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

[26]The groups are 2005-7, 2008-10, 2011-13, 2014-16, and 2017-18. Appendix figure A.1 plots the main effects (impacts on the white population).

the time difference for both manufacturing employment and trade exposure lengthens.[27]

Turning to non-manufacturing employment (panel B, column 1 of table 3), we see the effect for white workers is small and insignificant, which is consistent with ADH. Black workers, in contrast, experience strong positive effects on non-manufacturing employment relative to white workers. We estimate a 3.8 percentage point larger increase in the Black non-manufacturing employment rate of change, relative to the white, in a one unit more exposed CZ, significant at the 1% level. The Hispanic interaction term is negative and significant; Hispanic workers experience a 2.1 percentage point smaller non-manufacturing employment change, compared to white workers, significant at the 5% level. The upper right panel of figure 4 shows that the Black-white differential is positive and statistically significant at the 90% level or better in each time period, and point estimates are fairly stable. The Hispanic-white differential is most negative in 2009, with smaller magnitude point estimates and tighter confidence intervals in the later years.

Next panel C of table 3 examines overall employment-to-adult population ratios. The main effect in the column 1 specification indicates a significant overall loss for the white population of 1 percentage point, consistent with previous work. The Black-white differential is again positive. The combination of similar manufacturing impacts and positive impacts on non-manufacturing employment sum to relative improvements in overall employment for Black workers. Given a 0.5 interquartile range in exposure for the white population, our estimates imply that in a 75th percentile exposed CZ, the Black-white employment-to-population gap narrows by 1.5 percentage points, relative to a 25th percentile exposed CZ. As indicated by the t-statistics in the bottom rows, the overall effect (summing the negative effect for white workers and the positive differential for Black workers) is positive but not statistically significant. While we can robustly conclude that Black workers gain relative to their white counterparts within the same CZ, we cannot conclude that they gain relative to their Black counterparts across CZs.

The Hispanic-white differential of -0.01 for overall employment indicates that Hispanic workers living in exposed areas experience twice the employment loss of the white population, though the effect is insignificant. The t-stat at the bottom indicates that Hispanic workers living in more exposed areas do experience significant employment losses, relative to Hispanic workers living in less exposed areas.

The bottom left panel of figure 4 shows differential impacts on overall employment over time. These inherit much of their shape from the non-manufacturing employment effects with especially outsized point estimates for the 2009 data point (a 2008-10 average) that are also noisier. Estimates are fairly

[27] The most recent period again has somewhat wider confidence intervals but this point comprises an average of only two years (2017 and 2018) instead of three like the others, so may be more noisy for that reason.

stable (and more precise) in all other years. Black-white differentials are positive, significant in every year, and indicate a roughly 0.02 differential. Hispanic-white differentials are not statistically significant and have fairly tight confidence intervals towards the end of the period. Again, each point estimate reflects a long difference from the baseline 2000 period. We therefore estimate a positive cumulative effect on employment for Black, relative to white, workers in exposed locations and no cumulative differential Hispanic-white effect.

Finally, panel D, column 1 of table 3 examines effects on wages per hour worked.[28] While the main effect is close to zero and insignificant, the differentials are both positive and significant at the 5% level. Black-white wage gaps narrow by roughly 1.9 points in a one-unit more exposed CZ, compared to a less exposed one; Hispanic-white gaps narrow by 1.4 points. The bottom right panel of figure 4 shows that effects are especially large in the middle time periods, and converge towards zero in the later years. The t-stats (summing the main effect and minority-white differential) indicate that we cannot conclude that minorities in exposed locations earn significantly more than those in less exposed locations. Further, as we will discuss below, the positive differential wage growth is less robust across other specifications, especially for the Black-white differential. Still, we can typically rule out differential wage *losses* beyond roughly 0.5 points with 95% confidence. If minorities were experiencing relative employment increases but at lower wage rates, then our assessment of who was better off could be altered. However, our results show that neither group experiences wage losses relative to white workers, conditional on supplying an hour of labor.

Column 2 of table 3 adds CZ-by-year fixed effects to control flexibly for differential CZ-wide trends. Within these fixed effects, we can identify the minority-white differential impacts, though they absorb the main effect of ΔIP (i.e. the effect on white workers). The results are qualitatively similar to what we find using our primary specification. Hispanic-white gaps remain similar in magnitude while the Black-white gaps are somewhat compressed. However, our conclusion that Black-white employment gaps narrow significantly in exposed, compared to less exposed, locations with no evidence of negative relative wage consequences holds. Note, these within-CZ estimates are also reassuring in that they compare white and minority workers who experience the same shock, while the column 1 specification may, on average, compare groups who experience shocks generated by different industry mixes due to their differing geographies documented above.

In column 3 we implement the BHJ shift-share instrumental variable (SSIV) approach, which includes controlling for the CZ manufacturing employment share in 1990 instead of 2000 to address

[28] Wages are defined as annual wage and salary income divided by weeks worked last year times usual hours worked per week, excluding the self employed. We bottom code hourly wages to the first percentile in the year and topcode so that the implied full-time annual salary does not exceed topcoded income (1.5 times the top code value). We adjust to 2012 dollars using the Personal Consumption Expenditures price index.

the issue of incomplete shares at the time the instrument is measured (and otherwise include all the same controls) and clustering standard errors by three-digit SIC industry.

As has been shown by BHJ, the main effects for ΔIP are less robust to this approach. The effects on manufacturing and overall employment for white workers fall in magnitude and the latter becomes insignificant. However, these effects are not our primary focus. We are reassured to find that our conclusions about the differential effects by race and ethnicity are much more robust to the BHJ approach. For Black-white differentials, the effect on non-manufacturing employment is similar in magnitude to column 1 and significant at the 5% level (instead of the 1%). The effect on overall employment is also similar in magnitude though is now only significant at the 10% level. The positive differential effect on wages goes away, however we still see no evidence of negative relative wage effects for Black workers. Hispanic-white differentials experience similar variability, in particular showing a more pronounced and significant relative overall employment effect. Our overall conclusions hold for this approach.

3.3 Additional Specifications

Appendix table A.5 includes the results of several alternative identification strategies. Column 1 replicates our primary specification for comparison. Column 2 shows the results using OLS. Results are qualitatively similar for the most part using OLS, though magnitudes are smaller. One difference is that the Hispanic-white differential on manufacturing employment is negative and significant.

Column 3 uses an alternative IV strategy. One concern with our IV approach, which follows ADH and instruments for US imports from China using imports from China by other high-income countries, is that it might not remove all of the potential bias if demand shocks are correlated across countries. In our context, we may also be concerned that this bias could be race/ethnicity-specific if groups tend to live in different CZs and are thus exposed to shocks to different sets of industries, which could have different degrees of correlation between US and foreign demand shocks. The CZ-year fixed effects in column 2 of table 3 remove this concern about race-specific bias by conducting a within-CZ comparison so that differences across groups are identified off of the same distribution of shocks. However, for robustness, we also address concerns about correlated demand shocks following the approach of Antras et al. (2017), who use changes in Chinese market shares, rather than levels of imports, in other high income countries as an instrument. These results are very similar to the results using our primary specification.

Throughout this paper, we measure import exposure from China using the approach of Autor et al.

(2021). In the two final specifications presented in appendix table A.5, we follow the approach of 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.

In column 4 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 1990 industry employment shares within the CZ, following measurement for our main instrument.[29] For the main effects, this approach produces more negative manufacturing, overall employment, and wage impacts, but more positive non-manufacturing impacts. Point-estimates on the Black-white differentials are similar in magnitude to our preferred estimates, though they are substantially noisier so that none of the differential effects are statistically significant. And, while again imprecise, the Hispanic-white gap in overall employment becomes opposite signed. The NTR IV approach has the advantage of producing coefficients that are comparable to our other specifications. However, Appendix table A.3 shows that this instrument is fairly weak in our setting with F-stats just above 10, so our power is limited. We also provide a reduced form NTR estimate in column 5, which produces qualitatively similar results. The differential non-manufacturing employment effect for Black workers is positive and significant and their differential overall employment effect shows a similar pattern to other columns – opposite signed with a similar magnitude to the white main effect, though insignificant. Thus, our results hold up qualitatively to the NTR Gap approach.

The results described in this section show that in addition to their differential likelihoods of being exposed to imports from China, Black and Hispanic workers also exhibit differential responses relative to white workers conditional on exposure. The next section will explore why this may be the case.

[29]We obtain the NTR gap at the 8-digit HS product code level from Pierce and Schott (2016) and then average this measure over products within 4-digit SIC codes, weighting by product imports in 2000. We use County Business Patterns to measure CZ employment shares across these industry categories.

3.4 Heterogeneity by Observables

Black, Hispanic, and white workers differ across a wide range of observables including basic demographics and the types of jobs they tend to hold. In this subsection, we explore whether these differences can help account for our findings.

Direct Exposure

As noted in section 2, groups differ in their direct exposure to import competition within a CZ due to their likelihood of working in the most exposed areas of manufacturing, and this variation could drive differences in responsiveness to the CZ-wide shock. Indeed the CZ-wide shock will be most correlated with the group-specific shock for the majority population – white workers – and may differ from the direct exposure for minority workers. For this reason, columns 1 and 2 of appendix table A.6 compare the CZ-wide shock to results using the group-specific shock defined in equation 2. We find that Black-white differentials are very similar to the main specifications. Within a geographic area, the CZ-wide and race-specific shocks are highly correlated for Black workers.

The Hispanic-white differentials, however, vary much more across these shocks. Unlike with the CZ-level shock, in response to the group-specific shock, Hispanic workers experience slightly more negative, though insignificant, manufacturing impacts, and positive and significant growth in non-manufacturing employment, relative to whites. These results suggest that when the jobs Hispanic workers themselves are found in experience an import shock, the Hispanic population may move out of manufacturing at higher rates but 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.[30]

[30] To better parse out these stories, column 3 of table A.6 estimates 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, 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.

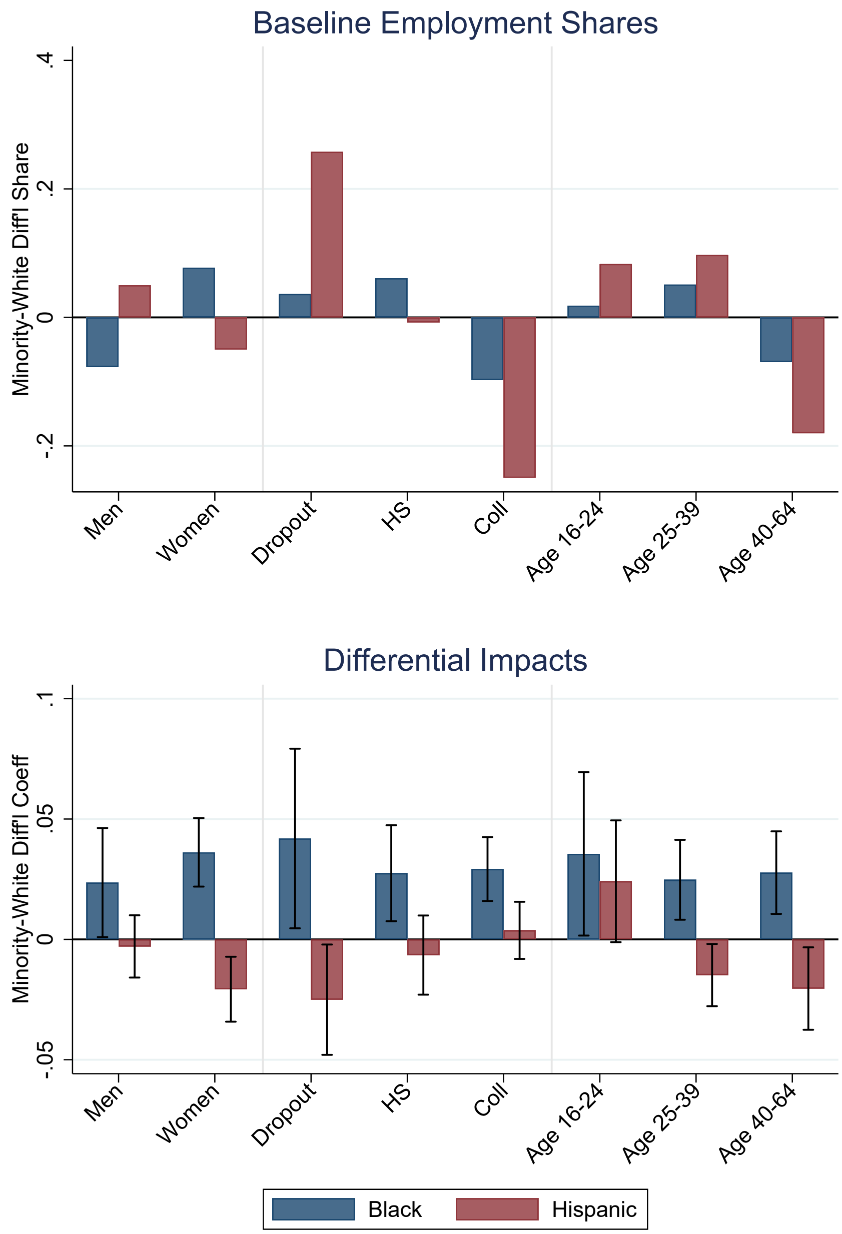
Basic Demographics

Figure 5 explores the extent to which demographic factors can explain the differential effects of import competition by race and ethnicity. In the top panel, we plot minority-white differentials in the fraction of employment with each characteristic in the baseline period, 2000. Black workers are more female than white workers, while Hispanic workers are more male. Both minority groups have less education than white workers, though this difference is larger for Hispanic workers who are substantially overrepresented among high school dropouts and underrepresented among those with any college. Finally, both groups, and especially Hispanic workers, are younger than white workers.

These differences in distributions across demographic groups can help us understand our findings in two ways. First, it may be that minorities are overrepresented among demographic groups that we should expect to fare better or worse in response to an import shock and therefore demographics alone can account for some of our findings. Second, it may be that Black or Hispanic workers exhibit a disproportionate response within a demographic group, which can be important especially if the group has a high employment share. To better understand both channels, we estimate equation 3 for the overall employment-to-population outcome, but limit the sample to the indicated subpopulation. The main effects of ΔIP (plotted in appendix figure A.2) tell us whether white workers experience import shocks differently depending on their demographics, while the interactions with Black and Hispanic (bottom panel of figure 5) tell us whether these groups face disproportionate impacts within a demographic characteristic.

In terms of baseline demographics, education levels have been shown to be particularly salient for determining who is harmed the most by the China shock (Autor et al., 2013, 2021; Eriksson et al., 2021). Appendix figure A.2 confirms this finding, showing that high school dropouts experience substantially more negative impacts of import exposure. We also find large negative impacts for the youngest age group. These differences can potentially account for our finding that Hispanic workers as a whole are marginally worse off, relative to white workers in exposed locations. As a simple back of the envelope calculation, we take a weighted average of white coefficient effects from figure A.2 using group-specific employment shares from the top panel of figure 5 as weights. We indeed find that differences in educational attainment can more than account for the -0.01 differential effect on overall employment for Hispanic workers that we found in table 3. Differences across the age distribution can also account for the worse outcomes for Hispanic workers. In contrast, these demographic shares cannot account for the Black-white differentials we find. Based on demographics, Black workers would also be predicted to fare worse than white workers when

Figure 5: Minority-White Differences in Baseline Characteristics and Impacts of Import Exposure



Notes: The top panel reports minority-white differentials in the share of employment that has a given characteristic in 2000. Education categories are defined as those with less than 12 years of school, those with exactly 12, and those with any college. The bottom panel reports minority-white differential impacts of CZ-wide import exposure within the characteristic. For the latter, we estimate equation 3 for the overall employment outcome, restricting to the indicated subpopulation. We plot coefficients on $\Delta IP * Black$ and $\Delta IP * Hispanic$, as well as 90% confidence bars.

facing an import shock, though at smaller magnitudes than for the Hispanic population. Yet we find a positive and significant differential effect of import competition on Black relative to white workers in table 3.

Next, we ask whether Black and Hispanic workers experience disproportionate responses to the China shock within a demographic group. Precision is an issue when disaggregating the data by race or ethnicity and demographic subgroup – as indicated by the 90% confidence bands – so these results are merely suggestive. However, for Black-white differentials, the bottom panel of figure 5 shows similar positive and significant effects for both men and women, across all education groups, and across all age groups. We therefore conclude that these demographic factors do not drive our differential results for Black workers.

For Hispanic workers, despite wide confidence intervals, we find suggestive evidence that Hispanic women fare worse than white women and that Hispanic high school dropouts fare worse than their white counterparts. Since women and dropouts are less likely to be working in manufacturing at baseline but more likely to be working in services, this result is consistent with the notion that negative spillover effects from shocks to white manufacturing workers drive our results. At the same time, we find suggestive evidence that young Hispanic workers fare better than young white workers, while the opposite is true for older workers. On the whole, the education differences across Hispanic and white workers stand out as being quite important in accounting for our main results – Hispanic workers are substantially overrepresented among high school dropouts, high school dropouts fare worse in response to an import shock regardless of race, and Hispanic high school dropouts in particular face disproportionately negative consequences.

The analyses in figure 5 take the population shares across demographic groups as given, while it could be that there is differential migration. If population subgroups move away from their CZ at differential rates (or reduce their inflows) 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.3, we summarize a specification similar to ADH, examining log population changes by race/ethnicity and demographic group. We limit the sample to 2015 onwards in order to allow time for any population changes to accrue. Our results are imprecise with wide confidence bands. The point estimates for differential Hispanic population changes are almost all negative, suggesting possibly increased net out-migration for that group, but estimates are generally too noisy to draw strong conclusions. For Black populations, point estimates are quite small and we see no evidence of systematic differences.

Industrial and Occupational Mix

Black, Hispanic, and white workers tend to hold different types of jobs, which could impact how they experience spillover effects from the China shock to non-manufacturing sectors. Here we try to gain some intuition for these dynamics.

Figure 6 summarizes our analyses across major industry categories. The top panel plots minority-white differentials in employment shares at baseline (2000). The bottom panel plots differential employment impacts of the China shock. We structure our analyses so that the differential impacts across industry will approximately sum to the differential impacts in overall employment rates from table 3.[31]

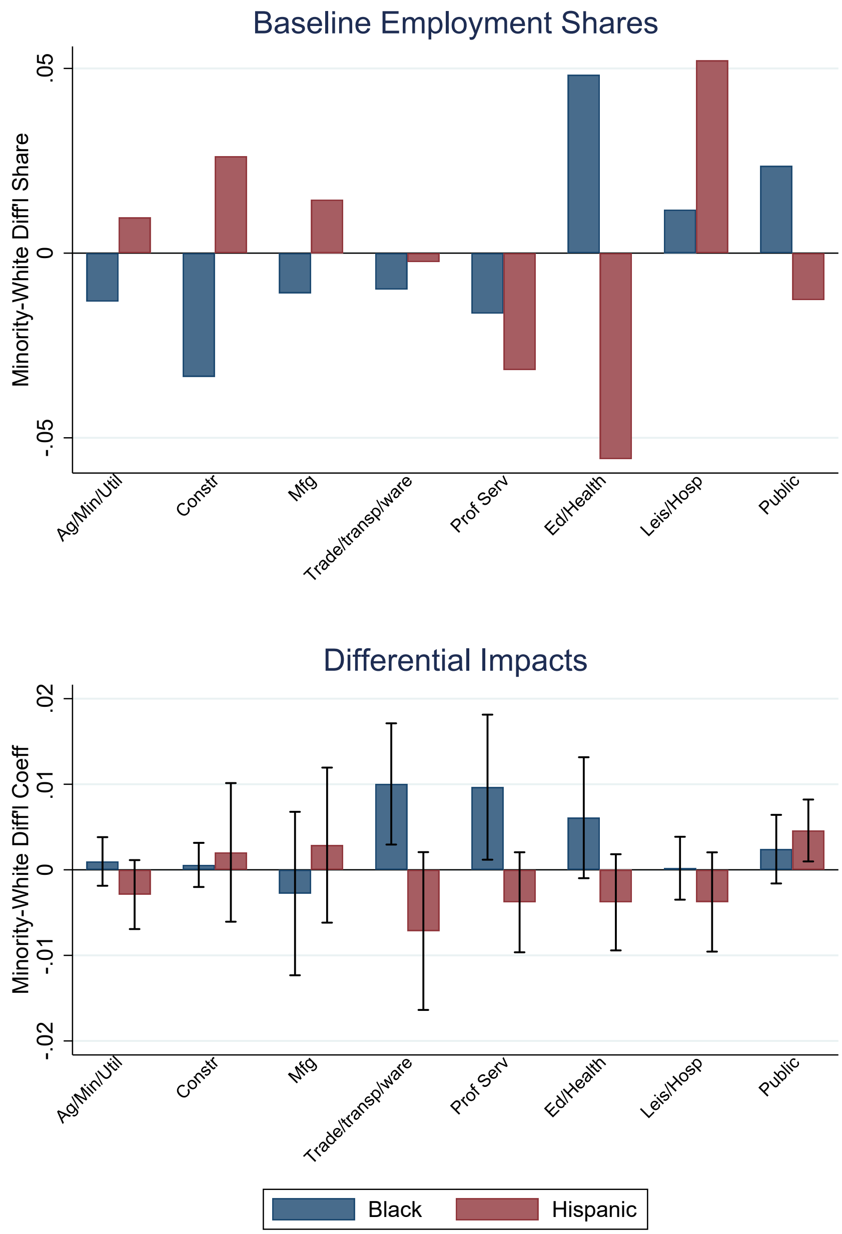
Looking first at employment shares, Hispanic workers are overrepresented in manufacturing, construction, and leisure and hospitality. Naturally, manufacturing was most directly impacted by the China shock. Other sectors may lose employment because they represent close complements or would be negatively impacted by an aggregate demand slump generated by the China shock. Demand for leisure and hospitality services is typically quite cyclical. Construction is another example and is especially relevant given the more negative Hispanic-white employment gaps we found around the time of the Great Recession. Recent work by Xu et al. (2023) found a positive correlation between CZ-level China shock exposure and the severity of the housing bubble burst. Indeed, depressed local labor demand caused by the China shock may itself have been a driver for lowering housing values (Feler and Senses, 2017). Hispanic workers especially may have suffered from the dual impacts of import competition and the housing bubble burst around that time and, notably, recovered thereafter, possibly accounting for the differential negative impacts on Hispanic workers.[32]

Next, for differential impacts, the bottom panel of figure 6 shows generally noisy results for Hispanic-white gaps. Indeed, the differential impact on overall employment we found in table 3 was not statistically significant. So we aren't able to say with precision which industries were driving the suggestive -0.01 point estimate.

[31] Specifically, because table 3 uses the change in log employment per adult population as the dependent variable, we use $(\frac{E^s_{rct}}{Pop_{rct}} - \frac{E^s_{rc2000}}{Pop_{rc2000}})/(\frac{E_{rc2000}}{Pop_{rc2000}})$ as dependent variables for sectors, s. That is, we use the change from 2000 in sector-specific employment per adult population for a race/ethnicity group and commuting zone, expressed as a fraction of overall employment per population for the group-CZ in 2000. These rates sum to the rate of change in overall employment per adult population, which is approximately equal to the change in logs we use above.

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

Figure 6: Minority-White Differences by Industry



Notes: The top panel reports minority-white differentials in the share of employment that is in a given industry in 2000. The bottom panel reports minority-white differential impacts of CZ-wide import exposure on industry-specific employment per adult population within the race/ethnic group. Industries are defined with the following NAICS codes: Ag/Min/Util (11, 21, 22); Constr (23); Mfg (31-33); Trade/transp/ware (42, 44-45, 48-49); Prof Serv (51, 52, 53, 54, 55, 56); Ed/Health (61, 62); Leis/Hops (71, 72, 81); Public(92).

At baseline, Black workers were especially overrepresented in education and health services and the public sector; they were especially underrepresented in construction. Based solely on their baseline employment shares, it is not clear why we should expect differential positive impacts, other than that Black workers didn't have a relatively high presence in manufacturing or construction,

On the other hand, from the bottom panel, we can say more about which industries drive Black employment gains. Even with generally wide confidence intervals, we find positive and significant differential gains for Black workers within the trade/transportation/warehousing and professional services industries.

These areas are consistent with the broader literature on sectoral reallocation. For example, Fort et al. (2018) show that while manufacturing firms were reducing employment at their manufacturing plants, these firms were simultaneously increasing employment in their non-manufacturing establishments, primarily through net non-manufacturing plant birth. About one-third of the overall growth in non-manufacturing employment of manufacturing firms between 1977 and 2012 was in retail, about one-third was in professional services, and the remaining third was in other non-manufacturing industries. Bloom et al. (2019) look specifically at the impact of the China shock across geographic areas and industries. They find that almost all of the manufacturing job losses resulting from Chinese import competition are in large, multinational firms that are simultaneously expanding in services, especially professional services and wholesale trade. They find this expansion is especially pronounced within high human capital CZs. It is reasonable to expect that the retail and wholesale sectors would benefit from increased imports from China, as imported goods need to be distributed and sold to consumers once they reach the US. Indeed, Bernard et al. (2010) document that in 2002 the majority of US imports from China were imported by wholesalers or retailers. Professional services, which include things like legal, accounting, advertising, research, design, engineering, and management, are also likely to be present across firms in all industries. To the extent that firms that cut manufacturing jobs simultaneously expanded in other areas, it's not surprising that these professional services are among the areas that have been shown to expand. For example, Bernard and Fort (2015, 2017) have shown that manufacturing firms often respond to import competition by offshoring the physical production of goods while increasing their domestic focus on research, design, and engineering.

Appendix figure A.4 conducts a similar exercise by broad occupation groups and reinforces the industry-level patterns. Hispanic workers are overrepresented in transportation/construction/ mechanical occupations and they experienced significant relative declines in these occupations, while Black workers experienced significant relative gains in both managerial/professional/technical and clerical/retail occupations.

In summary, Black workers' employment gains are concentrated in areas of the economy that we might expect to benefit from China shock-induced reallocation. To the extent that these forces were at play within CZ's, we show that it was Black workers who were better able to take advantage of them. However, it may be surprising that Black workers in particular were able to capture these gains, particularly when their baseline employment shares were, for the most part, unrelated to which areas would gain. We explore the reasons why Black workers may have been more likely than white workers to take advantage of these shifts in section 4.2.

Controlling Directly for Baseline Characteristics

Finally, to better understand the role of these observables in driving our main results, we perform a mediating analysis which controls for baseline characteristics and we also allow impacts of baseline characteristics to vary by race/ethnicity. These results are presented in column 4 of appendix table A.6. The power of these specifications is limited because we can only leverage differences across CZs in baseline demographic and industry/occupation mixes within the white or minority populations. For example, if Hispanic workers have similar low educational attainment in all CZs, then these baseline differences will be absorbed in the race/ethnicity group fixed effects. However, these specifications can still be instructive. Indeed, we find that the point estimates for the differential non-manufacturing (Panel B) and overall employment (Panel C) effects of the China shock on Hispanic workers goes to zero when these controls are included. The differential effects on Black workers, however, remain largely unchanged. These results are consistent with the conclusions of our discussion above: the differential effects of the China shock on Hispanic workers seem to be driven by differences in observables, while the differential effects on Black workers seem to be driven by differences in responses.

4 Discussion

In this section, we provide two discussions. We first discuss combining the differential exposure effects found in section 2 and the differential coefficient effects found in section 3. We then interpret the results found in this paper in the context of broader trends in labor market outcomes by race and ethnicity.

4.1 Putting it all together

The results in Section 3 show how a given increase in import exposure affects employment outcomes for different racial and ethnic groups. However, as shown in Section 2, Black and Hispanic workers are differentially exposed to import competition compared to the white population. We can use the two sets of results to estimate fitted effects for each race/ethnicity group. These fitted effects should be interpreted with caution, as the regressions estimate *relative* impacts and cannot be easily extrapolated to generate aggregate impacts. Still, this simple exercise is enough to provide intuition for the main channels we would like to highlight.

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 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. These fitted effects are averaged 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. We can also calculate the amount of the differential that is due to either the population weights by fixing the coefficients to be the same across groups, or vice versa.[33]

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

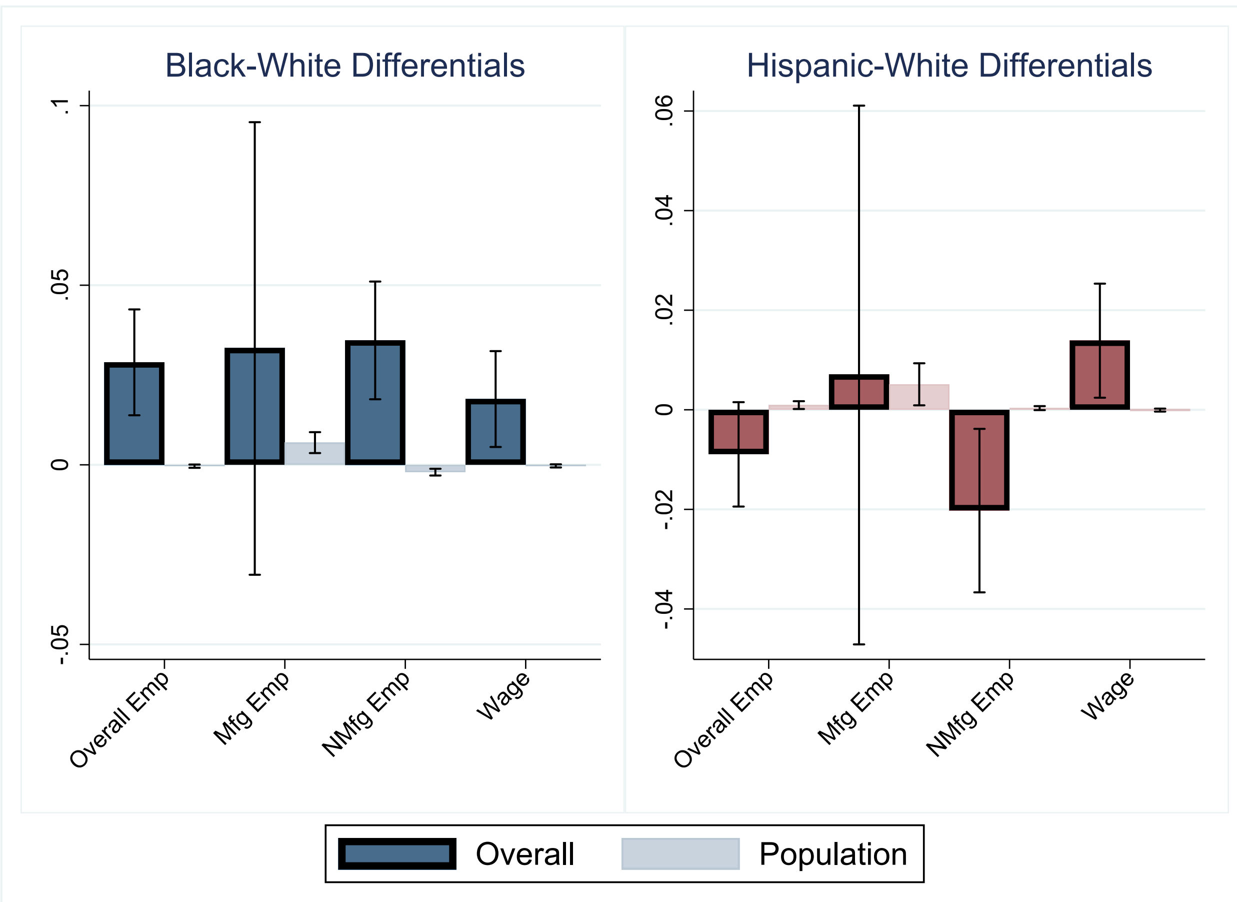
Figure 7 plots the minority-white differential for each dependent variable. We also plot the amount that is driven by population effects along with 90% confidence intervals. The amount driven by coefficient effects equals the difference between the overall effect and the population component.[34]

Beginning with the far left bar, we find that the overall Black-white employment-to-population gap narrows by 2.9 points due to the China shock. We find no role for population effects in this overall estimate. As shown with the next two sets of bars, population effects generate a non-

[33]We abstract away from the differences in exposure generated by differences in baseline industrial mix. As noted, in section 3, the group-specific ΔIP shock produces similar results in most instances, except for Hispanic non-manufacturing employment where the negative effect is actually driven by exposure of the white population.

[34]To estimate the population effect, we calculate a differential that fixes the coefficient effect to be the same for both groups and only allows for differences in population weights. We can use either the minority group coefficients or the white coefficients and in practice we present an average of the two different decompositions. We calculate bootstrapped standard errors with 1000 draws.

Figure 7: Overall Impacts of Import Exposure across Groups



Notes: We plot minority-white differentials for the overall fitted effects of import exposure for each dependent variable, as defined in equation 4. We also plot in the lighter shade the amount of the overall effect that is due solely to differences in population weights across CZs. The difference between solid and light bars is the amount attributable to coefficient effects. 90% confidence intervals are also shown.

trivial and positive differential manufacturing employment effect. Black workers experience a 3.3 percentage point smaller manufacturing employment decline, compared to what the average white worker experiences and the population effect accounts for about 20% of this offset.[35] Because Black workers live in less exposed areas, their population is spared somewhat from manufacturing employment losses. On the other hand, the population effect is negative for non-manufacturing employment: Black workers tend to experience relative gains in non-manufacturing employment in exposed locations, so the fact that they are less exposed means they benefit less from these gains. For overall employment, the positive population effect for manufacturing employment exactly offsets the negative population effect for non-manufacturing employment.

Hispanic workers also experience a positive population effect for manufacturing employment and, because they experience negative non-manufacturing employment effects, their lower exposure helps them there as well. For overall employment, we find population effects offset about a tenth of their negative differential in overall employment, though this differential is not significant.

Based on these decompositions, we conclude that the coefficient effects estimated in section 3 are more important than the differential exposures estimated in section 2.

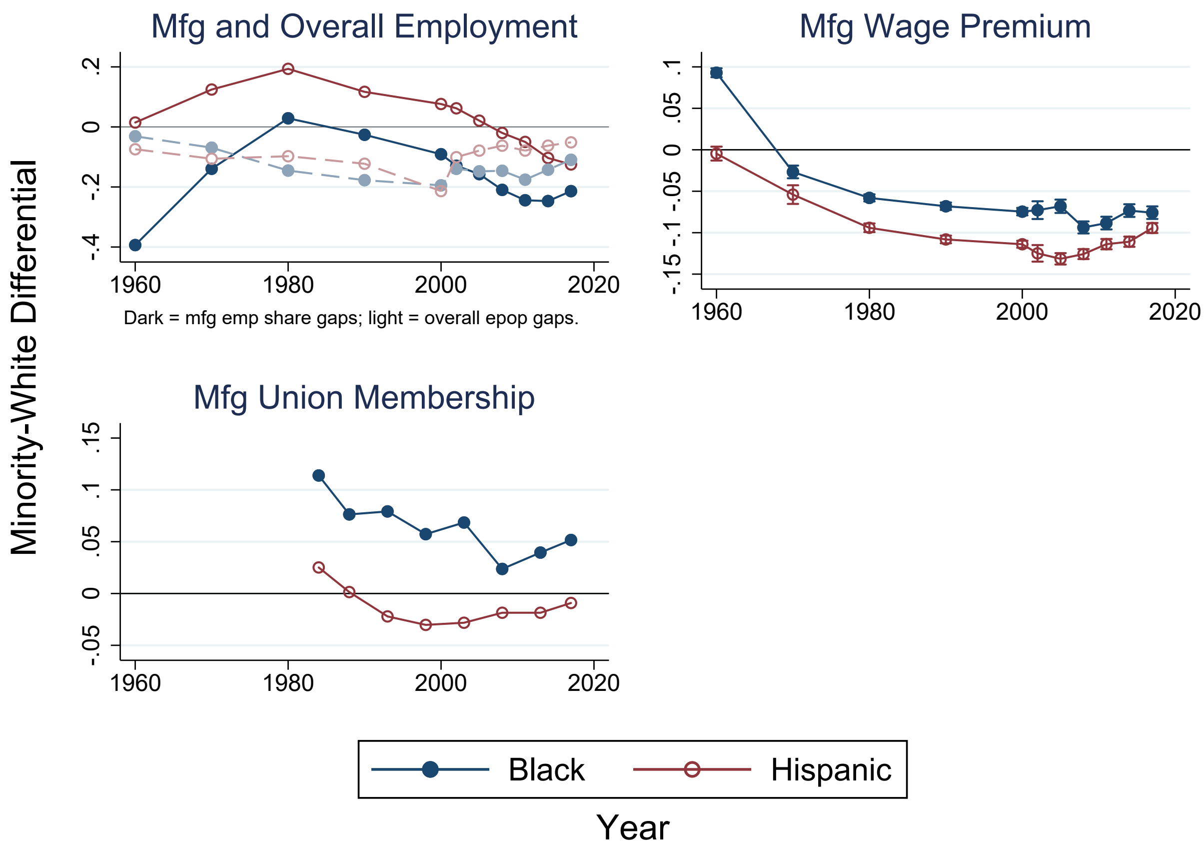
4.2 Minorities in Manufacturing: Historical Context

How were Black workers able to capture large gains in non-manufacturing employment, relative to white workers, with no wage losses, while Hispanic workers experienced short-lived but negative relative employment effects? Figure 8 considers a historical view of minority representation in manufacturing. Here we plot minority-white gaps in manufacturing employment shares and wage premia going back to 1960. We also show gaps in union representation within manufacturing, which became available in the Current Population Survey beginning in 1983.

Focusing first on the Black-white gap and the upper left figure, 1980 marks a turning point: after two decades of progress spurred in part by anti-discrimination legislation (Donohue and Heckman, 1991), Black workers had reached parity in manufacturing employment shares. However, this progress is immediately reversed such that by 2000, Black workers had gone from being about a point overrepresented in 1980 to almost two points underrepresented. This relative exit was likely due to a combination of automation shocks (Dicandia, 2021), disproportionate impacts of the trade shock with Japan (Batistich and Bond, 2023; Enriquez and Kurtulus, 2023), and secular manufacturing declines during that period (Gould, 2021). Previous work has explained the disproportionate

[35] Though not shown, we find that the fitted effect for white workers is -0.087 (0.021) in manufacturing, 0.0049 (0.0043) in non-manufacturing, -0.011 (0.0052) in overall employment and -0.0062 (0.0069) in hourly wages.

Figure 8: Minority-White Gaps in Manufacturing Outcomes



Notes: The upper left panel plots differences in log manufacturing employment share (dark lines) and log employment per adult population (light lines). The upper right plots gaps in log weekly wages among manufacturing workers estimated from regressions that control for state fixed effects and age (decade dummies)-sex-education (college dummy) interactions. Data sources for the top panel are Decennial censuses to measure data points from 1960-2000 and three-year averages of ACS waves. The bottom left panel uses current population survey data, averaged to 5-year bins.

negative impacts as due to observables such as occupation and educational attainment.

Though their relative exit from manufacturing continued after 2000, Black workers did not exhibit relative employment declines overall (light dashed line). That pattern is in contrast to the 1980-2000 period where the relative manufacturing decline of Black workers was accompanied by a widening of the Black-white employment-to-population gap. For the earlier period, Black workers were unable to make up their relative exit from manufacturing employment elsewhere. The figure thus supports the notion that by 2000, the Black workforce had a range of employment substitutes that were closer to their manufacturing jobs compared to white workers in 2000 or Black workers in the 1980s.

Table 4 provides further evidence of closer options outside of manufacturing for Black workers. Here we show job transitions in 2000 using the Census J2J database. First, Black workers made more job-to-job transitions overall than white workers. Second, Black workers were more likely to move to another sector when exiting a manufacturing job. About 76% of Black workers in manufacturing moved to non-manufacturing employment when making a job-to-job transition, compared to 68% of white and Hispanic workers. Third, Black workers also moved to non-employment at higher rates, though the gap with white workers is not nearly as large as that for Hispanic workers.

Table 4: Job Transitions

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

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

Minority workers are generally less attached to specific employers, and Black workers are especially less attached to their manufacturing jobs. This form of agility could come with disadvantages (e.g., less access to internal labor markets and lower human capital formation) but could help in weathering a localized manufacturing shock.

Why were Black workers exiting manufacturing at higher rates than white or Hispanic workers, even in 2000? Figure 8 provides two additional pieces of evidence that manufacturing rents had likely eroded for Black workers, relative to whites. From the bottom left panel, in the early 1980s, Black workers in manufacturing were more likely to be union members than white workers in manufacturing, but their relative likelihood of union membership fell during the 1980s, 1990s, and 2000s. Unions may facilitate greater rent sharing between management and workers. Patterns in relative manufacturing wage premia (top right) are also instructive.[36] Black workers earned similar wage premia in manufacturing to white workers at the beginning of the time period, but by 2000 the relative return for Black workers had eroded to well below the white premium. These premia are difficult to interpret given the large changes in relative supply happening over the same time period and the fact that it is difficult to infer economic rents, even from wage regressions. For instance, differences in job amenities across sectors and race groups could be important, as well as unobserved productivity. However, figure 8 as a whole paints a consistent picture that the Black workforce was much more invested in manufacturing in 1980 than it was in 2000.

That Black workers had lower employment shares in manufacturing, smaller wage premia, and declining union representation suggest rents were lower in manufacturing and therefore the existing nonmanufacturing jobs in the economy were more appealing.[37] Black workers would then have had less to lose when manufacturing was hit by a negative shock in 2000, compared to their position in the 1980s – a point at which they had high employment shares, high union representation and a more similar wage premium to that of whites. Indeed, Schmieder and von Wachter (2010) find that in mass layoff events, workers who hold higher economic rents are more likely to be laid off and suffer longer term wage consequences. The difference in economic rents in the manufacturing sector post-2000 could then rationalize the more negative response of white workers to the China shock.

Following the China shock, Black workers gained relative to white workers. Moreover, Black workers did not experience negative overall effects in exposed locations. Instead, point estimates for the overall impact on employment for Black workers are small and positive but not statistically distinguishable from zero. The China shock has been shown to have generated reallocation which could have occurred both across, but even within local labor markets.[38] Destruction of manufacturing jobs paved the way for growth in non-manufacturing endeavors. Above, we showed that this em-

[36]We estimate regressions of log weekly wages on race/ethnicity dummies and other controls (state fixed effects and age (decade dummies)-sex-college interactions) separately by year. We plot the race/ethnicity coefficients in the upper right panel of figure 8.

[37]A simple Roy model of self selection can rationalize that economic rents will be higher in the high return sector, the larger its employment share. When employment shares are higher, the average worker in the sector is one that is experiencing a much higher return than the marginal worker (Roy, 1951; Heckman and Honoré, 1990).

[38]See Bloom et al. (2019). More broadly, the idea that a large shock can result in reallocation is hardly new to economics and has been shown to be important for recessionary shocks (Schumpeter, 1939; Blanchard and Diamond, 1990; Davis and Haltiwanger, 1992; Hershbein and Kahn, 2018), competition shocks (Nickell, 1996; Syverson, 2004), and other trade shocks (Bernard et al., 2010; Bloom et al., 2015).

ployment growth was especially salient in the trade/transportation/warehousing, and professional services industries. By the time of the China shock, manufacturing was a much less important part of Black employment and Black workers were naturally more poised to take advantage of this growth.

Hispanic workers, in contrast, were over-represented in manufacturing, even in 2000. Their job-to-job transitions also reflect the fact that manufacturing was a much more important part of their employment than it was for Black workers: table 4 shows that Hispanic workers beginning in non-manufacturing employment were slightly more likely than Black or white workers to move to manufacturing when making a job-to-job transition, in addition to their overall larger mobility rates to other jobs and to non-employment.

Hispanic workers had a lower manufacturing wage premium, relative to white workers. This fact could explain why Hispanic workers do not experience relative wage losses in response to the China shock. As shown above, unlike for Black workers, the negative relative employment effects for Hispanic workers can largely be explained by observables. Hispanic workers have lower educational attainment than white workers, and less educated workers have been shown to be more vulnerable to the China shock. Hispanic workers were also overrepresented in construction at baseline, an industry that was especially hard hit, particularly around the Great Recession.

Taken together, the results presented above show not only how important it is to understand the different effects that import shocks will have on different racial and ethnic groups, but also how crucial understanding current and historical group-specific trends in demographics, industry representation, job attachment, and manufacturing wage premia are to contextualizing these differential responses. We show that, especially for Black workers, the landscape changed substantially over a half century. This context matters not just for researchers, but also for policy makers as they consider the potential effects that actions such as signing new trade agreements or escalating trade wars may have on racial and ethnic inequality.

5 Conclusion

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 or work in affected areas and industries. Black workers actually experienced relative benefits from this import competition in terms of increased employment in non-manufacturing industries. It is important to consider these results in the context of broader trends in racial and ethnic employment disparities. The Black-white employment and earnings gaps in the U.S. economy are large and have stagnated in recent decades. However, the China shock presents a modest force pushing against the many other factors driving these trends. We find convergence in the Black-white employment-to-population gap on the order of 30% of its 2018 level. According to some metrics, the China shock widened income inequality in exposed locations (Autor et al., 2014). However, it did not result in widening Black-white employment and income gaps, which is surprising in light of the typical comovement of overall inequality and Black-white gaps (Bayer and Charles, 2018).

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 was a moderate negative force undoing some of these recent gains, widening the Hispanic-white employment-to-population gap by about 20% of its 2018 level. 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 our research also points to a loss of manufacturing rents for white workers and a lack of close employment substitutes. The barriers to entry for high-paying non-manufacturing jobs could be high for some workers. Our findings then point to an even greater need for improving employment options for those impacted by trade, perhaps through retraining (Hyman, 2018) or wage insurance (Hyman et al., 2021). 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).

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

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A Appendix

A.1 Data Appendix

Census and American Community Survey Data

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

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

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

Defining Import Exposure

To calculate the CZ-wide import penetration measure (equation 1) we follow Autor et al. (2021) (hereafter ADH). We use trade data for 1997 to 2018 from the UN Comrade Database,[39] 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.[40]

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.[41] 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 (ind1990dd). Import

[39] https://comtrade.un.org
[40] https://www.nber.org/research/data/nber-ces-manufacturing-industry-database
[41] https://www.census.gov/programs-surveys/cbp/data.html

exposure then 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.

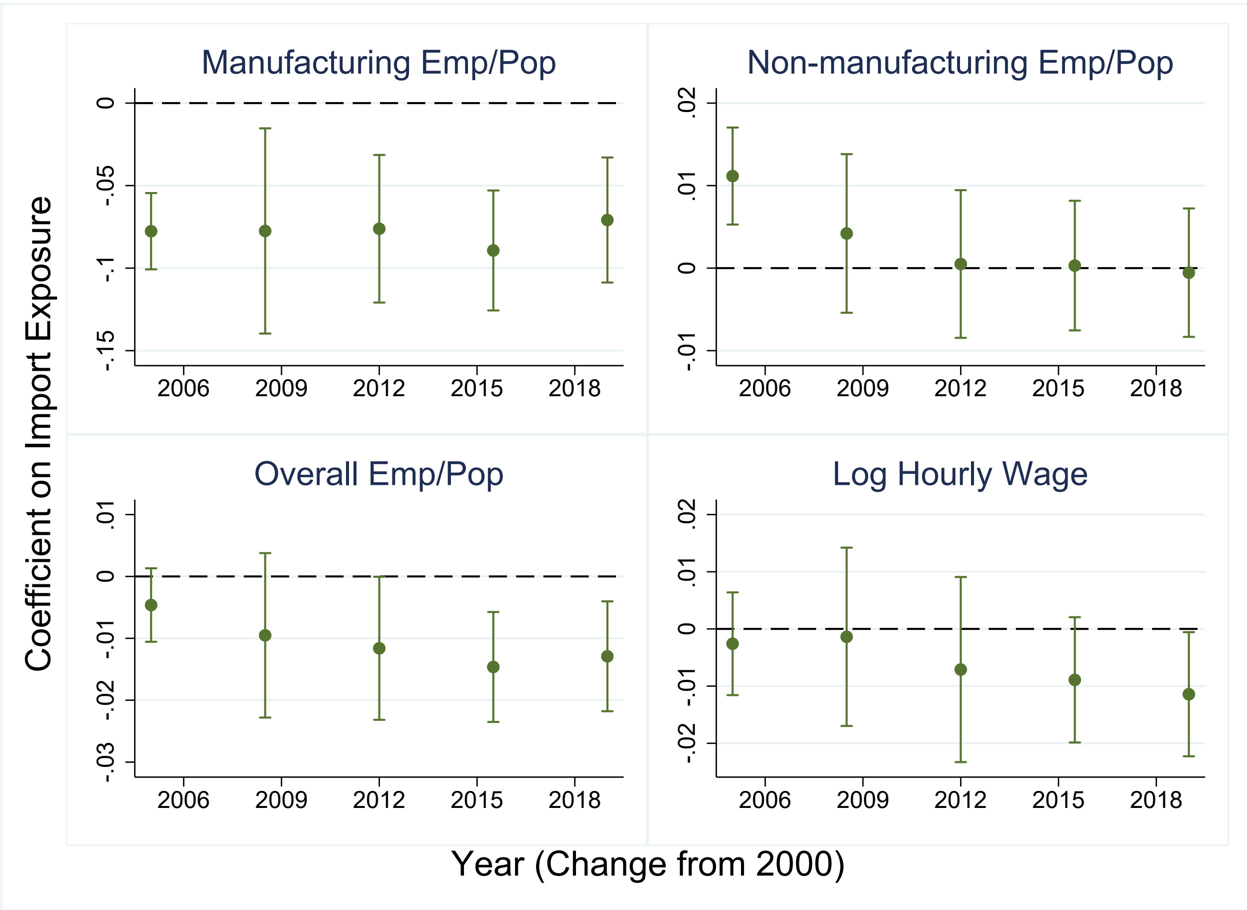
Job-to-Job Flows

For table 4, we derive race and ethnicity-specific quarterly job-to-job flows in year 2000 from the Job-to-Job Flows (J2J) Explorer[42], 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 sectors from the Quarterly Workforce Indicators (QWI)[43] for the same period. The QWI is also based on LEHD, so it should be consistent with J2J.

[42] https://j2jexplorer.ces.census.gov
[43] https://www.census.gov/data/developers/data-sets/qwi.html

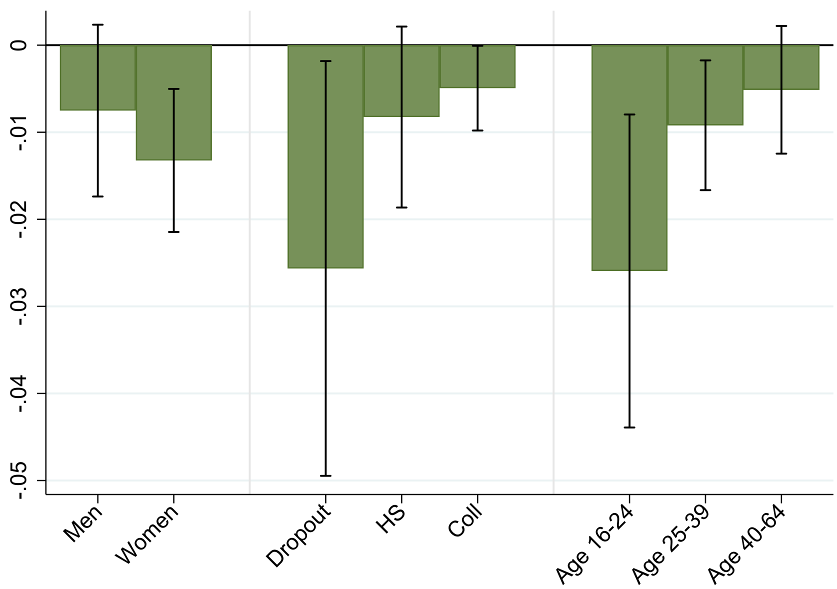
Additional Tables and Figures

Figure A.1: Import Exposure over Time: Effects on White Population



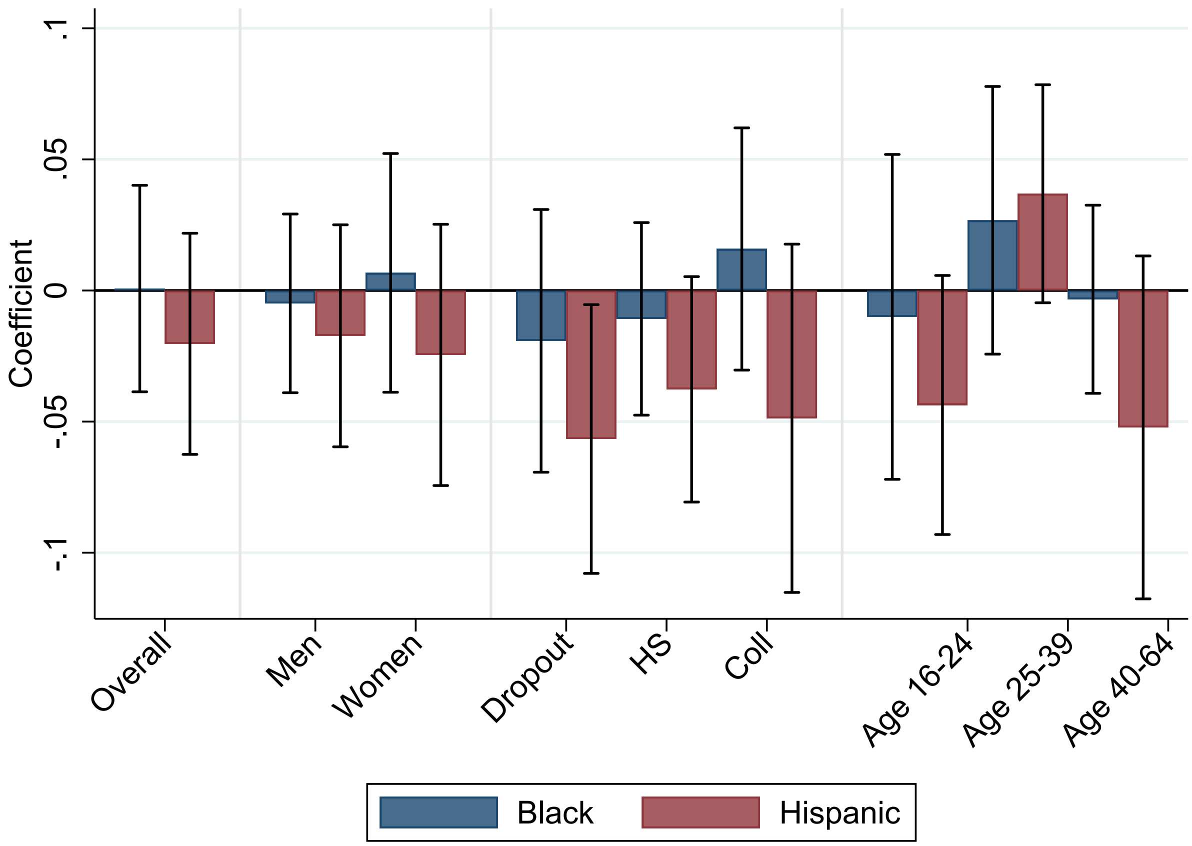
Notes: See figure 4. This figure plots coefficients on ΔIP – the impact on the white population – and their 90% confidence intervals.

Figure A.2: Impacts by Demographic Group: Effects on White Population



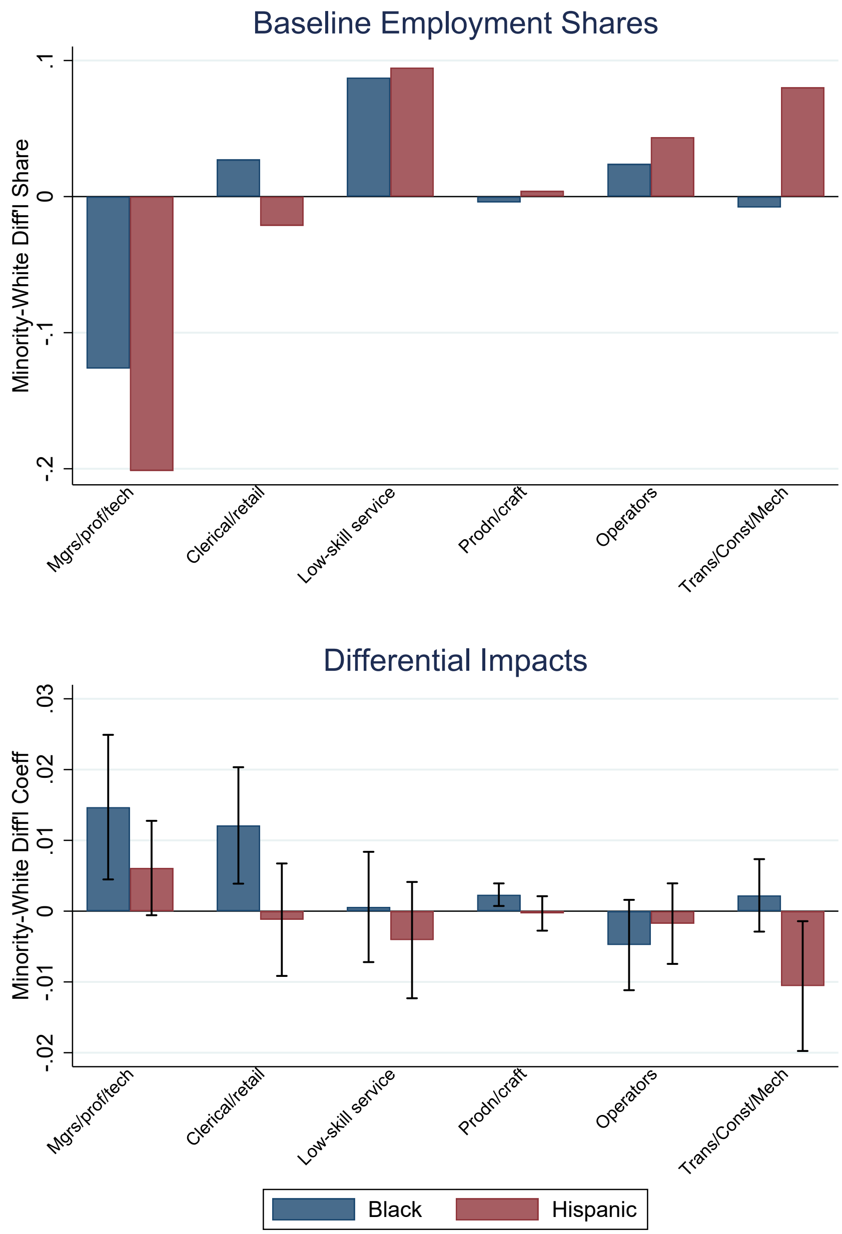
Notes: See figure 5. Here we plot the main effects of import competition on overall employment within demographic group, i.e., impacts on the white population. 90% confidence intervals are shown.

Figure A.3: Differential Impacts on log population counts



Notes: This figure plots coefficients on ΔIP*Black and ΔIP*Hispanic and their 90% confidence intervals. The dependent variable is the change in log population for the indicated group. Observations are limited to the working age population (age 16-64). We estimate equation 3, restricting the sample to years 2015 in order to allow time for any population changes to accrue.

Figure A.4: Minority-White Differences by Occupational Composition



Notes: The top panel reports minority-white differentials in the share of employment that is in a given occupation in 2000. The bottom panel reports minority-white differential impacts of CZ-wide import exposure on occupation-specific employment per adult population within the race/ethnic group. Occupation categories come from the Level 1 Autor and Dorn (2013) classification.

Table A.1: Summary Statistics

	White	Black	Hispanic
Group-specific ΔIP	0.844	0.719	1.026
	(0.483)	(0.604)	(0.570)
CZ-level ΔIP (ADH)	1.023	0.936	0.961
	(0.738)	(0.715)	(0.603)
Mfg Emp per pop, 2000	8.290	5.716	7.205
	(3.514)	(3.691)	(4.264)
Non-mfg Emp per pop, 2000	62.99	55.75	59.42
	(5.569)	(7.686)	(5.817)
Overall Emp per pop, 2000	71.28	61.47	66.63
	(4.946)	(6.118)	(4.804)
Log Hourly Wage, 2000	2.843	2.605	2.543
	(0.197)	(0.186)	(0.116)
Change in log Mfg Emp	-0.288	-0.396	-0.311
	(0.148)	(0.282)	(0.258)
Change in log Non-Mfg Emp	0.00694	0.0635	0.179
	(0.0381)	(0.0910)	(0.0918)
Change in log Overall Emp	-0.0324	0.0126	0.115
	(0.0366)	(0.0857)	(0.0707)
Change in log Hourly Wage	-0.224	-0.292	-0.245
	(0.0747)	(0.103)	(0.0770)
Obs in group-CZ-year cell	8202.6	2269.9	8422.3
	(7323.8)	(2197.9)	(10838.6)
Obs in group-CZ cell, 2000	39027.2	10845.6	32038.4
	(36536.2)	(10335.2)	(41129.2)
Group-CZ-year cells	10108	10054	10102

means; sd in parentheses

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

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

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

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

Table A.3: First Stage Regressions

	(1)	(2)	(3)
Panel A:	ADH Instrument		
Dependent Variable:	CZ-level ΔIP (ADH)		
CZ-level IV (ADH)	0.441***	0.422***	0.523***
	(0.070)	(0.064)	(0.062)
Observations	10,108	10,054	10,102
R-squared	0.668	0.665	0.799
F-stat on instrument	40	43	71
Panel B:	Chinese Import Share Instrument		
Dependent Variable:	CZ-level ΔIP (ADH)		
Chinese Shares IV	0.262***	0.291***	0.259***
	(0.031)	(0.028)	(0.021)
Observations	10,108	10,054	10,102
R-squared	0.695	0.719	0.812
F-stat on instrument	73	107	147
Panel C:	NTR Gap Instrument		
Dependent Variable:	CZ-level ΔIP (ADH)		
NTR Gap IV	0.085***	0.087***	0.102***
	(0.021)	(0.026)	(0.028)
Observations	10,108	10,054	10,102
R-squared	0.602	0.622	0.719
F-stat on instrument	16	11	13
Panel D:	Own-Group Shock		
Dependent Variable:	Group-level ΔIP (ADH)		
Group-specific Instrument	0.571***	0.408***	0.438***
	(0.057)	(0.036)	(0.034)
Observations	10,108	10,054	10,102
R-squared	0.804	0.795	0.718
F-stat on instrument	100	129	168
White	X		
Black		X	
Hispanic			X

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. Panel A uses as an instrument 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.4: 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.5: Impacts of Import Exposure: Alternative Identification Strategies

	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	Panel A					Panel B				
Dependent Variable:	Δ log Mfg Emp per Adult Pop					Δ log Non-Mfg Emp per Adult Pop				
CZ-level ΔIP (ADH)	-0.085***	-0.024***	-0.093***	-0.116***		0.005	0.006***	0.008**	0.007	
	(0.021)	(0.008)	(0.019)	(0.038)		(0.004)	(0.002)	(0.004)	(0.008)	
$\Delta IP * Black$	0.027	0.011	0.028	0.033		0.038***	0.010*	0.022**	0.040	
	(0.040)	(0.013)	(0.030)	(0.049)		(0.011)	(0.006)	(0.011)	(0.025)	
$\Delta IP * Hispanic$	0.002	-0.031**	0.031	-0.087		-0.021**	-0.003	-0.021	0.037	
	(0.033)	(0.015)	(0.028)	(0.073)		(0.010)	(0.010)	(0.014)	(0.030)	
NTR Gap					-0.980***					0.059
					(0.297)					(0.068)
NTR Gap*Black					0.262					0.352*
					(0.378)					(0.179)
NTR Gap*Hispanic					-1.093*					0.384
					(0.568)					(0.301)
Observations	26,772	26,772	26,772	26,772	26,772	30,105	30,105	30,105	30,105	30,105
	Panel C					Panel D				
Dependent Variable:	Δ log Employment per Adult Pop					Δ log Hourly Wages				
CZ-level ΔIP (ADH)	-0.010**	0.000	-0.012***	-0.025***		-0.006	-0.000	-0.010	-0.017	
	(0.005)	(0.002)	(0.004)	(0.009)		(0.007)	(0.002)	(0.006)	(0.011)	
$\Delta IP * Black$	0.030***	0.008**	0.019**	0.022		0.019**	0.001	0.013**	0.012	
	(0.010)	(0.003)	(0.008)	(0.018)		(0.009)	(0.002)	(0.006)	(0.018)	
$\Delta IP * Hispanic$	-0.010	-0.008*	-0.006	0.016		0.014**	0.000	0.012	0.048***	
	(0.007)	(0.005)	(0.007)	(0.017)		(0.007)	(0.004)	(0.008)	(0.017)	
NTR Gap					-0.209***					-0.144
					(0.066)					(0.094)
NTR Gap*Black					0.190					0.100
					(0.154)					(0.153)
NTR Gap*Hispanic					0.121					0.458***
					(0.181)					(0.132)
Observations	30,159	30,159	30,159	30,159	30,159	30,221	30,221	30,221	30,221	30,221
Main IV	X					X				
OLS		X					X			
Shares IV			X					X		
NTR IV				X					X	
NTR RF					X					X

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

Notes: Column 1 reproduces the column 1 specification from table 3. Column 2 estimates OLS regressions. Column 3 instruments with changes in Chinese market shares, rather than levels of imports, in other high income countries. Column 4 instruments for the shock and its group interactions with the NTR Gap and its group interactions. Column 5 uses the NTR Gap in the reduced form. Standard errors in parentheses clustered by state.

Table A.6: Impacts of Import Exposure: Group-specific Shock and Observables

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Panel A				Panel B			
Dependent Variable:	Δ log Mfg Emp per Adult Pop				Δ log Non-Mfg Emp per Adult Pop			
CZ-level ΔIP (ADH)	-0.085***			-0.082***	0.005			0.003
	(0.021)			(0.019)	(0.004)			(0.004)
$\Delta IP * Black$	0.027			0.027	0.038***			0.032***
	(0.040)			(0.033)	(0.011)			(0.012)
$\Delta IP * Hispanic$	0.002			0.018	-0.021**			-0.002
	(0.033)			(0.033)	(0.010)			(0.006)
Group-specific ΔIP		-0.093***	-0.050			0.015***	0.011	
		(0.024)	(0.043)			(0.006)	(0.009)	
$\Delta IP * Black$		0.017	-0.087			0.036***	0.040*	
		(0.032)	(0.074)			(0.011)	(0.023)	
$\Delta IP * Hispanic$		-0.011	-0.064			0.033**	0.058**	
		(0.060)	(0.095)			(0.016)	(0.023)	
Cross-group ΔIP			-0.041				0.004	
			(0.037)				(0.008)	
Cross $\Delta IP * Black$			0.130				-0.005	
			(0.085)				(0.027)	
Cross $\Delta IP * Hispanic$			0.070				-0.059***	
			(0.084)				(0.019)	
Observations	26,772	26,772	26,712	26,772	30,105	30,105	30,045	30,105
	Panel C				Panel D			
Dependent Variable:	Δ log Employment per Adult Pop				Δ log Hourly Wages			
CZ-level ΔIP (ADH)	-0.010**			-0.009*	-0.006			-0.003
	(0.005)			(0.005)	(0.007)			(0.005)
$\Delta IP * Black$	0.030***			0.025***	0.019**			0.016*
	(0.010)			(0.009)	(0.009)			(0.008)
$\Delta IP * Hispanic$	-0.010			-0.000	0.014**			0.013**
	(0.007)			(0.006)	(0.007)			(0.006)
Group-specific ΔIP		-0.011*	-0.017*			-0.009	-0.018*	
		(0.006)	(0.010)			(0.007)	(0.011)	
$\Delta IP * Black$		0.023**	0.011			0.011	0.009	
		(0.011)	(0.025)			(0.008)	(0.020)	
$\Delta IP * Hispanic$		0.016	0.034*			0.033***	0.050***	
		(0.011)	(0.020)			(0.009)	(0.017)	
Cross-group ΔIP			0.006				0.009	
			(0.009)				(0.012)	
Cross $\Delta IP * Black$			0.020				0.007	
			(0.028)				(0.021)	
Cross $\Delta IP * Hispanic$			-0.037**				-0.028	
			(0.017)				(0.020)	
Observations	30,159	30,159	30,099	30,159	30,221	30,221	30,161	30,221
Group-specific controls				X				X

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

Notes: 2SLS estimates. Column 1 reproduces the column 1 specification from table 3. Column 2 uses the group-specific import penetration shock (equation 2). Column 3 additionally controls for (instrumented) cross-group import exposure – minority observations use the white ΔIP while white observations use the population-weighted average of Black and Hispanic ΔIP. Column 4 revisits the CZ-wide shock but adds controls measured at the race/ethnicity level: college share, female employment share, age group distribution, manufacturing share, routine occupation share, and outsourcing index.