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ABSTRACT

Minority workers tend to be disproportionately harmed by negative economic shocks. Indeed, we show that Hispanic populations experienced worse employment losses due to import competition from China, relative to whites, largely due to lower education levels. In contrast, Black-white employment and wage gaps actually narrowed due to relative growth in non-manufacturing sectors. We show that Black workers were less attached to manufacturing by 2000, compared to whites, and were therefore more poised to take advantage of China shock induced reallocation to services. The lasting negative impacts of the China shock on exposed communities were primarily driven by white workers.

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1 Introduction

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, recessions, Covid-19, and 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 World Trade Organization (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. Autor et al. (2013) show that U.S. commuting zones (CZs) that were more exposed to import competition 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, displacement effects will also depend on differences in skill mixes, effects of discrimination, and differences in adaptability post displacement. That minority workers are more vulnerable to recessions (Hoynes et al., 2012), for instance, may imply worse impacts of the China shock due to these channels. However, the China shock generated reallocation towards other areas of the economy. These spillover effects could benefit minority workers if they are better poised to transition into the new jobs, compared to white workers.

In this paper, we document differences in exposure to import competition across Black, white, and Hispanic populations, finding that minority groups are slightly less exposed to the China shock due to where they live.[3] Using American Community Survey and Census data, we then examine whether the China shock differentially impacted minorities living in exposed CZs, compared to whites. We find that all groups experience similar magnitude reductions in manufacturing employment for a given sized shock. However, the estimates are noisy and we cannot rule out positive or negative differential impacts with precision.

With considerably more precision, we find that increased import competition generates sta-

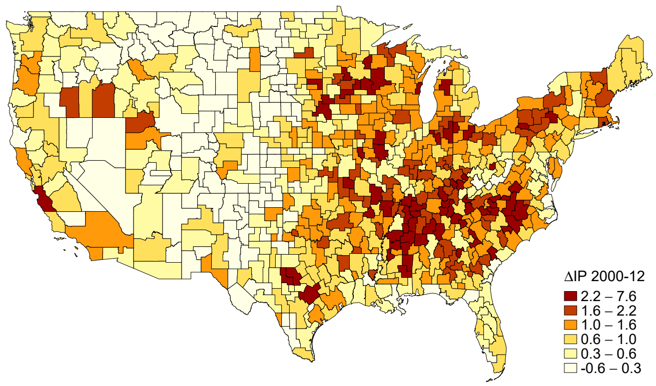
[1] See Dettling et al. (2017); Bayer and Charles (2018); Casey and Hardy (2018); McIntosh et al. (2020).

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

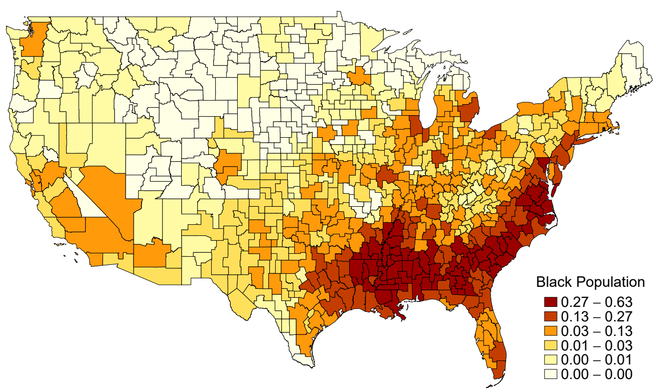
[3] We use the terms Black and white to refer to non-Hispanic Black and non-Hispanic white individuals.

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

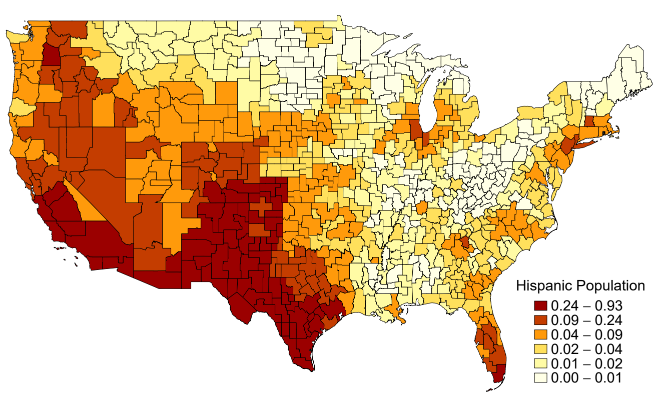
Panel A: Change in Import Exposure from China 2000-2012



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.

tistically significant *increases* in non-manufacturing employment for Black, relative to white, workers in exposed locations. Furthermore, overall Black-white employment-to-population and wage gaps narrow. These results are largely stable over time, and do not appear to be driven by educational, demographic or occupational differences across groups. Because of these relative gains in employment and wages, we find that differential geographic exposure (highlighted in figure 1) is not the most important factor – lower exposure shelters Black workers from manufacturing employment losses but also means they benefit less from non-manufacturing employment gains. Instead, differential responses for a given sized shock are the primary driver of the narrowing Black-white gaps. However, we do find a portion of the effects are driven by higher concentrations of Black workers in more resilient cities, as results attenuate somewhat when controlling for CZ fixed effects.

In contrast, Hispanic workers suffer larger hits to non-manufacturing employment as a result of the China shock, compared to white workers. The Hispanic-white employment-to-population gap widens, though, conditional on working, wage gaps do not. Differences in observables, namely educational attainment, appear to be important for Hispanic workers.

Ours is the first paper to look at the effects of the China shock across race and ethnic groups, to our knowledge.[4] A large body of literature has shown negative and surprisingly long-lasting relative impacts on manufacturing employment in locations exposed to import competition from China (Autor et al., 2013, 2014; Pierce and Schott, 2016; Autor et al., 2021) as well as a wide range of negative social and health consequences (Pierce and Schott, 2020; Autor et al., 2020, 2019).[5] 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), as well as from manufacturing to non-manufacturing employment within firms (Fort et al., 2018). Gains have primarily manifested in retail and wholesale trade, which provide a distribution mechanism

[4]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.

[5]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).

for getting imported goods to consumers, and in professional services as manufacturing companies take advantage of cheap overseas labor and shift their domestic focus to areas such as management, advertising, and design. To the extent that these changes occurred at a localized level, we should see the China shock coinciding with growth in these areas of employment.

Consistent with the literature on reallocation, we find that the disproportionate relative employment gains for Black workers manifest primarily in trade/transportation/warehousing and in professional services. Black workers appear to have shifted into exactly the sectors that should benefit most from China shock induced reallocation, while white workers did not. These patterns are in contrast to the 1980s and 1990s when Black workers were disproportionately harmed by manufacturing declines stemming from the Japan trade shock (Batistich and Bond, 2023; Enriquez and Kurtulus, 2023), automation (Dicandia, 2021), and general secular movement (Gould, 2021). In fact, the earlier shocks likely changed the role that manufacturing played for Black workers at the end of the 20th century. We show that by 2000, Black workers had been exiting manufacturing at faster rates than white workers, had experienced relative declines in their manufacturing wage premium, and experienced a relative reduction in unionization rates. These trends combined suggest manufacturing rents diminished for Black, relative to white, workers, which likely explains their greater ability to shift sectors in response to the China shock. Historical impacts from previous manufacturing declines were certainly harmful to Black workers at the time, yet because Black workers had already largely suffered the adjustment costs of exiting manufacturing, they were better positioned to take advantage of reallocation by the time the China shock hit. 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. Minority populations tend to earn lower wages, on average, and their employment rates are more cyclically sensitive (Hoynes et al., 2012). These patterns raise the concern that minorities 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 employment.

Black workers, in contrast, have experienced stagnating wage gaps with whites in recent decades and even widening employment gaps (Bayer and Charles, 2018).[6] Many trends over this time period have served to disadvantage the Black population including widening income inequality which exacerbates wage gaps (Juhn et al., 1993; Blau and Kahn, 1997) and rising incarceration and technological change which have depressed labor force participation of Black workers (Neal and Rick, 2014; Hurst et al., 2021). In this paper, we find that trade presents a modest force pushing in the opposite direction. Because Black workers were less attached to manufacturing, they could take better advantage of the offsetting positive effects generated by trade at a localized level. We find that in a 75th percentile exposed CZ, Black-white employment-to-population and wage gaps both narrow by roughly 10%, relative to a 25th percentile exposed CZ, due to the China shock.[7]

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 without negative 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 better safety net could play a role. However, it could also be that white workers who were anticipating high-rent manufacturing jobs now find few, if any, similar options available and leave the labor force as a result.

This paper proceeds as follows: Section 2 describes differential import exposure across race and ethnic groups. Section 3 describes our data and methods. Section 4 analyzes race and ethnicity-specific impacts on employment at the CZ-level and explores mechanisms. Section 5 discusses our results in the context of the historical position of minority workers in manufacturing. Section 6 concludes.

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

[7] Our findings complement two contemporaneous political science papers: Mutz et al. (2021) find that minorities are more supportive of trade than whites; 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, providing as a possible explanation that minorities were less impacted.

2 Differences in Import Exposure

To understand 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, 2021) (hereafter ADH). As such, we take as our unit of analysis the Commuting Zone (CZ) level. ADH measure the change in import competition for a CZ, c using equation 1. $\frac{Emp_{ic}}{Emp_c}$ is the share of CZ employment that is in industry i, measured in a benchmark time period. ΔM_i is the change in U.S. imports from China in industry i from the benchmark year to a chosen end date. These are normalized ($Norm_i$) by domestic absorption in the industry i (gross output plus imports minus exports) measured in the benchmark year. In other words, ADH allocate national industry-level shocks across CZs, depending on employment shares within the CZ in the benchmark time period.[8]

$$\Delta IP_c = \sum_i \frac{Emp_{ic}}{Emp_c} \frac{\Delta M_i}{Norm_i} \tag{1}$$

In practice, as in ADH, we will focus on the 2000 to 2012 change in imports because the benchmark year falls just before the rapid acceleration in imports from China, following their World Trade Organization (WTO) accession in 2001, and the 2012 end date falls just after the stabilization of import growth and the financial crisis of 2008.

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. We measure populations in the 2000 U.S. Census, focusing on three mutually exclusive (but not exhaustive) groups: the white non-Hispanic, Black non-Hispanic, and Hispanic populations.[9] Further data details can be found in the online appendix.

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.

[8]Note different race and ethnic groups within a CZ may face different levels of direct exposure depending on the mix of industries they are employed in at baseline. The CZ-wide measure in equation 1 abstracts away from this concept but we return to it in section 4.3.

[9]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.

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, Dallas, TX, 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).[10] The negative relationship is evident and strong in both magnitude and statistical significance.

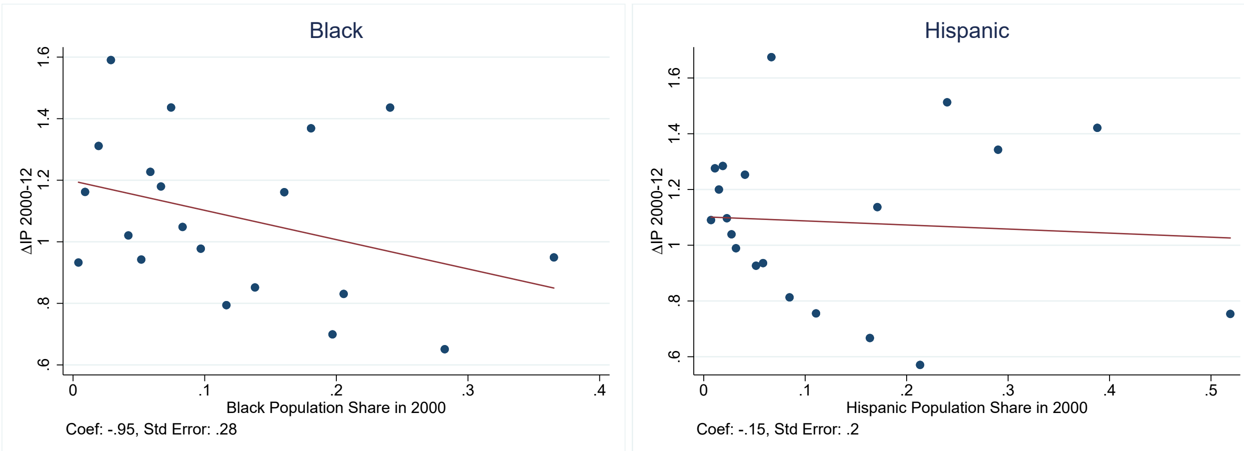
The Hispanic population is largely located in the southwest. Many cities in this area have among the highest increases in import exposure (e.g., San Jose and Los Angeles, CA, and Austin and Dallas, TX), while others (e.g., Las Vegas, NV) have low exposure. In addition, Hispanic population centers in 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 three of the rightmost datapoints (comprising 15% of the overall population) have very high Hispanic population shares and also high import exposure.

Online appendix table OA.1 provides summary statistics of our main variables by race and ethnicity. The average shock experienced by the white population is 1.1 with an interquartile range of roughly 0.75 (not shown). The Black and Hispanic populations experienced shocks of, on average, 1.01 and 1.06, respectively. White and Hispanic workers also had stronger representation in manufacturing in 2000 at 11% and 9.6% of their adult populations, compared to 8.3% for the Black population. As is well known, white workers were advantaged in terms of overall employment and wages in 2000. Their employment-to-adult population ratio (epop) was 74%, compared to 61% and 59% among the Black and Hispanic populations, respectively, while white log wages were on average 0.17 and 0.28 points higher compared to Black and Hispanic averages, respectively.

We will next examine employment impacts across white, Black, and Hispanic workers for a given sized CZ-level shock. Even though Black workers and, to a lesser extent, Hispanic workers live in communities that are less likely to be impacted by a trade shock, it could be

[10] Specifically, we divide CZs into 20 population-weighted bins based on their minority population share and plot the average minority population share and ΔIP within each bin.

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.

that minorities experience a disproportionate share of layoffs or a more difficult transition to other sectors for a given CZ level shock.

3 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 in a stacked sample of CZ-race/ethnicity group cells.

$$\begin{aligned} Y^s_{rct} - Y^s_{rc2000} = \beta^t_1 \Delta IP_c + \beta^t_2[\Delta IP_c * Black_r] + \beta^t_3[\Delta IP_c * Hispanic_r] \\ + \mathbf{X}_c \beta^t_4 + [\mathbf{X}_c * Black_r]\beta^t_5 + [\mathbf{X}_c * Hispanic_r]\beta^t_6 \\ + \beta^t_7 Black_r + \beta^t_8 Hispanic_r + \varepsilon_{rct} \end{aligned} \tag{2}$$

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.[11] We measure labor market variables by race or ethnic group, CZ, and year using American Community Survey data from 2005-2019.[12] Outcomes are expressed as the change relative to a 2000 benchmark, measured using the Census. We also use the 1980 and 1990 Censuses as detailed below. See the online appendix for detail.

Our primary regressors of interest are CZ-level import penetration from 2000-2012 (ΔIP_c in equation 1) and its group interactions ($\Delta IP_c * Black_r$ and $\Delta IP_c * Hispanic_r$, where $Black_r = 1$ if group r is Black and $Hispanic_r$ is analogous) which allow the effect of import penetration to differ in the Black and Hispanic populations. X_c is a vector of controls, which we describe below, and all of which are interacted with race and ethnicity indicators (we also include main effects for Black and Hispanic).

We estimate equation 2 separately for two different time periods. The first time period, which we refer to as 2010-2000, incorporates the short-run effects of the China shock, as Autor et al. (2021) have shown that Chinese imports stop rising after roughly 2010. To construct this interval, we use changes from the 2000 base year to outcomes measured in ACS survey waves from 2008-2013, taking an unweighted average across years. The second time period looks at changes from 2000 to an average over 2014-2019 (which we refer to as the 2016-2000 time period). This interval incorporates any long-run adjustment effects to the initial shock in addition to marginal impacts from new imports. This approach that first combines and then estimates effects on a snapshot set of years is standard in the literature using ACS data at the CZ-level (Autor et al., 2013, 2021) because it offers greater precision when working with survey data. While 3-year groupings are most commonly used, results are more stable across specification for the larger 6-year windows because of the greater disaggregation required for identifying race/ethnicity interaction effects in our context. However, we also show that our conclusions hold for the more disaggregated 3-year groupings (figure 3). For some analyses that split the sample further (e.g., by demographic subgroup), we gain additional precision by grouping all 12 years into a single aggregation (figures 4 and 5, appendix table A.2 and online appendix figure OA.1).

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.

[11] We use a change in logs specification, rather than levels (as some previous work as done), because populations differ in baseline employment rates and we wish to estimate the proportionality of responses.

[12] 2005 is the first year that the American Community Survey (ACS) includes the PUMA codes that we use to identify CZs and we stop our analysis after 2019 to avoid any COVID-related impacts.

While precision is a potential concern and some group-CZ-year cells comprise a small number of survey respondents, these cells have little influence given the population weighting, and so results are extremely robust to dropping small cells.

We can estimate equation 2 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. 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.[13] First-stage regressions can be found in online appendix table OA.2 for the main specification, as well as for other IV strategies detailed below.

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.[14] 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 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. 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.

We provide results that follow their shift-share instrumental variables approach (SSIV): using SSIV robust standard errors, clustering by three-digit SIC industry, and controlling for the manufacturing employment share in 1990 instead of 2000 to address the issue of incomplete

[13]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).

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

shares in the year the instrument is measured.[15]

Identifying β_2 and β_3 in equation 2 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 gain intuition for this assumption, table A.1 provides correlations between Black-white or Hispanic-white employment-to-population gaps in the preceding decades and the China shock. We also examine the 1980-90 pre-trend in these gaps.[16] We use the IV specification but include only group fixed effects as controls, since most other covariates are measured in the future or simultaneously with respect to these pre-period analyses.[17] We find that race gaps in 1980, 1990, and 2000 are uncorrelated with the China shock. We furthermore find that minority-white employment gaps were not trending over the 1980s in a manner correlated with the eventual China shock.

4 Import Exposure and Labor Market Outcomes

4.1 Main Results

Table 1 summarizes regression results for employment and wage outcomes across two time periods using our preferred specifications: the baseline in equation 2 (columns labeled 1) and the BHJ SSIV approach (columns 2).[18]

Beginning with panel A, estimates for manufacturing employment-to-population ratios, we find effects for the white population are negative and commensurate with those found by other researchers when examining the population as a whole.[19] The baseline effects are

[15]BHJ build on the work of Adao et al. (2019), who first raised the issue of correlated residuals across regions with similar sectoral shares in shift share regressions. An alternative approach by Goldsmith-Pinkham et al. (2020) shows how identification can be achieved assuming exogeneity of the shares, rather than the shifters. However, they argue this assumption is not apt for the China shock.

[16]Note the 1990-2000 pre-trend is not a clean test since some outcomes will be almost mechanically related to the instrument, which predicts China shock exposure applying employment shares in 2000 with employment shares in 1990.

[17]This approach is consistent with Autor et al. (2013), who also omit these controls when examining the correlation between the China shock and pre-period manufacturing employment growth.

[18]Sample sizes differ across columns and panels in table 1 for two reasons. First, the BHJ approach has race/ethnicity by 4-digit SIC industries as observations, rather than race/ethnicity-by-CZ. 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.

[19]For instance, Autor et al. (2021) find a 1 point drop in manufacturing employment over the long run

Table 1: The Impact of Import Exposure on Employment and Wages: Preferred

	Panel A				Panel B			
Dependent Variable:	Δ log Mfg Emp Rate				Δ log Non-Mfg Emp Rate			
Time Period:	2010-2000		2016-2000		2010-2000		2016-2000	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
ΔIP (ADH)	-0.069***	-0.042	-0.095***	-0.062**	0.002	0.002	0.003	0.001
	(0.023)	(0.026)	(0.027)	(0.025)	(0.004)	(0.006)	(0.004)	(0.006)
$\Delta IP * Black$	0.048	0.040	-0.003	-0.027	0.029**	0.024*	0.029***	0.023**
	(0.044)	(0.032)	(0.048)	(0.033)	(0.011)	(0.014)	(0.011)	(0.010)
$\Delta IP * Hispanic$	-0.001	0.009	-0.007	-0.005	-0.023**	-0.029*	-0.023*	-0.027
	(0.038)	(0.045)	(0.036)	(0.049)	(0.011)	(0.015)	(0.012)	(0.017)
T-stat Black overall	–0.45	–0.05	–1.98	–3.31	2.51	1.83	3.01	2.32
T-stat Hispanic overall	–1.93	–0.82	–2.79	–1.63	–1.73	–1.86	–1.39	–1.52
Observations	2,052	1,176	2,059	1,176	2,166	1,176	2,166	1,176
	Panel C				Panel D			
Dependent Variable:	Δ log Overall Emp Rate				Δ log Hourly Wages			
Time Period:	2010-2000		2016-2000		2010-2000		2016-2000	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
ΔIP (ADH)	-0.009*	-0.003	-0.013**	-0.006	-0.005	0.003	-0.009	-0.000
	(0.006)	(0.006)	(0.005)	(0.004)	(0.008)	(0.008)	(0.008)	(0.007)
$\Delta IP * Black$	0.028**	0.027*	0.019**	0.016**	0.029***	0.023*	0.035***	0.029
	(0.011)	(0.014)	(0.008)	(0.008)	(0.010)	(0.013)	(0.009)	(0.021)
$\Delta IP * Hispanic$	-0.011	-0.016*	-0.008	-0.011**	0.021**	0.010	0.017***	0.005
	(0.007)	(0.008)	(0.008)	(0.006)	(0.009)	(0.009)	(0.006)	(0.008)
T-stat Black overall	1.36	1.47	0.74	1.13	1.90	1.72	1.94	1.39
T-stat Hispanic overall	–2.54	–1.74	–2.16	–2.24	1.54	1.02	1.08	0.37
Observations	2,166	1,176	2,166	1,176	2,166	1,176	2,166	1,176
Main controls	X		X		X		X	
BHJ Approach		X		X		X		X

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

Notes: 2SLS estimates of equation 2 on group-CZ cells. We aggregate ACS waves into year groupings by taking averages over the following intervals: 2008-2013 (labeled 2010-2000) and 2014-2019 (2016-2000), restricting 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 14. Columns labeled 2 follow the Borusyak et al. (2022) approach: observations are at the group-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.

across the 75th and 25th percentiles of exposure (using their decadalized measure). To make this number comparable to our functional form (changes in logs), we note that their estimate is about 10% of their baseline mean. Our column 1 long-run estimate for the white population applied to the inter-quartile range significant at the 1% level in both time periods, while, as has been shown, effects are less robust to the BHJ approach with falling magnitudes and statistical significance. However, these main effects are not our focus.

Coefficients on the interaction terms are noisily estimated for the manufacturing sector. For Hispanic-white differentials, point estimates are very close to zero across both time periods and specifications. Black-white point estimates are large and positive in the early period but not in the long-run. Generally our results point to no strong evidence that Black or Hispanic workers suffer *worse* manufacturing employment losses for a given exposure. However, confidence intervals are such that we cannot rule out a positive or negative 0.08 differential impact with 90% confidence for either group. Estimating impacts by subgroup and sector of employment are especially difficult using survey data and we next turn to broader employment and wage effects where we can obtain more precision.

For non-manufacturing employment-to-population ratios (panel B), 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 and effects are stable across the short- and long-run. Using the baseline specification, we estimate a 2.9 percentage point larger increase in the Black non-manufacturing employment rate of change, relative to the white, in a one unit more exposed CZ. Effects are significant at the 5% level or better. Results are fairly robust to the BHJ approach though magnitudes fall slightly and are slightly less statistically significant. We therefore find that that Black workers experience non-manufacturing employment gains, relative to their white counterparts, when a CZ experiences an import shock.

The Hispanic interaction terms, in contrast, are negative and marginally significant; Hispanic workers experience a 2.3 percentage point worse non-manufacturing employment loss, compared to white workers, though the results are again noisier when applying the BHJ correction, such that the long-run estimate is insignificant at conventional levels. Thus, we have suggestive evidence that Hispanic workers fare worse on non-manufacturing employment, relative to their white counterparts, when a CZ experiences an import shock.

Next panel C of table 1 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 roughly 1 point that widens across the two time periods, consistent with previous work.[20]

is about 7% (0.095*0.75), which is similar in magnitude to their 10% estimate on the population as a whole.

[20]Our column 1 long-run estimate for the white population implies a roughly 1% drop across the interquartile range of exposure (0.013*.75). Even though our sample and functional form are different, this

Though these main effects are not robust to the BHJ correction, again as is known.

The Black-white differential for the overall employment-to-population ratio is positive and significant. The combination of similar manufacturing point estimates and positive impacts on non-manufacturing employment sum to relative improvements in overall employment for Black workers. Effects are similar across baseline and BHJ specifications. The short-run effects are a bit larger in magnitude than the long-run effects indicating some convergence in race gaps as CZs adapt to the China shock. Still, our estimates imply that in a 75th percentile exposed CZ, the Black-white employment-to-population gap narrows by over a point in the long run, relative to a 25th percentile exposed CZ. That reflects convergence on the order of 10% of the mean gap around this time period.

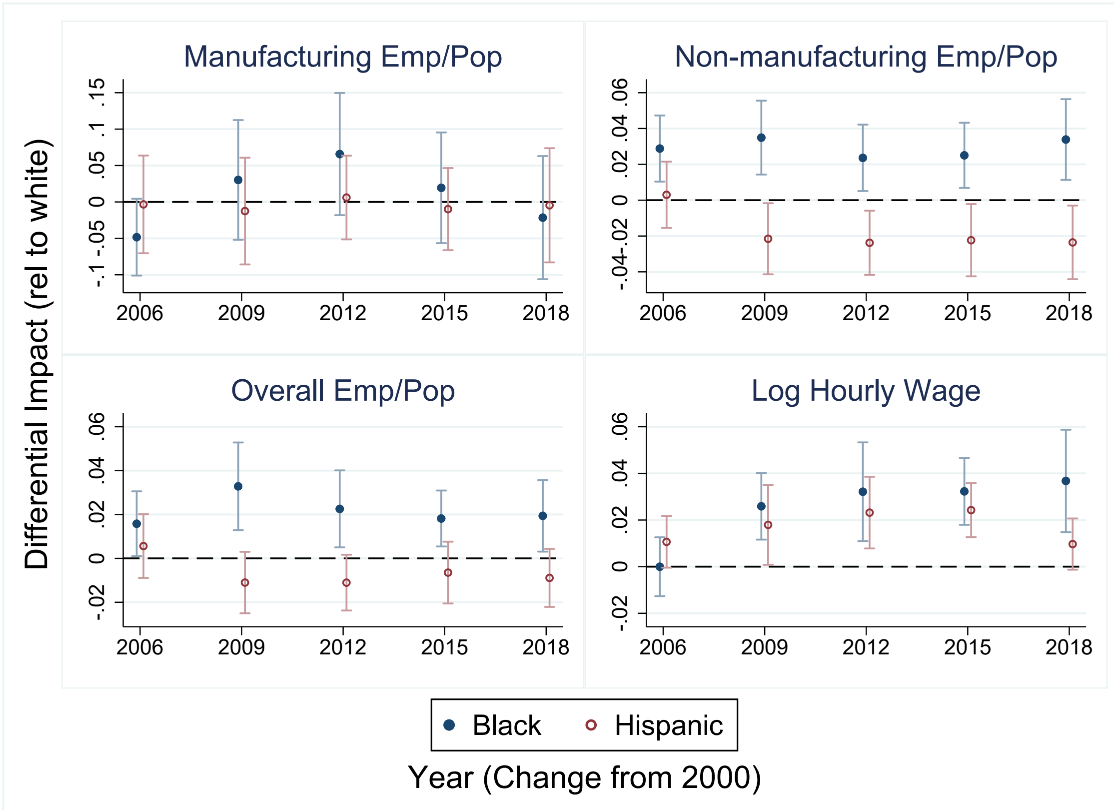
The Hispanic-white differential is roughly -0.01 across specifications and indicates that Hispanic workers living in exposed areas experience twice the employment loss of the white population, though the effects are insignificant in the baseline specification.

Finally, panel D examines effects on wages per hour worked. While the main effect is close to zero and insignificant, the differentials are both positive. In a 75th percentile exposed CZ, Black-white wage gaps narrow by roughly 2 points, compared to those in a 25th percentile CZ. That magnitude is roughly 10% of the Black-white wage gap around this time period. Effects are strongly significant in the baseline specification and magnitudes widen over time. The BHJ approach produces similar magnitudes that are significant at the 10% level in the short-run. In the insignificant long-run BHJ specification, we can rule out differential wage *losses* beyond roughly 0.3 points with 90% confidence. These effects are particularly striking given the employment effects we find: because Black workers experience relative increases in employment, we might expect employed Black workers to be negatively selected relative to employed white workers, yet they still make wage gains.

For Hispanic-white wage gaps we find mixed evidence with positive and significant point estimates across time periods in the baseline specification but small and insignificant estimates with the BHJ approach. Still, we can again rule out relative wage *losses* outside 0.8 points at most with 90% confidence. Because we find Hispanic workers suffer larger employment losses, relative to white workers, those remaining in the labor force could be positively selected and such selection could rationalize the suggestive positive wage differentials.

estimate is comparable to Autor et al. (2021) who find a 0.8 point drop in overall employment over the long run, which to make comparable to our estimate, we note is 1% off their baseline mean.

Figure 3: Differential Impacts of Import Exposure over Time



Notes: See column 1 in table 1. Here we first aggregate annual observations into 3-year groupings by taking averages over the following intervals: 2005-7, 2008-10, 2011-13, 2014-16, and 2017-19. Next we estimate separate regressions for each year group. This figure plots the coefficients on ΔIP*Black and ΔIP*Hispanic and 90% confidence intervals.

In summary, we find that the China shock generated convergence in Black-white employment and wage gaps, while we find suggestive evidence of widening Hispanic-white employment gaps. Figure 3 shows that these conclusions are fairly stable across the time period studied and not sensitive to the particular time windows selected. Here we plot Black-white and Hispanic-white differential impacts for 3-year groupings from 2005-2019, using the baseline specification.

When paired with the differences in exposure illustrated in section 2, we note that on average Hispanic workers will be a bit less impacted by the negative manufacturing and overall employment differentials because of their geographic representation but the exposure impact is small. For Black workers, their lower exposure shelters them from manufacturing employment losses but, on the other hand, means they benefit less from non-manufacturing employment gains in exposed locations. So for the Black population as a whole, the exposure effects wash out.

The positive effects on employment and wages for Black workers are quite striking in that summing the main effects and Black-white differentials yields positive point estimates. In the long-run, a Black worker in a more exposed CZ has a roughly 1% employment increase and more than 2% wage increase, relative to one in a less exposed CZ. The t-statistics in the bottom rows of table 1 indicate that these overall effects are not statistically significant for the most part. Still, why might exposed Black workers gain when their labor market as a whole was hit? Even while the China shock could generate negative spillover effects outside of manufacturing, companies benefiting from cheap overseas labor might expand their local employment in non-production activities. A broader literature on import competition finds evidence of such sectoral reallocation, especially concentrated within retail and wholesale trade and in professional services. Retail and wholesale trade serve as distribution mechanisms for getting imported goods from China to U.S. customers, and manufacturing companies shift their focus in the U.S. toward professional services (such as advertising and design). There is empirical support for this kind of reallocation, even within firm and/or at a localized level (Fort et al., 2018; Bloom et al., 2019; Bernard et al., 2010; Bernard and Fort, 2015, 2017). Thus import competition will generate winners as well as losers, even within a CZ.[21]

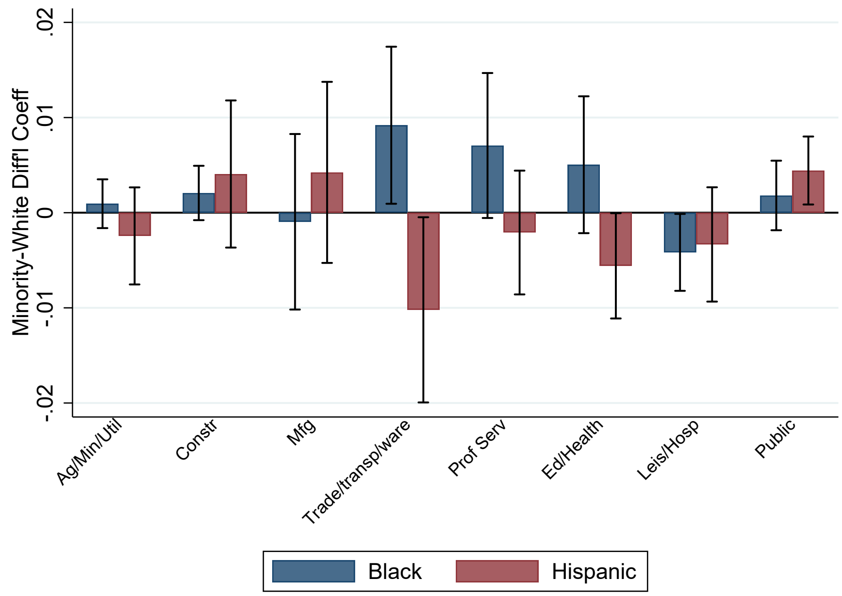
To better understand these reallocation channels, we decompose employment effects across major industry categories and plot the Black-white and Hispanic-white differentials in figure 4. We structure our analysis so that the differential impacts across industries will approximately sum to the differential impacts on overall employment.[22] These decompositions demand a lot of our data, so to gain power, we aggregate across the short- and long-run time periods, taking an unweighted average across 2008-2019. Even aggregating across a 12 year timespan, precision is an issue – as indicated by the 90% confidence bands – so these results are merely suggestive.

We find the largest gains for Black workers within the trade/transportation/warehousing

[21] 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).

[22] Specifically, because table 1 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 in the sector-specific employment rate, expressed as a fraction of the overall employment rate.

Figure 4: Minority-White Differential Impacts by Industry



Notes: We report minority-white differential impacts of import exposure on industry-specific employment. 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). Outcomes are the group-specific change from 2000 in industry employment per population expressed as a fraction of the overall employment-to-population ratio in 2000 so that these effects across industries will roughly sum to the effect on overall employment.

category, which includes retail and wholesale, as well as professional services industries. Together these account for about three-quarters of the overall Black-white employment differential. These areas of relative growth are consistent with the broader literature on sectoral reallocation. Hispanic workers, in contrast showed the largest losses in trade/transportation/warehousing as well as in education and health services.

Figure OA.1 in the online appendix conducts a similar exercise by broad occupation groups and reinforces the industry-level patterns: Black workers experienced significant relative gains in both managerial/professional/technical and clerical/retail occupations. The fact that we find Black relative gains exactly in the areas of the economy that would be predicted due to China shock-induced reallocation is reassuring evidence that the employment gains we estimate are indeed driven by the China shock and not some unrelated channel. Furthermore, these patterns help rationalize why our evidence points to, if anything, positive impacts on more, compared to less, exposed Black workers overall. To the extent that reallocative forces were at play within CZ's, we show that it was Black workers who were better able to take advantage of them. We explore reasons why Black workers may have been more likely than white workers to take advantage of these shifts in section 5.

4.2 Alternative Identification Strategies

Online appendix table OA.3 includes the results of several alternative identification strategies. Columns labeled 1 replicate our primary specification for comparison. Column 2 shows OLS estimates. 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. Also the positive differential employment effects for Black workers appear to fade out in the long-run and there is no evidence of differential wage effects when using OLS. The literature has tended to focus exclusively on the 2SLS results so we emphasize those conclusions in this paper. An additional benefit of the IV strategy in this setting is that it can help to reduce measurement error since we use one (potentially noisy) measure of exposure to instrument for another. Splitting the samples by CZ and race/ethnicity place even more demands on the data than the original China shock papers so our approach might then benefit more from addressing any measurement error.

Column 3 uses an alternative IV strategy. One concern with our IV approach, which follows ADH, is that it might not remove all of the potential bias if demand shocks are correlated across countries. In our context, this bias could also 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 U.S. and foreign demand shocks. For robustness, we follow Antras et al. (2017) and use changes in Chinese market shares, rather than levels of imports, in other high income countries as an instrument. The intuition is that the market share will be generated by Chinese comparative advantage even if the level is driven by demand shocks. Reassuringly, this approach produces very similar conclusions.

Column 4 uses an IV that follows the approach of Handley and Limão (2017) and Pierce and Schott (2016), leveraging changes in expected tariffs when the U.S. granted Permanent Normal Trade Relations (NTR) to China. We construct a CZ-level instrument that uses industry-level differences between NTR and non-NTR tariff rates (the NTR gap) instead of industry-level changes in imports in equation 1 and applies these to baseline employment shares. For the main effects, this approach produces more negative manufacturing and overall employment results. Point-estimates on the Black-white differentials are similar to our preferred estimates, though they are substantially noisier so that most of the differential effects are not statistically significant. And, while again imprecise, the Hispanic-white gap in overall employment becomes opposite signed. However, a downside of the NTR IV applied to our setting is that the instrument is fairly weak with F-stats at 9 for each of the minority groups (appendix table OA.2), so power is limited.

4.3 Heterogeneity by Observables

Black and Hispanic workers differ not only in their geographic clustering – as highlighted above – but also along a wide range of observables including basic demographics and the jobs they tend to hold. In this subsection, we explore whether these differences can help account for our findings.

Geographic Differences

Black and Hispanic populations may experience the China shock differently because they are geographically clustered in certain parts of the country. A main concern over this time period is the Great Recession (GR), which disproportionately impacted minorities (Hoynes et al., 2012) and had some degree of spatial heterogeneity. Effects in figure 3 emerge only around the 2008-10 window and though they persist well after the recession ends, we cannot thus far rule out the possibility that the China shock and local-level GR shocks interact to produce race differences.

In columns 1 and 2 of table 2, we compare our main specification (column 1 of table 1) to one that controls for a CZ-level GR shock interacted with race/ethnicity. We follow Autor et al. (2021) and Yagan (2019) and use a Bartik-style shock that predicts a CZ's employment loss between 2006 and 2009 with baseline industry shares and nationwide employment changes by industry. We find results are nearly identical with the inclusion of these controls. While there is an unconditional positive correlation between the China shock and the GR shock at the CZ level, once the usual controls are included there is no longer a correlation.

Next, it could be that Black (Hispanic) workers tend to live in locations that overall experience a less (more) negative impact of the China shock. For instance, Bloom et al. (2019) posit that the impacts of the China shock were less negative in larger cities and these would be locations where minorities tend to cluster. To explore this story, we add CZ fixed ef-

Table 2: Import Exposure and Employment and Wage Outcomes: Robustness

Time Period:	2010-2000					2016-2000				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Δ log Mfg Emp Rate									
ΔIP (ADH)	-0.069***	-0.063***		-0.068***	-0.056***	-0.095***	-0.092***		-0.095***	-0.068***
	(0.023)	(0.021)		(0.021)	(0.015)	(0.027)	(0.026)		(0.026)	(0.020)
$\Delta IP * Black$	0.048	0.036	0.006	0.043	0.001	-0.003	-0.002	-0.037	-0.001	-0.008
	(0.044)	(0.044)	(0.049)	(0.040)	(0.029)	(0.048)	(0.047)	(0.050)	(0.044)	(0.028)
$\Delta IP * Hispanic$	-0.001	-0.006	0.021	0.013	-0.036	-0.007	-0.009	0.008	0.010	-0.069
	(0.038)	(0.038)	(0.040)	(0.035)	(0.037)	(0.036)	(0.036)	(0.031)	(0.036)	(0.052)
Observations	2,052	2,052	2,052	2,052	2,052	2,059	2,059	2,059	2,059	2,059
Dependent Variable:	Δ log Non-Mfg Emp Rate									
ΔIP (ADH)	0.002	0.003		0.002	0.005	0.003	0.003		0.002	0.007
	(0.004)	(0.004)		(0.004)	(0.004)	(0.004)	(0.004)		(0.004)	(0.005)
$\Delta IP * Black$	0.029**	0.026***	0.017	0.023*	0.022***	0.029***	0.029***	0.020*	0.022**	0.021***
	(0.011)	(0.010)	(0.011)	(0.013)	(0.008)	(0.011)	(0.011)	(0.010)	(0.011)	(0.007)
$\Delta IP * Hispanic$	-0.023**	-0.024**	-0.028**	-0.006	0.029**	-0.023*	-0.023*	-0.029**	-0.008	0.034**
	(0.011)	(0.010)	(0.012)	(0.006)	(0.013)	(0.012)	(0.012)	(0.013)	(0.007)	(0.015)
Observations	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166
Dependent Variable:	Δ log Overall Emp Rate									
ΔIP (ADH)	-0.009*	-0.007		-0.009*	-0.007*	-0.013**	-0.012**		-0.012***	-0.007**
	(0.006)	(0.005)		(0.005)	(0.004)	(0.005)	(0.005)		(0.004)	(0.004)
$\Delta IP * Black$	0.028**	0.021***	0.010	0.023**	0.015*	0.019**	0.016**	0.004	0.014**	0.008
	(0.011)	(0.008)	(0.009)	(0.010)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.005)
$\Delta IP * Hispanic$	-0.011	-0.013*	-0.013	-0.000	0.016*	-0.008	-0.008	-0.010	-0.000	0.011
	(0.007)	(0.007)	(0.008)	(0.007)	(0.009)	(0.008)	(0.008)	(0.007)	(0.006)	(0.009)
Observations	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166
Dependent Variable:	Δ log Hourly Wages									
ΔIP (ADH)	-0.005	-0.003		-0.004	-0.007	-0.009	-0.007		-0.009*	-0.009*
	(0.008)	(0.008)		(0.005)	(0.005)	(0.008)	(0.008)		(0.005)	(0.005)
$\Delta IP * Black$	0.029***	0.025***	0.020**	0.025***	0.009	0.035***	0.029***	0.022***	0.034***	0.018***
	(0.010)	(0.009)	(0.008)	(0.009)	(0.006)	(0.009)	(0.007)	(0.007)	(0.010)	(0.006)
$\Delta IP * Hispanic$	0.021**	0.019**	0.029***	0.023***	0.032***	0.017***	0.015***	0.020**	0.018***	0.028***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)
Observations	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166
Main Controls	X	X	X	X	X	X	X	X	X	X
GR Controls		X					X			
CZ FEs			X					X		
Group-Specific Controls				X					X	
Group-Specific Shock					X					X

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

Notes: Columns labeled 1 reproduce the 1 spec from table 1. Columns 2 add to the baseline (column 1) controls for the CZ-level Great Recession employment shock interacted with group dummies. Columns 3 add to the baseline CZ fixed effects. Columns 4 include controls measured at the race/ethnicity level: college share, female employment share, age group distribution, manufacturing share, routine occupation share, and outsourcing index. Columns 5 replace the CZ-level ΔIP and its group interactions with group-specific import exposure ($\Delta IP_{rct} = \sum_i \frac{Emp_{irc}}{Emp_{rc}} \frac{\Delta M_{it}}{Norm_i}$).

fects to the baseline specification. We can no longer identify the main effect on the white population but can still identify the differentials.

In column 3 of table 2, for manufacturing employment, we still find noisy interactions that are difficult to draw strong conclusions from. For non-manufacturing employment, we find that magnitudes on the Black-white differentials fall by roughly one-third, are no longer significant in the short-run and are marginally significant in the long-run. Effects on overall employment-to-population are much smaller and insignificant. Effects on Black-white wage differentials are still strongly significant but fall in magnitude by about one-third. Furthermore, we can reject that the Black-white differential effects are the same across the baseline and CZ fixed effects specifications with at least 90% confidence for all three employment categories and hourly wages. Hispanic-white differentials are quite similar with the inclusion of CZ fixed effects; for all outcomes we cannot reject that they equal the baseline specifications.

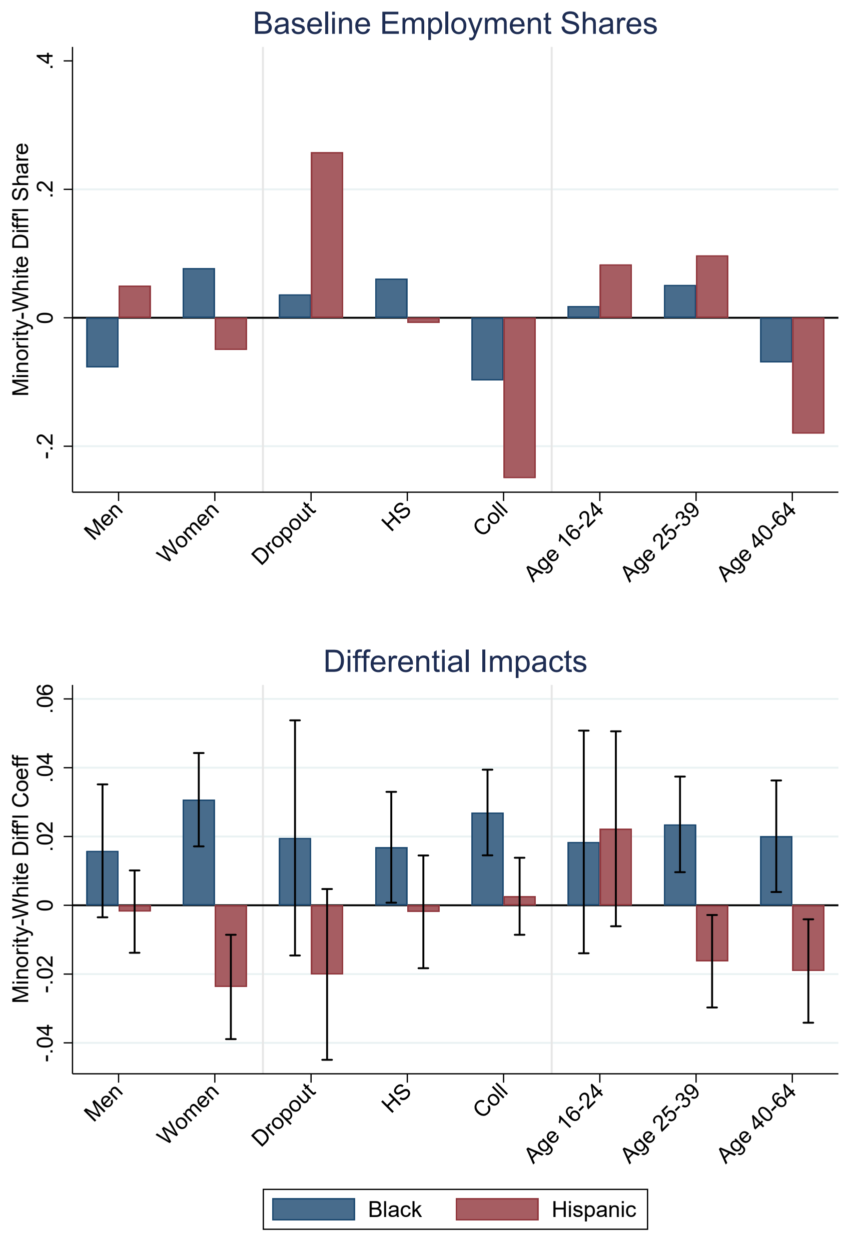
So it does appear that the Black-white differential effects are in part driven by heterogeneity in impacts of the China shock across CZ's and a concentration of Black population in less responsive areas. To provide further intuition, we split the sample of CZs evenly by whether they have above median Black or Hispanic population share (appendix table A.2). We do find that in locations with relatively high Black population shares, white workers are also somewhat sheltered. However, we also find that in high Hispanic population areas, white workers again fare better than their counterparts in low Hispanic share areas, going in the opposite direction of our finding of worse impacts on Hispanic populations.

The Bloom et al. point is that some cities had better conditions for taking advantage of growth in spillover sectors, namely larger cities that have highly educated populations and are on the coasts. Black overrepresentation in such CZs can account for part of our effect. Within CZ's, Black workers benefit from spillovers to non-manufacturing employment and wage growth, at roughly two-thirds the magnitude of our overall impacts, though overall effects load primarily on wages, rather than employment.

Basic Demographics

Groups also differ on a range of baseline demographics that have been shown to matter for resiliency to the China shock. In the top panel of Figure 5, we plot minority-white differentials in the fraction of employment across characteristics in the baseline period, 2000. Black workers are more likely to be female than white workers, while Hispanic workers are more likely to be 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

Figure 5: Differences in Observables



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 2 for the overall employment outcome, restricting to the indicated subpopulation. We take an unweighted average of outcomes across the full time period explored in table 1: 2008-2019. We plot coefficients on $\Delta IP * Black$ and $\Delta IP * Hispanic$, as well as 90% confidence bars.

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, minorities may be overrepresented among demographic groups that we should expect to fare worse in response to an import shock. Workers with less education have been shown to be particularly vulnerable to the China shock (Autor et al., 2013, 2021; Eriksson et al., 2021). We perform a simple back of the envelope calculation based on our own estimates of impacts across education group on the white population (not shown) and the group-specific distributions from the top panel of figure 5. For Hispanic workers, we find that differences in educational attainment can account for about two-thirds of the -0.01 differential effect on overall employment that we found in table 1. Differences in the age distribution can account for some of the effect as well (roughly 20%), since young workers bear the brunt of the China shock and the Hispanic workforce is substantially younger. In contrast, these demographic shares cannot account for the positive Black-white differentials we find since they would imply effects in the opposite direction.[23]

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 this channel, we estimate equation 2 for the employment-to-population outcome, but limit the sample to the indicated subpopulation – again aggregating across the short- and long-run to gain power. The minority-white differentials (bottom panel of figure 5) tell us whether these groups face disproportionate impacts within a demographic characteristic. Though precision is again an issue, for Black-white differentials we find similar positive 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

[23] Baseline industrial or occupational differences cannot account for our findings. Black workers were not, for instance, overrepresented in trade or professional services, the areas that account for the bulk of their relative employment growth (online appendix figure OA.3). Across occupations, while minority workers are less likely to hold professional jobs, they are also less likely to hold production jobs which were hard hit.

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/ethnicity, 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 in- or out-migration in response to a negative shock. 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.1, we summarize a specification similar to ADH, examining changes in log population counts by race/ethnicity and demographic group. We limit the sample to the long-run period (2014-2019) to allow time for any population changes to accrue. Our results are imprecise with wide confidence bands. Our (insignificant) point estimates indicate that across the inter-quartile range of exposure, each minority population declined by roughly 2 percentage points more than the white decline due to the China shock. However, based on standard errors, we cannot rule out much larger relative declines than these, nor can we rule out small positive differentials, and it would be difficult to pinpoint whether any particular demographic subgroup was the primary driver.

To better understand the role of 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 table 2. 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, rather than using individual variation in observables. 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 Hispanic-white differential non-manufacturing and overall employment effects go 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: Hispanic-white gaps seem to be driven by differences in observables, while Black-white gaps seem to be driven by differences in responses.

Industry Exposure

In section 2, we showed that groups differ in their exposure to import competition due to their geography. However, groups may also differ in their direct exposure within a CZ due to their likelihood of working in the most exposed areas of manufacturing. For example, as noted, white and Hispanic populations were overrepresented in manufacturing in 2000, compared to the Black population. The CZ-wide shock we use will be most correlated with the "true" exposure for the majority population – white workers. Perhaps the smaller impacts on Black workers that we find are driven by the fact that the CZ-wide shock in some sense mis-measures their actual exposure.

To better understand impacts of direct exposure, we define a group-specific import penetration measure that allows the changes in imports to vary by race/ethnicity due to their baseline industry employment shares.[24] This group-specific import exposure measure may miss spillover effects from shocks to different subpopulations. However, 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. In fact, we find Black populations are less exposed than whites when taking into account differences in baseline industrial composition, while Hispanic populations are significantly more exposed due to their overrepresentation in low-skilled manufacturing. See online appendix figure OA.2 for density plots of group-specific import exposure across CZs.

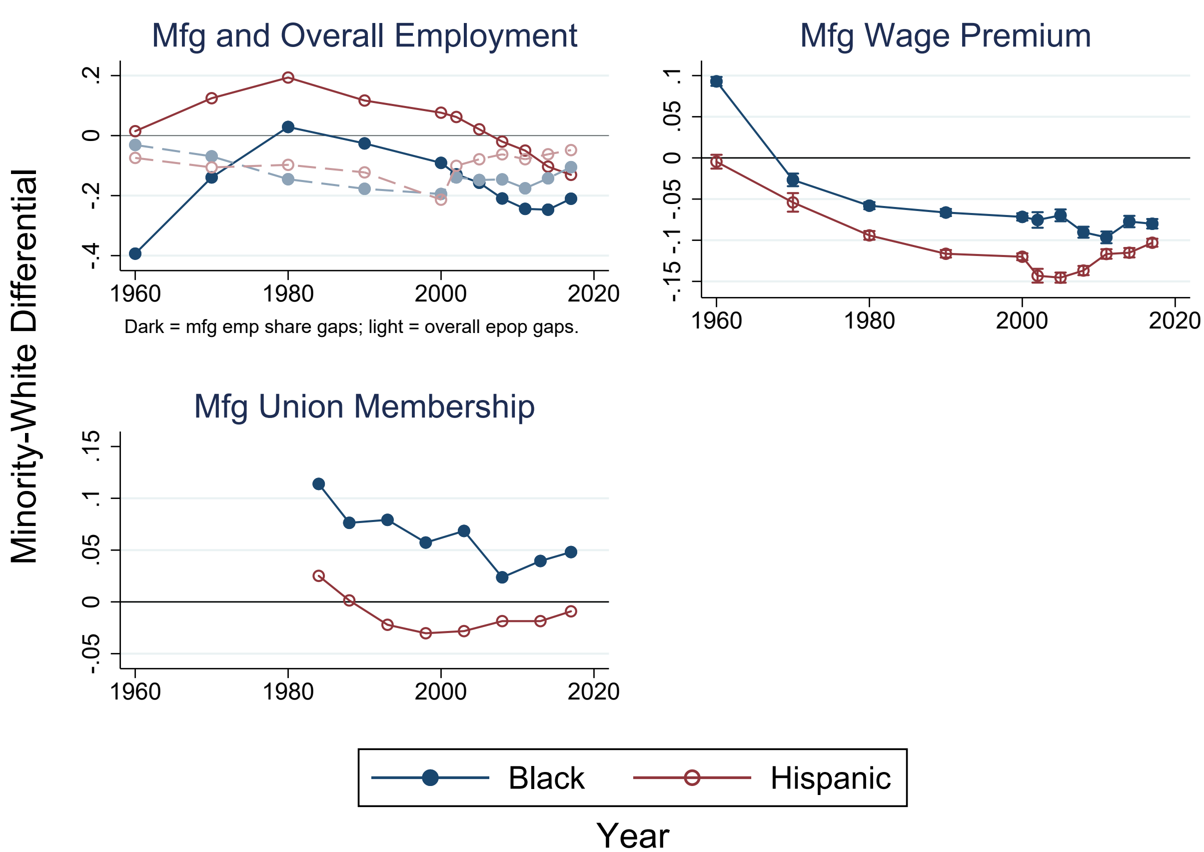
Columns 5 of table 2 use the alternative group-specific import penetration measure. We find that Black-white differentials are similar to the main specifications, though magnitudes on overall employment and wages a bit smaller. Hispanic-white differentials vary a bit more: they experience more negative, though insignificant, manufacturing impacts and positive differentials on non-manufacturing and overall employment, relative to whites. These results suggest that when the jobs Hispanic workers themselves occupy experience an import shock, the Hispanic population may move out of manufacturing at higher rates but does not suffer disproportionately in non-manufacturing employment. On the other hand, table 1 indicated that 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.

[24]Specifically, we replace the CZ-level employment shares in equation 1 with group-specific employment shares for the age 16-64 population measured in the 2000 Census (or in the 1990 Census for the instrument). These employment shares must be used at a three-digit level of industry aggregation: We use ind1990DD from Autor et al. (2013) and aggregate imports from six-digit Harmonized System product codes from the UN Comtrade Database to this three-digit level using the crosswalk in Pierce and Schott (2012).

5 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 negative relative employment effects? Figure 6 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.

Figure 6: 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.

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, as noted above, 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 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 3 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, conditional on making a transition, Black workers are more likely to move towards non-manufacturing. Even conditional on working in manufacturing (middle panel), Black workers were more likely to move to another sector. About 75% 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 moved to non-employment at higher rates.

Table 3: Job Transitions

	All			Manufacturing			Non-Manufacturing		
	White	Black	Hispanic	White	Black	Hispanic	White	Black	Hispanic
J-to-J Flow Rate	6.4	9.0	7.5	3.7	4.8	4.7	6.9	9.6	8.1
Share to Mfg.	8.7	7.1	11.6	32.2	25.2	32.3	6.5	5.9	9.1
Share to Non-Mfg.	91.3	92.9	88.4	67.8	74.8	67.7	93.5	94.1	90.9
Flow to Non-emp	5.9	7.7	7.5	3.4	4.7	5.4	6.3	8.1	7.9

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 6 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.[25] Black workers earned similar weekly 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 6 as a whole paints a consistent picture that the Black workforce was much more invested in manufacturing in 1980 than it was in 2000.

[25]We estimate regressions of log weekly wages on a manufacturing dummy, race/ethnicity dummies, their interactions, and other controls (state fixed effects and age decade-sex-college interactions) separately by year. We plot the race/ethnicity interactions in the upper right panel of figure 6.

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 non-manufacturing jobs in the economy were more appealing.[26] Black workers would 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. It could also explain why Black workers were more poised to take advantage of China shock induced reallocation towards other sectors, such as retail and wholesale trade and professional services, compared to white workers. By the time of the China shock, manufacturing was a much less important part of Black employment so Black workers viewed these new positions as closer substitutes.

The trends documented in figure 6 can also help explain the differences between our results and the impacts of earlier manufacturing shocks on race gaps. For example, Dicandia (2021) found negative effects of automation shocks on Black workers. Batistich and Bond (2023) and Enriquez and Kurtulus (2023) identified disproportionate impacts of the trade shock with Japan on Black workers. Gould (2021) documented that secular manufacturing declines were especially harmful to minorities. However, these papers focus on shocks occurring in the 1980s and 1990s, a period when manufacturing was much more important for Black workers. By the time the China shock hit, this was no longer the case. Ironically, the declining importance of the manufacturing sector for Black workers due in part to the earlier shocks contributed to the more rapid adjustment to the China shock for Black workers.

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 3 shows that Hispanic workers were more likely than Black or white workers to move to manufacturing when making a job-to-job transition. From the upper left panel of figure 6, the Hispanic-white employment-to-population gap narrowed substantially since 2000, by about 15 percentage points. The -0.01 relative loss due to the China shock is a modest force pushing against this broader

[26] 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).

trend.

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.

6 Conclusion

In this paper, we show that the negative effects of increased import competition from China primarily affected white and Hispanic workers. 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 and wage gaps on the order of 10% across the inter-quartile range of exposure. 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 wage gaps.

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 younger age distribution. The Hispanic-white employment gap is smaller than the Black-white gap and has been narrowing in recent decades. The China shock was a small negative force undoing some of these recent gains, undoing about 7% of their progress in more exposed areas.

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. Our findings then point to an even greater need for improving employment options for those impacted by trade, perhaps through retraining (Hyman, 2018; Card et al., 2018; Katz et al., 2022; Dillon et al., 2022) or wage insurance (Hyman et al., 2021).

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 gains from the China shock come in part from declining labor market outcomes of white workers. Further, these outcomes occur against the backdrop of persistent racial inequality in the U.S. and an eroding position for Black workers in manufacturing over the 1980's and 1990's. As we show, this position played a role in the relative increase in Black non-manufacturing employment and wages following the China shock. So while the China shock did not exacerbate Black-white gaps, these gaps still persist, which means that there is still a great need for policies targeting racial inequality.

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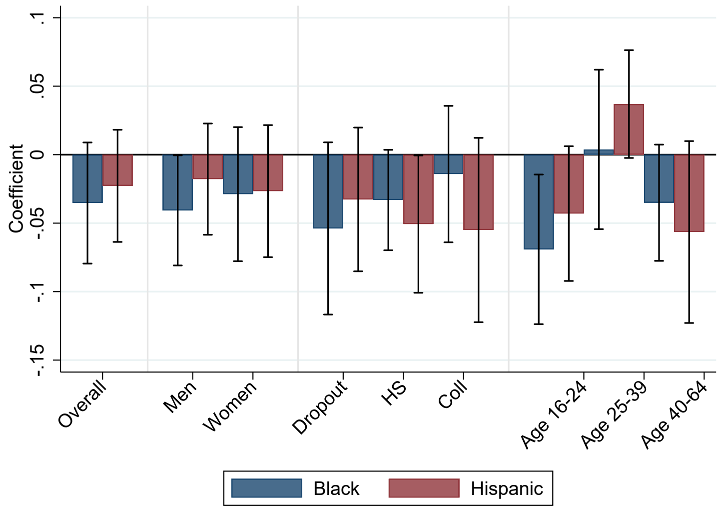
Appendix tables and figures

Figure A.1: Differential Impacts on log population counts



Notes: This figure plots coefficients on ΔIP*Black and ΔIP*Hispanic and their 90% confidence intervals. Observations are limited to the working age population (age 16-64). We estimate equation 2, restricting the sample to the 2014-19 period in order to allow time for any population changes to accrue. The dependent variable is the average log population over 2014-19 minus log population in 2000 for the indicated group.

Table A.1: Correlations between Pre-Period Race and Ethnicity Gaps and Import Exposure

Dependent Variable:	Minority-white Epop Gaps			
		Levels		Trend
	1980	1990	2000	1980-90
$\Delta IP * Black$	0.001	0.007	0.001	0.006
	(0.010)	(0.014)	(0.009)	(0.011)
$\Delta IP * Hispanic$	0.005	0.002	-0.003	-0.003
	(0.013)	(0.012)	(0.010)	(0.006)
Observations	1,429	1,431	1,444	1,417
R-squared	0.080	0.124	0.006	0.006

*** 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 minority-white employment-to-population gap or change in gap on import exposure from 2000-2012, exhaustively interacted with minority group indicators, using the IV specification. Regressions control for race fixed effects but no other covariates. We weight by the CZ race-specific population in 2000 and cluster standard errors by state.

Table A.2: Split by CZ Minority Share

	(1)	(2)	(3)	(4)	(5)
Sample:	All	Split by Black Share		Split by Hispanic Share	
		High	Low	High	Low
Dependent Variable:		Δ log Mfg Emp Rate			
ΔIP (ADH)	-0.082***	-0.079***	-0.109***	-0.082***	-0.076***
	(0.024)	(0.026)	(0.041)	(0.027)	(0.023)
$\Delta IP * Black$	0.022	0.020	0.133	0.052	-0.047
	(0.042)	(0.043)	(0.185)	(0.056)	(0.047)
$\Delta IP * Hispanic$	-0.004	0.011	0.051	0.002	0.092
	(0.035)	(0.038)	(0.079)	(0.034)	(0.101)
Observations	2,063	1,081	982	1,044	1,019
Dependent Variable:		Δ log Non-Mfg Emp Rate			
ΔIP (ADH)	0.002	0.004	-0.008	0.005	-0.006
	(0.004)	(0.005)	(0.008)	(0.005)	(0.005)
$\Delta IP * Black$	0.029***	0.026***	0.123	0.014	0.042***
	(0.010)	(0.010)	(0.080)	(0.011)	(0.012)
$\Delta IP * Hispanic$	-0.023**	-0.016	-0.106*	-0.024**	0.016
	(0.011)	(0.011)	(0.057)	(0.012)	(0.034)
Observations	2,166	1,083	1,083	1,083	1,083
Dependent Variable:		Δ log Overall Emp Rate			
ΔIP (ADH)	-0.011**	-0.007	-0.028**	-0.007	-0.022***
	(0.005)	(0.006)	(0.014)	(0.005)	(0.005)
$\Delta IP * Black$	0.023***	0.019**	0.042	0.017*	0.014
	(0.008)	(0.008)	(0.048)	(0.010)	(0.010)
$\Delta IP * Hispanic$	-0.009	-0.005	-0.047**	-0.013*	0.029
	(0.007)	(0.006)	(0.018)	(0.007)	(0.027)
Observations	2,166	1,083	1,083	1,083	1,083
Dependent Variable:		Δ log Hourly Wages			
ΔIP (ADH)	-0.007	-0.002	-0.024**	-0.005	-0.016***
	(0.008)	(0.010)	(0.012)	(0.010)	(0.006)
$\Delta IP * Black$	0.032***	0.027***	0.102	0.047***	0.007
	(0.009)	(0.009)	(0.067)	(0.017)	(0.010)
$\Delta IP * Hispanic$	0.019***	0.019**	0.041	0.018**	0.028
	(0.007)	(0.009)	(0.033)	(0.009)	(0.023)
Observations	2,166	1,083	1,083	1,083	1,083

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

Notes: Column 1 reproduces the column 1 specification from table 1. For precision, we aggregate over the full 2008-2019 time period. The remaining columns split the sample by the CZ-level Black or Hispanic population share in 2000. We split at the (unweighted) median across CZs; columns 2 and 4 restrict to high minority population share, while columns 3 and 5 restrict to low.

Online Appendix, not for publication

Data Appendix

Census and American Community Survey Data

The primary datasets used in this paper are the 2000 5% U.S. Census and the American Community Surveys (ACS) for 2005 through 2019. We also use the 1980 and 1990 5% Censuses to measure pre-trends in employment gaps. 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 U.S. 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.

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 (when both continuous and categorical variables are available) 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 each year 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 and military.

The main control variables (listed in footnote 14) are obtained from Autor et al. (2021) along with the Great Recession controls used in table 2, column 2. We use the 2000 Census to calculate the group-specific controls used in table 2, column 5. These include the share of the working age (16-64) population that graduated from college, the share of the working age female population that is employed, the share of employed that are working in a routine occupation and the average offshorability of the working age employed (Autor et al., 2013), and the share of the population that is 17 or less, 40-64, and 65+.

Our analyses aggregates several ACS waves (e.g., 2008-2013 or 2014-2019) and compares these to outcomes in the 2000 Census. When we aggregate, we first use sampling weights to aggregate within a year and then take an unweighted average across years.

Defining Import Exposure

To calculate the CZ-wide import penetration measure (equation 1) we follow Autor et al. (2021) (hereafter ADH). We use measures they provide for imports and domestic absorption at the 4-digit Standard Industry Classification (SIC) level. For a given 4-digit industry, we calculate the change in import exposure in year 2012 as the change in industry imports from 2012 compared to 2000 divided by domestic absorption. The latter is measured in 1991 and is equal to gross output plus imports minus exports.

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 County Business Patterns (CBP) in 2000 from the U.S. Census Bureau to capture industry shares in the initial CZ employment.[27] 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 use a version of these data provided by Acemoglu et al. (2016) who map to CZ-by-4-digit SIC cells.

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

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 obtained from ADH. Domestic absorption is measured at a lag (1988 instead of 1991) and CZ-industry employment shares are also lagged, measured using the 1990 CBP.

For group-specific import exposure described in section 4.3, 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. (2019) to map 4-digit SIC codes to the 3-digit industry level (ind1990dd). Import exposure then sums the changes in imports from China across 3-digit industries (divided by 1991 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 1988) 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.

To measure the China shares instrument used in column 3 of online appendix table OA.3, we obtain Chinese imports in the 8 other developed countries directly from the UN Comtrade Database at the 6-digit Harmonised System (HS) product-level.[28] We map these to 4-digit SIC industries using the crosswalk from Autor et al. (2013). We then take the ratio of the sum of Chinese imports across the 8 countries for a given industry and the sum of all imports across the 8 countries for that industry. We take the difference across 2012 and 2000 and apply these to the CBP baseline employment shares in 1990.

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

For the NTR Gap shock, we obtain the spread between the NTR and non-NTR rate at the 8-digit HS product code level from Pierce and Schott (2016). We average this measure over products within 4-digit SIC codes (using the same HS6 to 4-digit SIC crosswalk from above), weighting by product imports in 2000. We use County Business Patterns in 1990 to measure CZ employment shares across these industry categories.

Historical Outcomes, Figure 6

The top 2 panels are constructed using 5% Censuses from 1960, 1980, 1990, 2000, along with the 1970 1% state form 1 and 2 Censuses and 3-year averages of ACS waves from 2001-2019. We obtain data from the Census Integrated Public Use Micro Samples (Ruggles et al., 2021). We restrict to ages 16-64 not living in institutional group quarters. We exclude the military from employment. We use the most detailed definition of race available in the given year.

The manufacturing weekly wage premium is calculated as follows. We exclude the self employed and replace top coded values for annual wage and salary income with 1.5 times the top code amount. We use the categorical weeks worked variable because not all years include the continuous weeks worked variable. We impute the midpoint for the category using 1980 continuous values for 1960, 1970, and 1980, 1990 continuous values for 1990, and 2000 continuous values for all years from 2000 onwards. We calculate weekly wages by dividing annual income by weeks worked. We then bottom code the first percentile in the national distribution for that year and top code so that weekly wages times full-year work (50 weeks) does not exceed the top coded value. We inflation adjust to 2012 using the PCE.

To obtain manufacturing wage premia, we then regress log weekly wages on a manufacturing indicator and interactions with Black and Hispanic. We control for group main effects, state fixed effects, and age-sex-education cell fixed effects. Age groups are decades and education groups are the general educ categories. We estimate these regressions separately by year and use sampling weights.

The bottom left panel on union membership uses CPS outgoing rotation groups (ORG) from 1983-2019 and March supplements from 1990-2019. These are also obtained from IPUMS (Flood et al., 2024). We restrict to ages 16-64. We use as much detail as available in a given survey year to classify race. We plot group differences in union membership though results are similar if we also include those covered by a union but who are not themselves members.

Job-to-Job Flows

For table 3, we derive race and ethnicity-specific quarterly job-to-job flows in year 2000 from the Job-to-Job Flows (J2J) Explorer[29], 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 industries 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. J2J do not provide the statistics at the subgroup level for many states because they do not meet U.S. Census Bureau publication standards. So, we aggregate the values only for the available states: Alaska, California, Delaware, Florida, Hawaii, Idaho, Illinois, Iowa, Kansas, Minnesota, Missouri, Nebraska, New Jersey, New York, North Carolina, Oklahoma, Oregon, Pennsylvania, South Carolina, South Dakota, Texas, Washington, and Wisconsin. 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)[30] for the same period and the same states. The QWI is also based on LEHD, so it should be consistent with J2J.

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

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

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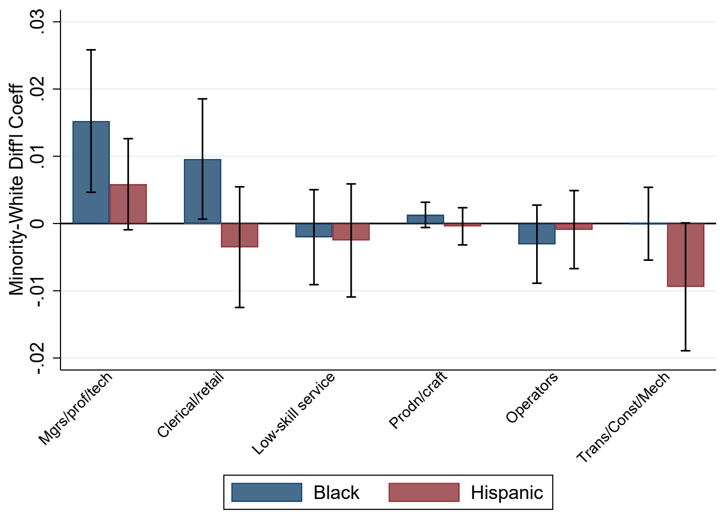
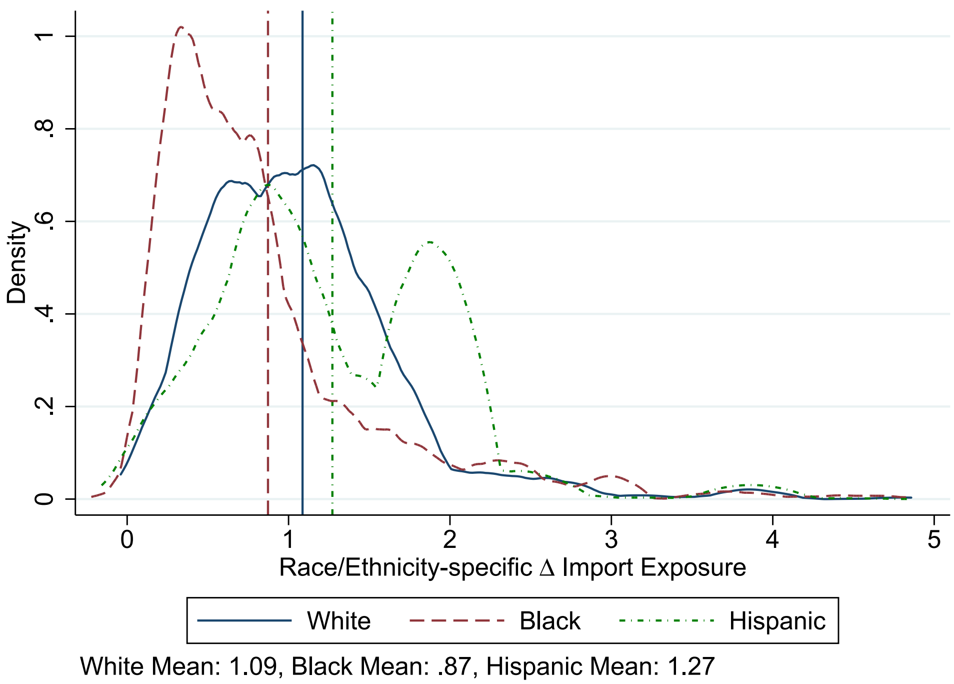
Additional Tables and Figures

Figure OA.1: Minority-White Differences by Occupation



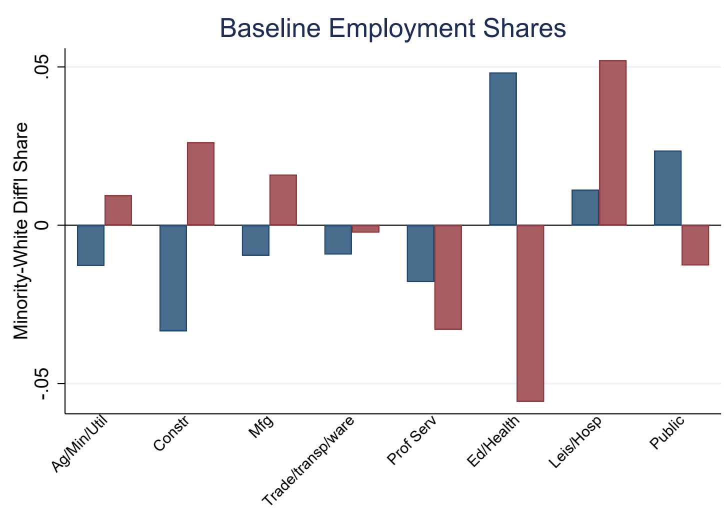
Notes: We report minority-white differential impacts of CZ-wide import exposure on occupation-specific employment per adult population within the race/ethnic group. Occupation categories come from the Level 1 Autor and Dorn (2013) classification. See figure 4.

Figure OA.2: Distributions of Group-Specific Measures of Import Exposure



Notes: We plot the distributions across CZs of group-specific change in import exposure from China (IP) from 2000-2012. Relative to the import exposure measure defined in equation 1 and taken from Autor et al. (2021), the measure plotted here allows for different baseline industry employment shares by race/ethnicity as measured in the 2000 Census ($\Delta IP_{rct} = \sum_i \frac{Emp_{irc}}{Emp_{rc}} \frac{\Delta M_{it}}{Norm_i}$). 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.

Figure OA.3: Minority-White Baseline Employment Shares by Industry



Notes: We report minority-white differentials in the share of employment that is in a given industry in 2000. 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).

Table OA.1: Summary Statistics

	White			Black			Hispanic		
	2000	2010	2016	2000	2010	2016	2000	2010	2016
ΔIP (ADH)	1.10			1.01			1.06		
	(0.75)			(0.73)			(0.64)		
Mfg Emp per pop	11.03			8.28			9.60		
	(4.55)			(4.89)			(5.13)		
Non-mfg Emp per pop	62.56			52.30			49.81		
	(5.58)			(7.11)			(5.93)		
Overall Emp per pop	73.59			60.58			59.42		
	(4.47)			(4.82)			(4.59)		
Log Hourly Wage	3.07			2.90			2.79		
	(0.17)			(0.15)			(0.09)		
Changes from 2000:									
log Mfg Emp		-0.30	-0.32		-0.44	-0.42		-0.32	-0.39
		(0.11)	(0.12)		(0.19)	(0.21)		(0.17)	(0.19)
log Non-Mfg Emp		-0.01	0.03		0.03	0.11		0.16	0.22
		(0.03)	(0.03)		(0.07)	(0.06)		(0.07)	(0.08)
log Overall Emp		-0.05	-0.02		-0.02	0.05		0.09	0.14
		(0.03)	(0.03)		(0.07)	(0.05)		(0.06)	(0.06)
log Hourly Wage		-0.20	-0.29		-0.26	-0.38		-0.23	-0.30
		(0.04)	(0.05)		(0.05)	(0.06)		(0.04)	(0.04)
# CZs	722	722	722	722	722	722	722	722	722

Notes: We summarize CZ cells by race/ethnicity, weighting by group-specific population in the CZ in 2000. 2000 data are from the Census. 2010 reflects an unweighted average of 2008-13 American Community Survey (ACS) waves. 2016 reflects an unweighted average of 2014-19 ACS waves. 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 and military. All employment measures exclude military employment.

Table OA.2: First-Stage Regressions

	(1)	(2)	(3)
Panel A:	ADH Instrument		
Dependent Variable:	ΔIP (ADH)		
ΔIP IV	0.426***	0.470***	0.504***
	(0.073)	(0.073)	(0.060)
Observations	722	722	722
R-squared	0.653	0.674	0.804
F-stat on instrument	34	42	71
Panel B:	Chinese Import Share Instrument		
Dependent Variable:	ΔIP (ADH)		
Chinese Shares IV	0.247***	0.292***	0.267***
	(0.033)	(0.035)	(0.025)
Observations	722	722	722
R-squared	0.670	0.710	0.814
F-stat on instrument	56	69	119
Panel C:	NTR Gap Instrument		
Dependent Variable:	ΔIP (ADH)		
NTR GAP IV	7.726***	8.362***	10.473***
	(2.302)	(2.797)	(3.399)
Observations	722	722	722
R-squared	0.565	0.596	0.717
F-stat on instrument	11	9	9
Panel D:	Own-Group Shock		
Dependent Variable:	Group-Specific ΔIP		
Group-specific IV	1.005***	0.742***	0.610***
	(0.111)	(0.101)	(0.070)
Observations	722	722	722
R-squared	0.766	0.712	0.713
F-stat on instrument	83	54	76
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 1. 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. Kleibergen-Paap Wald F-stats are reported. Models are weighted by race-specific CZ working-age population in 2000.

Table OA.3: Impacts of Import Exposure: Alternative Identification Strategies

Time Period:	2010-2000				2016-2000			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dependent Variable:	Δ log Mfg Emp Rate							
ΔIP (ADH)	-0.069***	-0.029***	-0.087***	-0.143***	-0.095***	-0.029**	-0.107***	-0.124**
	(0.023)	(0.009)	(0.020)	(0.051)	(0.027)	(0.011)	(0.027)	(0.051)
$\Delta IP * Black$	0.048	0.021	0.028	0.049	-0.003	-0.017	-0.003	0.018
	(0.044)	(0.016)	(0.035)	(0.068)	(0.048)	(0.019)	(0.034)	(0.084)
$\Delta IP * Hispanic$	-0.001	-0.027*	0.026	-0.035	-0.007	-0.049***	0.016	-0.093
	(0.038)	(0.016)	(0.029)	(0.065)	(0.036)	(0.017)	(0.035)	(0.070)
Observations	2,052	2,052	2,052	2,052	2,059	2,059	2,059	2,059
Dependent Variable:	Δ log Non-Mfg Emp Rate							
ΔIP (ADH)	0.002	0.004**	0.004	0.003	0.003	0.005**	0.005	0.011
	(0.004)	(0.002)	(0.004)	(0.010)	(0.004)	(0.002)	(0.004)	(0.009)
$\Delta IP * Black$	0.029**	0.012*	0.023*	0.036	0.029***	0.009*	0.021*	0.057*
	(0.011)	(0.006)	(0.013)	(0.026)	(0.011)	(0.005)	(0.011)	(0.034)
$\Delta IP * Hispanic$	-0.023**	-0.010	-0.023	0.027	-0.023*	-0.004	-0.025	0.011
	(0.011)	(0.010)	(0.014)	(0.026)	(0.012)	(0.012)	(0.016)	(0.032)
Observations	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166
Dependent Variable:	Δ log Overall Emp Rate							
ΔIP (ADH)	-0.009*	-0.001	-0.012***	-0.033**	-0.013**	-0.001	-0.014***	-0.027***
	(0.006)	(0.002)	(0.004)	(0.013)	(0.005)	(0.002)	(0.004)	(0.010)
$\Delta IP * Black$	0.028**	0.012**	0.023**	0.023	0.019**	0.005	0.015**	0.031*
	(0.011)	(0.005)	(0.010)	(0.024)	(0.008)	(0.003)	(0.007)	(0.017)
$\Delta IP * Hispanic$	-0.011	-0.012**	-0.006	0.017	-0.008	-0.010*	-0.006	0.002
	(0.007)	(0.005)	(0.007)	(0.017)	(0.008)	(0.006)	(0.008)	(0.017)
Observations	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166
Dependent Variable:	Δ log Hourly Wages							
ΔIP (ADH)	-0.005	-0.000	-0.008	-0.024*	-0.009	0.001	-0.011	-0.018
	(0.008)	(0.003)	(0.007)	(0.013)	(0.008)	(0.003)	(0.007)	(0.015)
$\Delta IP * Black$	0.029***	0.003	0.021***	0.024	0.035***	0.004	0.022**	0.020
	(0.010)	(0.003)	(0.008)	(0.020)	(0.009)	(0.003)	(0.011)	(0.027)
$\Delta IP * Hispanic$	0.021**	0.003	0.016*	0.064***	0.017***	0.003	0.011	0.057***
	(0.009)	(0.006)	(0.010)	(0.024)	(0.006)	(0.004)	(0.006)	(0.022)
Observations	2,166	2,166	2,166	2,166	2,166	2,166	2,166	2,166
Main IV	X				X			
OLS		X				X		
Shares IV			X				X	
NTR IV				X				X

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

Notes: Column 1 reproduces the column 1 specification from table 1. 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 IV and its group interactions. Standard errors in parentheses clustered by state.