Understanding the Racial Employment Gap: The Role of Sectoral Shifts*

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Abstract

The employment rate for Black men worsened significantly relative to White men during the second half of the 20th century. We explore the role of broad sectoral shifts in labor demand over this period in explaining this trend. We first quantify changes in local employment rates and population in response to local labor demand shifts for both groups of workers. We then combine our estimates with a stylized model that incorporates frictional local labor markets and imperfect mobility across markets. Our framework enables us to aggregate local responses while accounting for geographic mobility and regional employment composition. We find that sectoral reallocation can account for at most, one-fifth of the total exacerbation in the employment rate differential between Black and White men over 1970–2010. Out-migration from harder-hit markets, while large, only slightly mitigates the impact of negative labor demand shifts. We also find that most of the predicted change in the employment rate differential is due to differential response rather than differential exposure to sectoral shifts across groups.

Keywords: Employment Gap, Racial Disparities, Labor Demand Shifts

JEL: R12, J15, J21, J60

1. Introduction

Despite apparent progress in civil rights for African American individuals in the United States, the labor market outcomes of Black men deteriorated significantly compared to White men in the last three decades of the 20th century. As depicted in Figure 1, both groups experienced a decline in employment rates during this period, but the decline was more severe for Black men.[1] One proposed explanation for this phenomenon is that sectoral reallocation of economic activity over this period was especially detrimental for Black men.[2] This disparate impact could stem from Black workers being more exposed to sectoral shifts due to being overrepresented in declining sectors or being excessively located in areas with a concentration of declining sectors. However, it is also possible that adjustment to changes in labor demand varies by race, potentially due to differences in the capacity to relocate away from adversely affected sectors or locations.

In this paper, we quantify the extent to which sectoral reallocation can explain the divergence in the employment rates of Black and White men over 1970–2010.[3] Furthermore, we examine the extent to which the differential impact of sectoral

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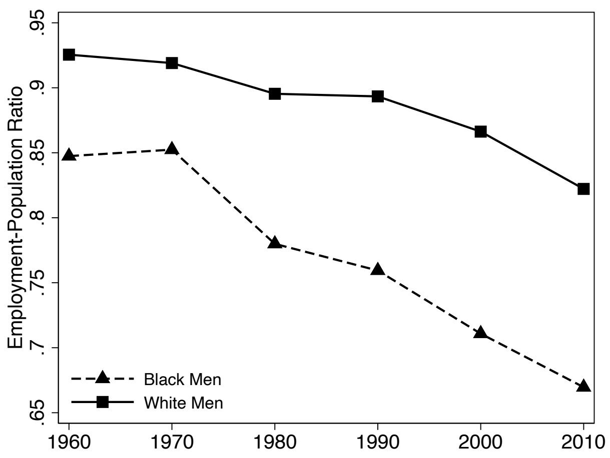
[1]We use the term *employment rate* to refer to the share of employed individuals in the population.

[2]This explanation was first proposed by Wilson (1987). Bound and Freeman (1992) and Bound and Holzer (1993) link the decline in the manufacturing sector to lower wages and employment for Black relative to White men in the 1970s and 1980s.

[3]We focus on this measure to avoid selection problems involved with analyzing wages due to differences in non-participation across groups and over time.

Figure 1: Employment Rates for Black and White Men



Notes: Data are from the U.S. Census, accessed through Integrated Public Use Micro Samples (IPUMS) (Ruggles et al., 2021). Employment and population are calculated for Black and White men between the ages of 25-55 who are not in the armed forces and do not reside in institutionalized group quarters.

shifts between the two groups can be attributed to differences in exposure versus differences in adjustment to these shifts. In order to accomplish these goals, we first exploit regional variation in exposure to sectoral shifts for each group to uncover differential patterns of labor market adjustment. In particular, we estimate the race-specific elasticity of the local employment rate and population with respect to local labor demand shifts. We then provide a framework that enables us to aggregate the local employment rate responses while accounting for population movements across locations. Lastly, we conduct counterfactual analyses to measure the contribution of population movements and initial sectoral and regional composition of Black and White workers in explaining the predicted increase in the aggregate disparity.

We use decadal data from the United States Census to measure changes in our outcome variables at the level of commuting zones (CZs). We create a race-specific *shift-share* measure for changes in local labor demand by combining lagged local employment shares by sectors for each group and national changes in sectoral employment (following Bartik (1991)). Our measure for local labor demand shifts varies by race due to differences in the initial sectoral composition of Black and White workers within local markets. As a result, the estimated elasticities capture responses to comparable shocks for both groups.[4] We document that the local employment rate and population vary positively with local labor demand shifts for both groups of workers. In our preferred estimates, we find an elasticity of 0.22 for Black men relative to 0.08 for White men for the employment rate. Although we observe significant changes in population in response to labor demand shifts for both groups, we find limited evidence for lower mobility among Black workers. The estimated elasticity of population for both Black and White workers is around 0.7 in our preferred specification.[5]

The large population responses highlight the importance of accounting for such movements when considering the aggregate impact of sectoral shifts on employment. In particular, one needs to account for individuals who have relocated and potentially secured employment in other locations. In order to do so, it is necessary to impose some structure on how shifts in labor demand in one region affect the population in other regions. To this end, we set up a location choice model where individuals have idiosyncratic preferences for different locations. In this model, we incorporate matching frictions in local markets following the approach of Kim and Vogel (2021). Hence, our model incorporates mobility frictions across markets and matching frictions within markets. The model implies that changes in local employment rates and population in response to local demand shifts depend on the structural parameters that govern these frictions, which can vary across different groups of workers. We show that the parameters of the model can be inferred directly from our estimated elasticities. Further, we use the model to derive a relationship between aggregate changes in employment rates for each group and the estimated local responses. The framework implies that the aggregate employment rate gap

[4] Using a measure of labor demand shifts that is common to both groups would conflate the impact of differential shares of workers in affected sectors across the two groups and differential effects of comparable shocks experienced by each group.

[5] Bound and Holzer (2000) also investigate differential population responses by race in response to labor demand shifts and find no difference between the two groups overall. However, they do observe lower population responses specifically for low-skill Black men.

depends on how employment changes *within* local markets and how population adjusts *across* markets for each group.[6] The contribution of both of these margins of adjustment to the aggregate employment gap rate depends on the initial composition of workers across locations and sectors, which determines how exposed workers of a particular group are to demand shifts.

Combining the estimated local elasticities with our aggregation framework, we find that sectoral reallocation can explain a 2.5 percentage point decrease in the employment rate for Black workers and a 1.2 percentage point decrease for White workers, resulting in a widening of the employment rate gap by 1.3 percentage points. In our sample, the employment rate gap between Black men and White men increased by 7.3 percentage points over 1970–2010. Therefore, our results imply that sectoral reallocation accounts for about 18% of the increase in the aggregate Black-White employment rate gap over this time horizon.

In order to understand the forces driving the change in the aggregate gap, we conduct several counterfactual analyses. First, we investigate whether population movements mitigate the overall decline in employment rates compared to a scenario without such movements. When we disable population responses for White workers, we observed no significant change. However, for Black workers, the predicted decline in the employment rate slightly increases from 2.5 to 2.8 percentage points. Consequently, we conclude that the overall change in the employment gap was only minimally influenced by population movements.[7] Finally, we consider counterfactuals where the initial distribution of employment across sectors and locations was similar for both Black and White workers, resulting in identical exposure to sectoral shifts. Surprisingly, our findings indicate that if this were the case, the employment gap between the two groups would have been even wider than the realized gap. Therefore, the initial employment composition of Black men did not place them at a disadvantage compared to White men. Hence, we conclude that the main factor driving the aggregate gap is not differential exposure to sectoral shifts but rather the differential responses of the two groups within local labor markets.[8]

To the best of our knowledge, ours is the first paper to formally quantify the role of sectoral shifts in widening the aggregate employment rate gap between Black and White men. Our reduced-form findings contribute to an existing body of evidence regarding the differential impacts of local labor demand shocks on the two groups (Bound and Holzer, 2000; Gould, 2020; Batistich and Bond, forthcoming).[9] However, none of these existing studies jointly analyze local employment rate and population responses, with the aim of aggregating the local responses to draw definitive conclusions about the overall trends in employment rates for Black and White men.[10] In contrast, our study not only examines the aggregate impact of sectoral shifts but also explores the role of differential sectoral or locational composition in explaining the disparate aggregate impact between the two groups.

In order to aggregate the local responses, we develop a framework that explicitly incorporates spatial links resulting

[6]Throughout our analysis, we assume that sectoral shifts do not impact the aggregate population of each group. This would not be the case if immigration patterns are influenced by these shifts. To address this concern, we show that our conclusions are unchanged when we limit our sample to the native-born population.

[7]Note that although both groups exhibited similar population elasticities, the impact of population movements can vary between them. This is because the effectiveness of population movements in mitigating shocks also depends on the likelihood of relocated individuals finding employment in their new location. The data indicates that there was limited geographic variation in employment rates for both groups in 1970. However, shocks affecting Black workers were more widely spread, which explains why relocation had a positive impact on this group.

[8]It is possible that Black and White workers hold different types of jobs even within the same sector. If Black workers are overrepresented in low-skill positions within a sector, and the shock primarily affects low-skill jobs in that sector, the impact on Black workers would be more negative. However, we observe similar responses to our measured shifts across groups when we consider responses within specific skill groups. Therefore, we believe our measure adequately captures comparable shocks for both groups.

[9]Bound and Holzer (2000) and Gould (2020) focus on the overall decline in manufacturing, while Batistich and Bond (forthcoming) specifically focus on the decline in manufacturing resulting from heightened competition from Japan. In our study, we consider all sectoral shifts during this period while estimating local responses. These shifts may be influenced by skill-biased technological change, trade, automation, or other factors and may not be limited to the manufacturing industry.

[10]Among these studies, only Bound and Holzer (2000) specifically investigate population responses for the two groups. However, their emphasis lies in highlighting the role, or lack thereof, of population responses in facilitating spatial arbitrage across regions. In contrast, our focus is on incorporating population movements when aggregating local outcomes.

from population movements across regions. Our framework provides an intuitive approach for aggregating local employment rate responses in the presence of migration dynamics. In doing so, our paper aligns with the expanding body of literature in macroeconomics (Nakamura and Steinsson, 2014; Mian and Sufi, 2014; Beraja et al., 2019) and international trade (Kim and Vogel, 2021; Adão et al., 2021) that employs causal evidence derived from local responses to shocks in order to understand the impact of these shocks on aggregate outcomes.

Finally, our paper contributes to the literature that seeks to understand the dynamics of racial disparities. An extensive literature on the wage gap between Black and White workers has traditionally attributed a portion of the wage gap to observable characteristics of workers and explained the remainder through theories of labor market discrimination.[11] However, given that over the 20th century, measures of racial prejudice declined steadily (Lang and Lehmann, 2012) and the skills gap converged (Card and Krueger, 1992; Neal, 2006), this approach has trouble capturing the persistence of economic disparities by race. Two recent studies by Bayer and Charles (2018) and Hurst et al. (2021) focus on slowed convergence in the earnings and wage gaps, respectively, since the 1970s–1980s and propose that the effects of decreased discrimination and increased educational attainment among Black workers were offset by increasing returns to certain types of skills that disproportionately benefited White relative to Black individuals. Our paper is complementary to these studies in the sense that we consider a different dimension of changes in labor demand—sectoral—rather than skill-specific, but share their emphasis on explaining stalled racial progress over this time horizon. Furthermore, while these authors consider trends at the level of aggregation of skill or occupation, we leverage the spatial dimension of the sectoral reallocation patterns that occurred during the 20th century by using local labor markets as our unit of analysis. Our findings indicate that while sectoral shifts do play a considerable role in accounting for the gap, there are other factors at play, as a large portion of the gap remains unexplained by sectoral shifts.

The rest of the paper is structured as follows. Section 2 discusses the data we use in our analysis and how we construct our measure of shocks to local labor demand. Section 3 presents our empirical analysis. In this section, we provide details on the methodology we use to estimate the relationship between local labor demand shocks and employment rate and population outcomes by group. We also provide detailed robustness checks of our main empirical results. In Section 4, we outline a model of labor market frictions and regional mobility that delivers key predictions about how employment rates and population respond to changes in labor demand for different groups. We show how the parameters of the model can be recovered from our estimates presented in Section 3. Section 5 derives a framework based on this model to analyze the aggregate effect of local labor demand shocks on the employment rate gap between Black and White workers. We also use the framework to compute several counterfactuals that shed light on the relevant margins of labor market adjustment in response to sectoral shifts. Section 6 concludes.

2. Data and Measurement

In this section, we describe the data used in our analysis. We then outline how we measure local labor demand shifts and present statistics on their distribution across regions.

2.1. Data Description

We study changes in local employment rates and population in response to changes in local labor demand from 1970–2010 separately for Black and White men. Over this period, the employment rates of Black and White men diverged considerably.[12] For our analysis, we require a measure of changes in labor demand over this period at the level of local

[11] Early studies include Smith and Welch (1977) and Brown (1984). See Lang and Lehmann (2012) for a review.

[12] See Figure 1. We focus only on men due to massive changes in female labor force participation over this period, which makes analysis for women more complicated.

labor markets. To construct this measure, we use local employment shares by sectors and national changes in sectoral employment composition for prime-age males.[13]

All variables used in our analysis are constructed using Census Integrated Public Use Micro Samples (IPUMS) (Ruggles et al., 2021) for the years 1960, 1970, 1980, 1990, 2000, and 2010.[14] Census data are particularly suited to our analysis as the large sample size enables us to conduct detailed regional analysis separately by race. We use commuting zones (CZs) as our measure of local labor markets. Commuting zones were developed by Tolbert and Sizer (1996) who used county-level commuting data from the 1990 Census data to create 741 clusters of counties based on the strength of commuting ties across counties. We use measures of geography provided in the Census data, in particular, public use microdata areas (PUMAs) for the years 1960, 1990, 2000, and 2010 and county groups for the years 1970 and 1980, to match Census data to commuting zones. We are able to obtain a consistent sample of 728 commuting zones for each year used in our analysis.[15]

We measure all outcomes using men between the ages of 25-55 who are not in the armed forces and do not reside in institutional group quarters. We restrict our main sample to commuting zones with at least 200 Black men employed in 1960 and non-zero employment among Black men in all decades. The cutoff of 200 in 1960 is to ensure a large enough sample size to calculate race-specific sectoral employment shares at the level of commuting zones. Our main sample includes 336 commuting zones.[16] The restriction mainly excludes commuting zones in the Mid-Western plains and Rocky mountains. Commuting zones in our sample accounted for 89% of the total employment in 2010. Table 1 presents summary statistics for our sample as well as for all commuting zones in 1970 and 2010. Because we restrict our sample on employment counts for Black men, the commuting zones in our sample are on an average larger and have a higher share of employment in manufacturing. However, the average commuting zone in our sample is comparable to the average commuting zone in the broader United States in terms of both employment rates and wages.

Table 1: Summary Statistics for Commuting Zones

	All CZs		Sample	
	1970	2010	1970	2010
	(1)	(2)	(3)	(4)
Log Population	9.44	9.93	10.52	11.08
Share of Manufacturing	0.23	0.17	0.28	0.19
Employment Rate: Black Men	0.82	0.68	0.84	0.65
Employment Rate: White Men	0.92	0.82	0.91	0.81
Log Wages: Black Men	9.87	9.70	9.78	9.76
Log Wages: White Men	10.30	10.16	10.32	10.19
Observations	741	741	336	336

Notes: All statistics are calculated based on noninstitutionalized civilian men between the ages of 25-55. Columns (1) and (2) present averages of variables across all commuting zones in the United States. Columns (3) and (4) present averages for commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 who were employed in 1960. Employment Rate is calculated by diving total race-specific employment by population in each commuting zone. Wages refers to total wage and salary income of employed workers.

2.2. *Measuring Local Labor Demand Shifts*

We aim to quantify how local employment rates and population respond to shifts in local labor demand. However, shifts in labor demand are not directly observable. Therefore, we use lagged employment shares by sector and national changes in sectoral employment composition between two time peri-

[13]For seminal papers using this approach to measure local labor demand shocks, see Bartik (1991) and Blanchard and Katz (1992). A large number of recent studies in the international trade literature have used shift-share measures to document the impact of trade shocks, for example, see Topalova (2010); Autor et al. (2013); Dix-Carneiro and Kovak (2017) among others.

[14]In particular, we use the following samples: 1960 5%, 1970 1% Form 1 Metro, 1970 1% Form 2 Metro, 1980 5% state, 1990 5% state, 2000 5%, and 2010 ACS sample.

[15]Census data is matched to commuting zones using crosswalk files provided on David Dorn's website https://www.ddorn.net/data.htm for 1970, 1980, 1990, 2000, and 2010. The crosswalk for 1960 was obtained from Evan K. Rose's website https://ekrose.github.io/resources/.

[16]In our panel regression specifications, we impose the additional restriction that CZs must have at least 200 Black men employed in *all* years 1960, 1970, 1980, and 1990. This yields a sample of 315 CZs. In Section 3.3, we show that our estimates under both strategies display little sensitivity to the choice of this cutoff.

ods $t-h$ and t to create a proxy for these shifts. In particular, we construct a proxy for changes in local labor demand over the period $t-h$ to t, denoted by $\Delta A_{cg,t}$, as follows:

$$\Delta A_{cg,t} = \sum_s \frac{L_{csg,t_0}}{L_{cg,t_0}} \cdot \left(\ln\left(\frac{L_{-c,s,t}}{P_t}\right) - \ln\left(\frac{L_{-c,s,t-h}}{P_{t-h}}\right)\right) \quad (1)$$

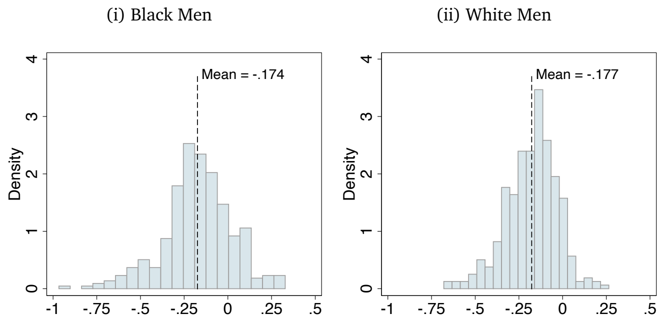
Here, L_{csg,t_0} represents total employment in commuting zone c in sector s for group g in some initial period t_0 and L_{cg,t_0} represents total employment in commuting zone c for group g in some initial period t_0. The expression $\ln\left(\frac{L_{-c,s,t}}{P_t}\right) - \ln\left(\frac{L_{-c,s,t-h}}{P_{t-h}}\right)$ denotes the leave-one-out growth rate of employment in sector s for commuting zone c over the time period $t-h$ to t. The leave-one-out growth rate for commuting zone c is constructed by aggregating sectoral employment in all commuting zones besides c in both the beginning and ending years in the relevant time period, dividing by the total population in the appropriate year, and computing the growth rate between these two periods.[17] For instance, in our regression analysis using long difference specifications, we set $t_0 = 1960$, $t = 2010$, and $t-h = 1970$ so that the "shift" component of our measure is given by $\ln\left(\frac{L_{-c,s,2010}}{P_{2010}}\right) - \ln\left(\frac{L_{-c,s,1970}}{P_{1970}}\right)$ and the "share" component is given by $\frac{L_{csg,1960}}{L_{cg,1960}}$.

Our measured labor demand shifts will be more negative in locations with a larger initial share of employment in declining industries. Additionally, note that we allow the employment shares that determine the weight each sector gets in the overall measure to be race-specific. For instance, suppose that the demand for durable goods goes down. If 30% of Black (B) men in Detroit-Flint, MI are employed in durable goods manufacturing vs. 20% of White (W) men, then our measured labor demand shocks will be more negative for Black workers in that location. In other words, our proxy takes into account differential initial sectoral composition of Black and White workers.

To construct the measure of local labor demand shocks, we use time-consistent industry codes from IPUMS and classify industries into 71 broad categories.[18] Figure 2 shows the distribution of local labor demand shifts over 1970–2010 ΔA_{cg} for Black and White workers. Given similar means of $\Delta A_{c,B}$ and $\Delta A_{c,W}$, the figure shows that both groups of workers' average exposure to broad shifts in labor demand was of similar magnitude over this time period. However, Black workers faced a larger dispersion of demand shifts across regions, as the standard deviation of $\Delta A_{c,B}$ is roughly 1.3 times that of $\Delta A_{c,W}$.

We also map the geographic dispersion of our proxy for local labor demand shifts for Black and for White men in Figure 3. It is apparent that there is a higher concentration of large, negative labor demand shocks in regions of the United States that were hardest hit by the decline of the manufacturing sector during the end of the 20th century. In the maps, areas such as the Rust Belt, Appalachia, and the North East display larger negative labor demand shifts. Even though our proxies are designed to capture shifts in labor demand across *all* industries, the decline of the manufacturing sector in the

Figure 2: Distribution of Local Labor Demand Shifts



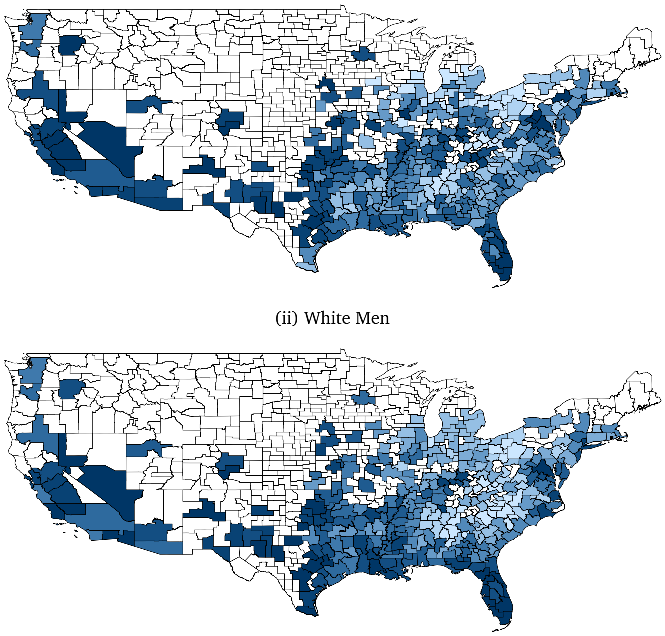
Notes: Figure shows the histograms of our proxies for labor demand shifts for Black and White workers. The proxy is constructed using employment shares by sectors in 1960 and national changes in sectoral employment over 1970–2010 according to Equation (1).

[17] We scale by the total population in each year in order to capture changes in employment within sectors net of population changes. The measure therefore implicitly captures the degree to which total employment keeps pace with population growth.

[18] In choosing a set of industries, we face a tradeoff. A larger number of industries strengthens the validity of our shift-share research design in which identification results from the quasi-random assignment of industry shares across commuting zones. However, calculating sectoral shares for a large number of industries with a small sample size for Black workers induces measurement error in our shift-share measure. Therefore, we explore robustness checks where we use a broader set of industry codes. Figures B.1 and B.2 in the appendix present changes in sectoral employment over 1970–2010 for each set of industry codes we use to construct our measures of local labor demand shocks. Industry crosswalks are available upon request.

Figure 3: Geographical Exposure to Sectoral Shifts

(i) Black Men



(ii) White Men

Notes: Maps show the geographic distribution of our proxies for local labor demand shifts across commuting zones in our sample for Black and White workers. The proxies are constructed using employment shares by sectors in 1960 and national changes in sectoral employment over 1970–2010 according to Eq. (1). Darker shaded areas represent lower values and lighter shaded areas represent higher values. Unshaded areas are those that are not included in our sample, which only includes commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 who were employed in 1960.

U.S. represents a large change in employment demand during the time period under consideration and therefore appears prominently in these measures.[19]

3. Empirical Analysis

Using the proxies described in the previous section, we estimate employment rate and population responses to local labor demand shocks separately for Black and White men over the period of our analysis. In this section, we first outline our empirical strategy and present our baseline results. Then, we discuss several robustness checks of our empirical results and show that our main conclusions remain intact.

[19]This is illustrated in Figures B.1 and B.2 in the Appendix as well.

3.1. Empirical Strategy

We use two different empirical strategies to estimate the elasticity of local employment rates and population with respect to local labor demand shifts. First, in our long difference specification, we take changes in employment rates and total population over the period 1970–2010 at the commuting zone by group level and regress them on the proxies for local labor demand shifts corresponding to this period. Second, we run panel regressions where both the outcomes of interest and the shift-share proxies are allowed to vary by decade within our sample period. The long difference specification captures the long-run response to shocks while the panel specification captures short-run responses. The equations that we estimate take the following form:

$$\begin{aligned}\Delta \ln l_{cg} = \alpha^l + \beta^l \text{Black}_g + \gamma^l \Delta A_{cg} + \delta^l \Delta A_{cg} \times \text{Black}_g \\ + \mathbf{X}_{cg} \zeta^l_g + \varepsilon^l_{cg}\end{aligned} \tag{2}$$

$$\begin{aligned}\Delta \ln P_{cg} = \alpha^P + \beta^P \text{Black}_g + \gamma^P \Delta A_{cg} + \delta^P \Delta A_{cg} \times \text{Black}_g \\ + \mathbf{X}_{cg} \zeta^P_g + \varepsilon^P_{cg}\end{aligned} \tag{3}$$

In these equations, $\Delta \ln l_{cg}$ represents the log change in the employment rate for group g in commuting zone c and $\Delta \ln P_{cg}$ represents the corresponding log change in population. We stack observations across groups within a commuting zone and include the dummy variable Black_g to capture group-specific effects. Therefore, we estimate group-specific intercepts α_l and α_P for White workers and $\alpha^P + \beta_l$ and $\alpha^P + \beta^P$ for Black workers. The coefficients γ^l and γ^P measure the elasticity of employment rates and population to local labor demand shifts for White workers, while $\gamma^l + \delta^l$ and $\gamma^P + \delta^P$ measure the corresponding elasticities for Black workers. $\mathbf{X}_{cg}$ contains controls that may vary by both commuting zone and group.

We are interested in capturing the degree to which different regions and groups of workers were differentially exposed to changes in sectoral labor demand. Our proxies for local labor demand shifts take the form of a shift-share research design. Rather than using these proxies as instruments, we regress changes in employment rates and population on them directly. Under the identifying assumption that the sectoral composition of employment for each group in 1960 is uncorrelated with other changes at the local level over 1970–2010 that might impact employment or induce migration, we will obtain unbiased and consistent estimates for the coefficients γ^l, δ^l, γ^P, and δ^P (Goldsmith-Pinkham et al., 2020).

A threat to this identifying assumption is if there are innovations in labor supply over 1970–2010 correlated with the industrial composition of employment across commuting zones in 1960. In this case, our shift-share proxies would capture both supply and demand-side factors that influenced the evolution of employment rates and population changes over 1970–2010. In order to address this concern, we include controls for the foreign-born population share as well as the institutionalized population share by group in 1970. These variables may be correlated with initial industrial composition and could predict subsequent trends in immigration and incarceration, respectively, across commuting zones from 1970–2010. We also include controls for educational composition to deal with similar concerns.[20]

3.2. *Baseline Results*

Table 2 shows the results of estimating Equations (2) and (3) under our long difference specification, where we use 1970 and 2010 as our starting and ending years, respectively. We obtain statistically significant and economically meaningful estimates of the degree to which changes in employment rates and population over 1970–2010 vary with local demand shifts. In general, positive changes in local labor demand induce positive responses in both employment rates and population. The results show that local employment rates of Black men during this time period were more sensitive to changes in local labor demand than those of White men.

Though we present results across a variety of specifications, we use the results in Column (3) as our preferred specification, which we refer to as Specification (3). This specification includes other additional controls and state-fixed effects but excludes educational composition. We argue that controlling for educational attainment is perhaps unnecessary as it is unclear whether the initial educational composition across commuting zones is more likely to reflect trends in labor supply or labor demand over the period 1970–2010. Rising returns to skill over this time period represents an important demand-side factor that we would like our measures of local labor demand shifts due to sectoral reallocation to encompass.

Under our preferred estimates, the employment rate for Black men in the average commuting zone in our sample decreased by 3.1 percentage points relative to a 1.3 percentage point decrease for White men in response to the measured labor demand shifts. This reflects previous findings in the literature that have argued that although de-industrialization in the 1970s and 1980s produced negative consequences for the average worker, it was relatively more damaging to labor market outcomes of Black workers. The table also shows that our results are robust to including additional controls for initial demographic composition as well as fixed effects at the state and commuting zone level. The estimates are fairly stable across specifications, giving us confidence that our measures of local labor demand shifts capture sectoral reallocation patterns over this time period that are unrelated to the initial demographic composition of different regions.

The one exception is the results in Column (5), where the statistical and economic significance on the coefficient on ΔA_{cg} in the population change regression diminishes considerably for White workers. We suspect that there is low statistical power associated with this coefficient because the regression is very saturated when we included commuting zone fixed effects. With commuting zone fixed effects, the only variation is coming from cross-group differences in population growth rates within a commuting zone, which we expect to be small. The fact that the relative magnitudes of the other coefficients in this column are stable, however, is reassuring.

[20] We perform several diagnostic checks of our research design as suggested by Goldsmith-Pinkham et al. (2020). We present the results of these diagnostic tests in the appendix and discuss them in Section 3.3.5.

Table 2: Employment and Population Responses to Labor Demand Shifts over 1970–2010

	(1)	(2)	(3)	(4)	(5)
			Employment		
ΔA_{cg}	0.14***	0.11***	0.08	0.07	0.13
	(0.04)	(0.04)	(0.06)	(0.05)	(0.09)
ΔA_{cg} × Black	0.14**	0.14**	0.14*	0.12*	0.12
	(0.06)	(0.05)	(0.07)	(0.07)	(0.08)
R-Squared	0.24	0.27	0.36	0.38	0.67
Observations	672	672	672	672	672
			Population		
ΔA_{cg}	1.00**	0.87**	0.67**	0.84***	0.27
	(0.37)	(0.37)	(0.32)	(0.30)	(0.49)
ΔA_{cg} × Black	-0.06	-0.01	0.01	-0.15	0.05
	(0.35)	(0.34)	(0.29)	(0.25)	(0.31)
R-Squared	0.25	0.27	0.43	0.49	0.74
Observations	672	672	672	672	672
Add. Controls		X	X	X	
Educ. Comp.				X	
State FEs			X	X	
CZ FEs					X

Notes: Sample is restricted to commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 who were employed in 1960. Table reports results from pooled linear regressions of log differences in employment rate and population over 1970–2010 on our measure of local labor demand shifts. Labor demand shifts for each group are constructed using employment shares of the respective group by sectors in 1960 and national changes in sectoral employment over 1970–2010 according to Equation (1). Additional controls include the share of the foreign-born population in 1970 as well as the share of the institutionalized population for each group in 1970. Educational composition includes controls for the share of the population who are high school dropouts by group as well as the share of the population with a college degree by group in 1970. Robust standard errors clustered at the state level are in parentheses.$^{*}p \leq 0.10$;$^{**}\ p \leq 0.05$;$^{***}\ p \leq 0.01$

Lastly, we include the results from panel regressions that allow both the outcome variables and our shift-share proxies for labor demand changes to vary by decade. Table 3 contains the results of estimating Equations (2) and (3) as a panel. In all specifications, we include group-specific, decade fixed effects to control for any time trends in employment rates or population changes. We also include the same set of controls across specifications as our results in Table 2. Namely, we include controls for demographic and educational composition that are allowed to vary by racial group, as well as fixed effects for geographical location.

As in the long difference results above, Table 3 shows that positive changes in local labor demand generate positive responses in employment rates and population for both groups of workers. The estimates also show that employment rates of Black workers are significantly more sensitive to changes in local labor demand than those of White men. Moreover, the coefficient estimates are fairly stable across specifications. Again, the only exception is when we include commuting zone level fixed effects (which now have more power due to the inclusion of multiple time periods), where the magnitudes of the population change coefficients diminish somewhat.

We interpret estimates from our long-difference specification as capturing the adjustment to labor demand shifts over the long run, while our panel estimates capture short-run changes. Comparing the results in Table 3 to those in Table 2, we observe that the employment rate elasticities for both groups are larger in magnitude when analyzing decadal changes. This suggests that employment rates decline significantly after a negative shock and then partially recover. Additionally, note that the population elasticities for Black workers in Table 3 are lower than those for White workers. Although this difference is not statistically significant, it suggests the possibility of a more sluggish population adjustment for Black workers compared to White workers.[21] Given our objective of aggregating the impact of sectoral shifts on employment rates, we consider the long-difference estimates to be more appropriate for our analysis. These estimates allow for sufficient time for complete adjustment to occur, aligning with our goal of capturing the overall impact on employment rates. Moreover, when shocks are correlated over time, the sluggish adjustment of shocks implies that panel estimates tend to conflate short-run and long-run responses (Jaeger et al., 2018).

3.3. Robustness

We conduct several different robustness checks of our main estimates in Tables 2 and 3. We explore the robustness of our results to different sample selection criteria and different industrial classification schemes. We also run separate long difference regressions for each time period in our sample to test whether certain years are driving our results. Additionally, we run diagnostic checks that help to unpack the main sources of variation in our measures of local labor demand shocks. We discuss the results of these robustness exercises below. Appendix C contains the corresponding tables.

3.3.1. Different Employment Cutoffs

In our main empirical analysis, we drop any commuting zones that had less than 200 noninstitutionalized civilian Black men between the ages of 25-55 employed in 1960 in the case of our long difference estimation strategy (see Table 2) and in all years 1960, 1970, 1980, and 1990 in the case of our panel regression estimation strategy (see Table 3). We do this to ensure that there are enough employed Black men in each commuting zone to reliably compute sectoral employment shares in the commuting zones in our sample. However, regression results may be sensitive to this specific choice of cutoff. Therefore, we show our results when we instead vary the employment cutoff between 100 and 300 using our preferred specification, Specification (3).

Table C.1.1 displays these results for both our long difference and our panel specifications. Comparing these results to Tables 2 and 3, we can see that our long difference estimates display very little sensitivity to the choice of employment cutoff. The same holds true for our panel estimation strategy. Coefficients are similar in magnitude and stable across specifications. This is true for the coefficients on changes in population to a lesser extent, where coefficient estimates are mildly sensitive to the choice of cutoff, but differences in magnitudes are quantitatively small. Moreover, note that the R-squared values in the regressions increase as we increase the employment cutoff. This indicates to us that setting a sufficiently high cutoff value reduces noise in the estimates. We conclude that our results are not very sensitive to sample selection and that our selection criterion is appropriate in terms of our choice of commuting zone-level employment cutoff for Black men.

3.3.2. Different Industrial Classification

In our main empirical results, we leverage cross-industry variation in employment over the years 1970–2010 for industries that we classify into 71 sub-categories. We use these specific categories in order to balance the following two concerns: (1) finer industrial classifications make it more likely that our shift-share measure satisfies the exclusion restriction and (2) broader industrial classifications are less prone to measurement error stemming from small cell size. To investigate whether our estimates may be sensitive to the specific

[21] To investigate the adjustment process more formally, we incorporate lags of our shift-share measure into the panel regression in Section 3.3.3.

Table 3: Employment and Population Responses to Labor Demand Shifts: Panel Regressions

	(1)	(2)	(3)	(4)	(5)
			Employment		
$\Delta A_{cg,t}$	0.20***	0.20***	0.20***	0.21***	0.22***
	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)
$\Delta A_{cg,t} \times$ Black	0.14*	0.13*	0.13*	0.12*	0.14*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
R-Squared	0.13	0.14	0.15	0.15	0.21
Observations	2520	2520	2520	2520	2520
			Population		
$\Delta A_{cg,t}$	0.94***	0.83***	0.65***	0.65***	0.47***
	(0.25)	(0.24)	(0.17)	(0.19)	(0.15)
$\Delta A_{cg,t} \times$ Black	-0.19	-0.17	-0.09	-0.08	-0.08
	(0.25)	(0.24)	(0.23)	(0.25)	(0.23)
R-Squared	0.21	0.21	0.28	0.31	0.38
Observations	2520	2520	2520	2520	2520
Add. Controls		X	X	X	
Educ. Comp.				X	
State FEs			X	X	
CZ FEs					X
Decade FEs	X	X	X	X	X

Notes: Sample is restricted to commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 employed in all years 1960, 1970, 1980, and 1990. Table reports results from panel regressions of log differences in the employment rate and population on our measure of local labor demand shifts. Labor demand shifts for each group are constructed using employment shares of the respective group by sectors and national changes in sectoral employment in the respective decades according to Equation (1). Additional controls include the share of the foreign-born population in each decade as well as the share of the institutionalized population by group in each decade. Educational composition includes controls for the share of the population who are high school dropouts by group in each decade as well as the share of the population with a college degree by group in each decade. Decade fixed effects are allowed to vary by group. Robust standard errors clustered at the state level are in parentheses. $^{*}p \leq 0.10$; $^{**}p \leq 0.05$; $^{***}p \leq 0.01$

choice of the industrial classification scheme, we construct our shift-share measure utilizing 33 broad industry categories.

The results using the shift-measure constructed using broader industry categories for both our long-difference and panel estimation strategies are presented in Table C.1.2. The table shows that employment rate and population elasticities are broadly similar to those in our main estimates. Though estimated population elasticities under this industrial classification scheme are lower for Black workers, the difference with respect to the population elasticities of White workers is not statistically significant. Given that we find similar results using broader industry categories, we conclude that our estimates are not sensitive to the choice of the industrial classification scheme used to construct the shift-share measure.

3.3.3. *Lagged and Decade-Specific Effects*

As discussed in Section 3.2, the discrepancy between the long-difference and panel estimates implies a sluggish adjustment to shocks. In this section, we investigate this possibility by incorporating the lagged values of our shift-share measure in the panel regressions, following the suggestion of

Jaeger et al. (2018), to capture the persistent effects of sectoral shifts. The results from this exercise are presented in Table C.2.3. The estimates from the table indicate that the lagged shift-share measure has a negative and statistically significant impact on employment rates for both groups of workers. This aligns with our interpretation that employment rates experience a decline following a negative shock and then exhibit partial recovery. We do not observe any significant differences in the adjustment process of employment rates between the two groups. However, in our preferred specification, the lagged shift-share measure has no significant impact on the population for White workers, while it has a positive and statistically significant impact for Black workers. This suggests that population adjustment may be more sluggish for Black workers, which explains why we find smaller population elasticities when analyzing decadal changes for Black workers compared to our long-difference specification. These findings emphasize the suitability of long differences for aggregation analysis in our paper, as they capture the full adjustment of outcomes to local labor demand shocks.

We also explore the implications of two additional specifications. First, we run a separate regression for each decade and vicennial in our sample and display the results in Table C.2.1 in the appendix. Second, we run panel regressions where differences are taken across 20-year periods (vicennials) instead of decades and display the results in Table C.2.2. These specifications allow us to test whether specific decades are driving our main results. This does not appear to be the case, as we obtain similar estimates for our main outcomes of interest for these specifications.

3.3.4. Different Sub-Samples and Sub-Groups

It is possible that individuals from outside the United States immigrate into areas that received more favorable local labor demand shocks. To test whether this immigration response is affecting our estimates of migration elasticities, we perform our analysis on a restricted sample that includes only individuals born in U.S. states.[22] We recompute both our outcome variables and our shift-share proxies for this restricted sample and estimate long-difference specifications with the same set of control variables as in the main analysis.

Results of this exercise are displayed in Table C.3.1. Comparing results to Table 2, we can see that the U.S.-born subsample displays similar employment rate and population elasticities as the full sample in both qualitative and quantitative terms. While the population elasticities for White men are slightly lower in comparison to our main estimates, as before, we do not find significant differences between the population elasticities for Black and White men. Consequently, we argue that the population responses estimated in our paper pertain to migration and accurately capture the movement of individuals within the country rather than immigration inflows or outflows.

Next, to test whether skill composition within groups is driving our main results, we repeat our analysis after conditioning outcome variables on education status. We construct local employment rates and population using only workers who did not complete college and regress these measures on the shift-share proxies used in our main analysis. Table C.3.2 contains the results, which show that our conclusions broadly hold within the sample of low-skill workers. Though the estimated employment rate elasticity for Black men diminishes somewhat relative to the results in Table 2, it remains larger than that for White men in all specifications. So we conclude that the differential employment rate response we document is not explained by educational differences between the two groups.

3.3.5. Bartik Diagnostics

We perform diagnostic tests of the shift-share research design used in the paper following the suggestions in Goldsmith-Pinkham et al. (2020). First, we compute Rotemberg weights, which help to assess the contribution of specific industries to the overall variation in our research design. Industries

[22] We exclude individuals with a birthplace code in IPUMS outside of the United States (`bpl > 99`).

with larger Rotemberg weights have a larger contribution to the overall variation in our shift-share proxy for local labor demand shocks. We display the ten industries that have the largest Rotemberg weights by group in Table C.4.1 in the appendix. The industries *Textile mill products and apparel* and *Metal industries manufacturing* have the largest Rotemberg weights for White and Black workers, respectively.

Next, in order to address the possibility that other trends besides sectoral reallocation contributed to the evolution of the Black-White employment differential, we display the correlation between the controls used in our long difference regression specifications and industry shares by group in 1960 $\pi_{csg,1960} \equiv L_{csg,1960}/L_{cg,1960}$ across commuting zones. We do so for the industries with the ten largest Rotemberg weights for each group. The results of this exercise are displayed in Table C.4.2 in the appendix.

The table shows that the correlations between our control variables and the key industries driving the variation in our shift-share proxies are not particularly strong, suggesting that our instrument is valid. It is worth noting that when we include commuting zone fixed effects in our regressions, we are leveraging the differences in sectoral composition between Black and White workers within locations, as well as the interaction of sectoral shares with industry trends in the case of panel regressions.

3.4. Summary of Empirical Results

In sum, our results suggest that Black men have a higher elasticity of employment rates to changes in local labor demand. We can also see that both Black and White men outmigrate in response to declining labor demand in local markets. Reduced-form population responses can inform us about how population in a local area changes due to changes in labor demand in that area. However, local populations are also affected by changes in labor demand in other areas. In order to fully capture population responses due to simultaneous changes in labor demand in several areas, we need to impose some structure on how individuals move across locations. We do so in the next section.

In the proceeding analysis, we use the estimates from our long-difference strategy, as we argue that they capture long-run responses to sectoral shifts. Table 2, Column (3) shows our preferred specification. However, we include the results for the aggregation exercise using the estimates from Columns (1), (2), (4), and (5) in the appendix. We also include the results for our aggregation exercise using the estimated elasticities from our panel regression specification (see Table C.5.1) in the appendix.

4. A Model of Labor Market Frictions

In this section, we present a simple model of local labor markets that incorporates matching frictions within markets and mobility frictions across markets. In our model, individuals have idiosyncratic preferences for each location drawn from an extreme value distribution. This is a common, tractable approach for modeling imperfect mobility across locations.[23] However, we depart from the conventional benchmark of perfectly competitive local labor markets with full employment and incorporate matching frictions in local markets as in Kim and Vogel (2021).[24]

In our model, firms post job vacancies specific to each group, considering location and group-specific productivity. This determines the equilibrium employment rate in each location. Workers, on the other hand, choose their location based on expected utility, which depends on wages, employment rates, and their idiosyncratic preferences for each location. Consequently, markets that experience a decrease in productivity will observe a decline in both population and employment rates. The extent of this effect depends on the elasticities governing mobility and matching frictions, which we allow to

[23] See Redding and Rossi-Hansberg (2017) for a review of spatial models.

[24] While the model in Kim and Vogel (2021) is a sectoral choice model, we adopt their approach to modeling frictional markets. Kim and Vogel (2021) derive their comparative static results assuming equal market tightness across markets. However, we relax this assumption to allow for varying employment rates across different locations. Additionally, we do not model other adjustment margins, as our main emphasis is on the employment rate rather than overall welfare.

vary across different groups. We consider sectoral reallocation as having an impact on a location through changes in local labor productivity. The comparative statics analysis of the model produces equations that resemble the reduced-form equations estimated in Section 3.

4.1. Model Setup

The economy consists of K local labor markets indexed by c. Workers belong to different, non-overlapping groups indexed by g. The total number of workers in the population for each group, denoted by P_g, is fixed. There are P_{cg} workers of group g and V_{cg} vacancies for workers of group g in local labor market c. If employed, a worker belonging to group g in location c produces flow output A_{cg}.[25] Workers choose a location based on their expected utility and search for employment opportunities in that location. Firms decide how many vacancies to post for each group in each location to maximize their profits. Employment for group g in location c, L_{cg}, is determined by the labor market tightness, $\theta_{cg} \equiv V_{cg}/P_{cg}$. Hence, markets are effectively indexed by location-group pairs cg. Both firms and workers are risk neutral.

4.1.1. Worker's location choice

Workers search for employment in the location that provides them the highest expected utility. We will assume that the expected utility for a worker belonging to group g from searching in location c is given by:

$$u_{cgi} = w_{cg} l_{cg} \varepsilon_{cgi}$$

where w_{cg} and l_{cg}, respectively, represent the wage and job-finding probability in location c for workers belonging to group g. ε_{cgi} represents an idiosyncratic utility component which captures individual-specific preferences for living in c. The cumulative density function for $\{\varepsilon_{cgi}\}_{i=1}^{K}$ is given by:

$$F_g(\varepsilon_1, ..., \varepsilon_K) = \exp\left(-\sum_{l=1}^{K} \varepsilon_c^{-1/\kappa_g}\right)$$

As will become clear in Section 4.4, the parameter κ_g governs the elasticity of labor supply across labor markets and can be interpreted as capturing costs of moving across locations.

4.1.2. Vacancy Posting

Firms incur a vacancy posting cost in each market F_{cg}. We assume free entry such that firms post vacancies until their profits from a new vacancy are zero. Therefore, total vacancies in each market are determined by the following condition, which equates marginal costs to marginal benefits of vacancy posting:

$$(A_{cg} - w_{cg})q_{cg} = F_{cg} \tag{4}$$

where q_{cg} denotes the probability of filling a vacancy for a firm. Note that, $A_{cg} - w_{cg}$ is the net gain for the firm from filling a vacancy.

4.1.3. Matching

We assume that local labor markets are frictional and the total number of matches in any market is determined by a Cobb-Douglas matching function as follows:

$$L_{cg} = m(V_{cg}, P_{cg}) = \gamma_{cg} V_{cg}^{\alpha_g} P_{cg}^{1-\alpha_g} \tag{5}$$

where $\gamma_{cg} > 0$ represents the efficiency of the matching technology and $\alpha_g \in (0,1)$ is the elasticity of matching with respect to vacancies.[26] Given the above matching technology, the job-finding rate for a worker of group g in location c is given by:

$$l_{cg} = \frac{L_{cg}}{P_{cg}} = \gamma_{cg} \theta_{cg}^{\alpha_g}$$

The employment rate for workers of the group with a higher α_g is relatively more sensitive to market tightness. The match

[25] We assume that workers of different groups have different productivity within each local labor market to account for differences in composition across sectors within each location.

[26] Conventionally, labor market tightness is measured as the ratio of vacancies to the number of unemployed workers. However, in our model, we define labor market tightness as the ratio of vacancies to the population. As a result, our estimated elasticities differ from the conventionally estimated elasticities, which assume that only unemployed individuals are actively searching for jobs.

technology also determines the probability of filling a vacancy, $q_{cg} = L_{cg}/V_{cg} = \gamma_{cg}\theta_{cg}^{-(1-\alpha_g)}$.

4.1.4. Timing and Wage Setting

The sequence of events in our model is as follows: first, the worker chooses a location to apply for a job. Once matched, output is produced, and finally, the worker and firm Nash bargain over the surplus. Essentially, both the worker and the firm face a hold-up problem, which implies that at the bargaining stage, their outside options are sunk. As a result, wages are solely determined by the productivity of the workers as follows:

$$w_{cg} = \omega_{cg} A_{cg} \tag{6}$$

where ω_{cg} represents the bargaining power of workers.

4.2. Equilibrium Outcomes

We now discuss the derivation of the equilibrium. From Equations (4) to (6) we can solve for equilibrium labor market tightness to obtain:

$$\theta_{cg}^{*} = \left[\frac{(1-\omega_{cg})\gamma_{cg}}{F_{cg}}\right]^{\frac{1}{1-\alpha_g}} A_{cg}^{\frac{1}{1-\alpha_g}}$$

This implies that the equilibrium job finding probability is given by,

$$l_{cg}^{*} = \gamma_{cg}\theta_{cg}^{*\alpha_g} = \gamma_{cg}\left[\frac{(1-\omega_{cg})\gamma_{cg}}{F_{cg}}\right]^{\frac{\alpha_g}{1-\alpha_g}} A_{cg}^{\frac{\alpha_g}{1-\alpha_g}} \tag{7}$$

Note that this expression depends only on parameter values and flow output in a market A_{cg}, which we take to be exogenously given. Then, combining these results with workers' location choices allows us to derive a simple expression for population shares in each location.

Proposition 1. *For each group g, the share of workers who reside in location c is given by:*

$$\pi_{cg}^{*P} = \frac{P_{cg}^{*}}{P_g} = \frac{\tilde{c}_{cg} A_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}}}{\sum_c \tilde{c}_{cg} A_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}}} \tag{8}$$

where $\tilde{c}_{cg} = \left(\omega_{cg}\gamma_{cg}\left[\frac{(1-\omega_{cg})\gamma_{cg}}{F_{cg}}\right]^{\frac{\alpha_g}{1-\alpha_g}}\right)^{1/\kappa_g}$.

(Proofs of all propositions are provided in the Appendix.)

This result allows us to also write simple, closed form expressions for population shares that depend solely on parameter values and flow output A_{cg}.

4.3. Comparative Statics

We next derive comparative statics to illustrate how changes in local productivity induce changes in employment rates and population shares depending on the strength of labor market frictions and mobility costs. Our model predicts that equilibrium responses of employment rates and population shares for each group depend in a simple way on the parameters that govern the degree to which each group faces locational and matching frictions.

Prior to presenting the result, we introduce the notation $\hat{x}_{cg} = x'_{cg}/x_{cg}$, where x'_{cg} represents the value of a variable in the new equilibrium and x_{cg} represents its value in an initial equilibrium.

Proposition 2. *Suppose local labor productivity changes from A_{cg} to A'_{cg}, then resulting changes in local employment rates and population shares can be expressed as follows:*

$$\ln \hat{l}_{cg} = \frac{\alpha_g}{1-\alpha_g} \cdot \ln \hat{A}_{cg} \tag{9}$$

$$\ln \hat{\pi}_{cg}^{P} = \frac{1}{\kappa_g(1-\alpha_g)} \cdot \ln \hat{A}_{cg} - \ln \sum_c \pi_{cg}^{p} \hat{A}_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}} \tag{10}$$

where $\pi_{cg}^{p} = P_{cg}/P_g$.

Equation (9) shows that if group g workers in market c experience a negative shock, their employment rate will decline in a manner proportional to the size of the match elasticity for workers in group g. This is because employment prospects worsen for workers in that market, as firms earn less profit per vacancy and post fewer vacancies as a result of the decline in A_{cg}. The degree to which the employment rate declines depends on the parameter α_g, such that groups with higher α_g experience larger drops in the employment rate for a given shock. This is due to the fact that α_g governs the elasticity of the matching function – in other words, how the total number of matches vary with the total number of vacancies posted by firms in a market.

Equation (10) shows that in response to a negative shock, we expect to see out-migration of workers as they decide to search for better employment opportunities in other areas. The second term in this equation takes into account that the overall change in population within a specific location is influenced not only by the shock in that location but also by shocks in other locations. This term arises due to the migration responses triggered by shocks in other locations, resulting in individuals moving into or out of location c. The magnitude of out-migration depends on the parameter κ_g. Hence, we interpret this parameter as representing costs of migration, since a larger κ_g implies a lower population response, ceteris paribus. We also see that α_g helps determine the response of population shares, since workers who choose to migrate must look for new jobs and will encounter matching frictions in other areas. In this equation, a larger $1-\alpha_g$ corresponds to a higher propensity of being crowded out by other job seekers, since it is the elasticity of matches with respect to population size in the matching function. Hence, groups with a higher $1-\alpha_g$ will be less likely to migrate since they internalize the fact that other workers moving to other markets may crowd them out as well.

4.4. Structural Parameters

As long as our shift-share measure is a valid proxy for changes in local labor productivity $\ln \hat{A}_{cg}$, the equations we estimated in Section 3 are the empirical counterparts of Eqs. (9) and (10) and allow us to recover the structural parameters of the model from the estimated elasticities.[27] Table 4 presents the estimated values for the structural parameters derived from our results. Notably, we observe that α_B is greater than α_W, implying that the match elasticity with respect to vacancy posting is much larger for Black than for White workers. In other words, the employment rate of Black men over this time horizon was much more sensitive to labor demand shifts to local areas. Although the mobility cost parameter κ_B is slightly higher than κ_W, the difference is not statistically significant. Hence, we do not observe substantial differences in the propensity to relocate between the two groups.

Table 4: Structural Parameters

Parameter	Explanation	Estimate	SE
α_B	Match Elasticity: Black men	0.18	(0.036)
α_W	Match Elasticity: White men	0.07	(0.055)
κ_B	Mobility Costs: Black men	1.78	(0.455)
κ_W	Mobility Costs: White men	1.60	(0.763)

Notes: The estimates for the model parameters are derived from the estimated elasticities presented in Table 2, Column (3). Standard errors (SE) are computed using the delta method. The p-value on the test for the difference in match elasticities is 0.097, while the p-value for the difference in mobility costs is 0.841.

5. Aggregation and Counterfactual Analyses

As mentioned above, it is not possible to directly infer the impact of sectoral shifts on aggregate employment solely from the local responses estimated in Section 3. Our estimates suggest that there are large movements in local employment rates in response to labor demand shifts. However, our findings also indicate that workers tend to migrate away from areas that experience more negative shocks, which has implications for the overall impact on aggregate employment. For instance, a negative shock to local productivity may decrease the employment rate in that specific area, but some individuals may choose to relocate in response to this shock. Thus, in assessing aggregate changes, we must account for the fact that individuals who migrate may find employment opportunities in other areas. Furthermore, the distribution of employment across regions also plays a role in determining the overall impact of local demand shifts on aggregate employment.

[27] If workers' decision-making was solely influenced by wages within a local area, disregarding employment probabilities, the mobility cost parameter κ_g would be the reciprocal of the coefficient on the shift-share measure in the population regression.

Table 5: Actual and Predicted Changes in Employment Rates

	Employment Rate			Change (1970-2010)	
	1970	2010	Predicted	Actual	Predicted
	(1)	(2)	(3)	(4)	(5)
Black Men	85.7	68.1	83.3	-17.7	-2.5
White Men	93.0	82.6	91.8	-10.4	-1.2
Gap: Black–White	-7.2	-14.5	-8.5	-7.3	-1.3

Notes: Sample is restricted to commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 who were employed in 1960. Columns (1) and (2) show actual values (in percentage points) in our sample for 1970 and 2010, respectively. Column (3) shows the predicted value for 2010 under the counterfactual scenario where only sectoral reallocation affects the employment rate. Column (4) shows the difference between the values in Columns (2) and (1), while Column (5) shows the difference between the values in Columns (3) and (1). The last row shows the difference between the values in the preceding two rows.

To illustrate, suppose there is an economic shock that has a potentially different impact in different regions. In this scenario, we can express the relative change in the aggregate employment rate for each group in the new equilibrium compared to the initial equilibrium as follows:

$$\hat{l}_g = \sum_c \pi_{cg} \hat{l}_{cg} \hat{\pi}^P_{cg}$$

Here, π_{cg} denotes the employment share of group g in region c, while $\hat{l}_{cg}$ and $\hat{\pi}^P_{cg}$ represent the change in local employment rates and population shares, respectively, for group g.[28] It is important to note that $\hat{\pi}^P_{cg}$ represents not only the change in the share of the population in a location caused by shocks in that same location, but also changes resulting from shocks in other locations. The estimated local responses by themselves would not allow us to capture $\hat{\pi}^P_{cg}$, but only the partial-equilibrium counterpart of it.[29] However, the model discussed in the previous section imposes additional structure on population movements, allowing us to express $\hat{\pi}^P_{cg}$ as a function of the estimated elasticities from our local regressions and the observed shocks.

By substituting the expressions for $\hat{l}_{cg}$ and $\hat{\pi}^P_{cg}$ derived from our model, as given by Eqs. (9) and (10), into the $\hat{l}_g$ term, we can express the aggregate change in the employment rate in terms of the estimated elasticities, observed shocks, and initial shares of employment and population. The following proposition formally presents this result.

Proposition 3. *As per the model described in Section 4, the change in the aggregate employment rate for group g in response to local labor productivity shifts can be expressed as follows:*

$$\hat{l}_g = \frac{\sum_c \pi_{cg} \hat{A}_{cg}^{\frac{\alpha_g \kappa_g + 1}{\kappa_g(1-\alpha_g)}}}{\sum_c \pi^P_{cg} \hat{A}_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}}}$$

The proposition above highlights that the aggregate changes in the employment rate for each group are determined by the elasticities related to migration and matching frictions, in addition to the distribution of shocks, initial employment, and population. Hence, our framework enables us to measure the overall impact of sectoral shifts by utilizing the estimated elasticities. Furthermore, it allows us to perform counterfactual analyses by considering different scenarios for the distribu-

[28] This identity can be derived as follows. First, note that $\hat{L}_g = L'_g/L_g = \sum_c (L'_{cg}/L_g)$. By dividing and multiplying the term inside the summation by L_{cg}, we obtain $\hat{L}_g = \sum_c \pi_{cg} \hat{L}_{cg}$. Finally, by substituting $\hat{L}_{cg} = \hat{l}_{cg} \hat{\pi}_{cg} \hat{P}_g$ into the previous equation, we obtain the final expression.

[29] This is a version of the so-called "missing intercept" problem — local regressions are unable to recover the aggregate impact of a shock when regions are spatially connected.

tion of shocks and initial employment and population, which determine the exposure to sectoral shifts. Additionally, we can explore counterfactual scenarios by varying the values of the elasticities, which determine the response to shocks.

5.1. Aggregation Exercise

According to Proposition 3, we now combine estimates of the structural parameters presented in Table 4 with data on regional employment shares in 1970 and our proxy for $\hat{A}_{cg}$ over 1970–2010 to document the change in aggregate employment for Black and White men over this period that can be explained by our measured labor demand shifts. Table 5 presents the results from this exercise. We report the actual and predicted changes in the employment rate for Black and White men from 1970–2010 in Columns (4) and (5), respectively.

From Table 5, we can see that our measured labor demand shifts capture little of the group-specific declines in employment rate for Black and White workers. From 1970–2010, the employment rate fell from 85.7 to 68.1 for Black workers and from 93 to 82.6 for White workers in our sample of CZs. Our measured labor demand shocks account for a decrease of 2.5 and 1.2 percentage points for Black and White workers, respectively. Consequently, the table shows that sectoral shifts explain only a small portion of the increase in the employment rate gap between Black and White workers over this time horizon. According to our analysis, sectoral reallocation accounts for about 1.3 percentage points of the total 7.3 percentage point increase in the Black-White employment rate gap, or just under one-fifth.

The results in Table 5 are computed using our preferred estimates from Column (3) of Table 2. However, Table C.5.1 in the appendix presents results from an analogous exercise for estimates from different specifications in Tables 2 and 3. Across different specifications and estimation strategies, we find that sectoral shifts in labor demand account for between 10–20% of the increase in the Black-White gap.

5.2. Counterfactuals

In order to unpack the forces that are responsible for driving changes in the Black-White gap, we next compute counterfactuals for the aggregate change in the employment rate gap under several alternative scenarios. This allows us to separate out the components of the overall change that are due to workers' migration responses as well as the contributions of shock exposure vs. shock response. With both our estimated local elasticities and our measures of local labor market shocks in hand, our aggregation framework allows us to study what would have happened to the employment rate gap if both group of workers (1) were not able to migrate to offset the negative impacts of shocks, (2) were exposed to the same distribution of shocks, and (3) responded in a similar manner to shocks at the local level.

Table 6: Counterfactuals

	Black	White	Gap
Predicted Change (1970-2010)	-2.5	-1.2	-1.3
Counterfactuals			
(1) Shutting Off Migration	-2.8	-1.2	-1.5
(2) Identical Shock Exposure			
(a) White Men Exposure	-2.9	-1.2	-1.8
(b) Black Men Exposure	-2.5	-1.0	-1.5
(3) Identical Response Elasticities			
(a) White Men Elasticities	-0.9	-1.2	0.3
(b) Black Men Elasticities	-2.5	-3.2	0.7

Notes: The first row shows the predicted change in the employment rate for Black men, the employment rate for White men, and the employment rate gap, respectively, implied by the model. Counterfactual (1) shows the predicted changes after setting local population responses $\hat{\pi}^P_{cg}$ to one for both groups. Counterfactual (2) shows the predicted changes after allowing both groups to have identical shock exposure (π_{cg}, π^P_{cg}, $\hat{A}_{cg}$). Counterfactual (3) shows the predicted changes after allowing both groups to have identical response elasticities (α_g, κ_g).

Table 6 shows the results of this exercise. The first row displays the predicted change in the employment rate for

[30] Note that this row is identical to Column (5) of Table 5.

each group of workers as well as the implied change in the employment rate gap under our baseline results.[30] The counterfactual labeled “Shutting Off Migration” shows the changes in these series if instead, workers were not able to migrate in response to shocks. We calculate this counterfactual by setting the term $\hat{\pi}^P_{cg} = 1$ in equation for $\hat{l}_g$ above. Under this scenario, the change in the employment rate for White men is approximately the same as in our baseline results, while the change in the employment rate for Black men is about -2.8, as compared to -2.5, percentage points. Therefore, we find that population responses for both groups have a very small effect on mitigating the impact of sectoral shifts, as they are responsible for offsetting the change in the gap by only about 0.3 percentage points.

We find a limited role for migration in mitigating the impact of negative labor demand shifts because the aggregate impact of population responses depends both on local population elasticities and on the distribution of shocks across regions. Even if local population responses are large in magnitude, population movements only help mitigate shocks if relocated workers can find jobs. Population movements for Black workers reduce the predicted change in the employment rate gap because these workers face a larger distribution of shocks (see Figure 2). Therefore there is more dispersion in employment opportunities for these workers, incentivizing relocation to less hard-hit markets.

Next, we investigate whether the larger response of the aggregate employment rate for Black workers stems from greater exposure to labor demand shifts or a larger response to a similar set of labor demand shifts. In order to formalize the contributions of these margins, the next two set of counterfactuals calculate the change in the employment rate gap assuming that workers face an identical distribution of labor demand shocks, given their group-specific local elasticities, vs. assuming that workers face identical local elasticities, given their group-specific distributions of labor demand shocks.

The counterfactual labeled “Identical Shock Exposure” uses the same set of local labor demand shocks $\hat{A}_{cg}$, employment shares π_{cg}, and population shares π^P_{cg} for each group in the equation stated in Proposition 3. Note that because our proxy for local labor demand shocks is calculated using group-specific sectoral employment shares in each region, the exposure to shocks differs between the two groups due to their initial composition across sectors and locations. We present the aggregation results by setting the set of shocks and initial shares for both groups equal to those corresponding to White men ("White Men Exposure") and those corresponding to Black men ("Black Men Exposure") separately. Under both of these counterfactual scenarios, we find that the employment rate gap between the groups would have been only slightly wider. This suggests that initial compositional differences between the two groups are not the primary force driving the employment rate differential.

Lastly, the counterfactual labeled “Identical Response Elasticities” corresponds to a scenario where each group faces its own set of shocks and initial shares, but both groups have the same local employment rate and population elasticities. In this analysis, we present aggregation results by setting both elasticities equal to the elasticities corresponding to White men (“White Men Elasticities”) and Black men (“Black Men Elasticities”) separately. In both cases, we find that if both groups had similar responses to shocks, the employment rate differential between them would have slightly *narrowed*, suggesting that most of the increase in the employment rate differential stems from differential elasticities.

In summary, we find a limited role of population movements in driving the employment rate differential. Additionally, our findings suggest that differential employment composition across regions or sectors is not a significant factor in exaggerating the employment rate differential. The primary factor driving the differential is the different local employment rate responses between groups to comparable local shocks. Note that we find similar results when utilizing estimated elasticities from different specifications in Tables 2 and 3. These results are presented in Table C.5.1.

6. Conclusion

We provide a simple framework to assess the degree to which sectoral shifts in labor demand played a role in the widening of the employment gap between Black and White workers from 1970–2010. We find that sectoral reallocation can explain about a fifth of the increase in the gap between the employment rate for Black men and White men, and a small share of the evolution of the employment rates for these groups individually over this period. Mirroring other results in the literature, we find that employment rates for Black workers are more responsive to changes in labor demand. Furthermore, most of the increase in the employment gap can be attributed to the differential response of Black workers to local labor demand shifts, rather than a higher incidence of shifts to sectors or regions in which Black workers are over-represented. In future work, we plan to further investigate what gives rise to these differential responses across groups.

Our results show that sectoral shifts were partially responsible for the decrease in the employment rate for Black men relative to White men over the second half of the 20th century, after several decades of convergence. The decline in the manufacturing sector, which some authors have argued hit Black workers harder than White workers, is an important example of these structural changes. However, they explain only a small portion of the evolution of the Black-White employment gap on aggregate and fail to account for why both Black and White workers experienced such a big decline in employment rates over this time period. In decomposing these effects, we highlight the importance of different margins of labor market adjustment arising from both imperfect regional mobility and frictional labor markets that may have differential effects across groups of workers. Our findings suggest that future studies should pay close attention to the aggregation of local effects, which may be offset by migration patterns, and look for other sources of divergence in employment opportunities for Black and White individuals in recent years.

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A. Proofs and Derivations

A.1. Proof of Proposition 1

Proof. Worker i chooses to search for employment opportunities in the location with the highest expected utility, such that

$$l_i^* = \underset{l}{\operatorname{argmax}}\{u_{cg}\varepsilon_{ci}\}$$

where $u_{cg} = w_{cg} l_{cg}$.

The probability that an individual chooses local labor market c' is given by:

$$\begin{aligned}
\frac{P_{c'g}}{P_g} &= \mathbb{E}_{\varepsilon_{c'}}[\Pr(u_{c'g}\varepsilon_{c'} > u_{cg}\varepsilon_c) \quad \forall c \neq c'] \\
&= \int_0^\infty \exp\left[-\sum_{c\neq c'}\left(\frac{u_{c'g}\varepsilon_{c'}}{u_{cg}}\right)^{-1/\kappa_g}\right] f(\varepsilon_c')d\varepsilon_c' \\
&= \int_0^\infty \exp\left[-\left(u_{c'g}^{-1/\kappa_g}\sum_{c\neq c'} u_{cg}^{1/\kappa_g} + 1\right)\varepsilon_{c'}^{-1/\kappa_g}\right] 1/\kappa_g \varepsilon^{-1/\kappa_g - 1} d\varepsilon_c' \\
&= \frac{u_{cg}^{1/\kappa_g}}{\sum_c u_{cg}^{1/\kappa_g}}
\end{aligned}$$

Derivation uses the fact that if ε is distributed Fréchet with $F(\varepsilon) = exp(-\varepsilon^{-1/\kappa})$, then $f(\varepsilon) = 1/\kappa\varepsilon^{1/\kappa-1}\exp(-\varepsilon^{1/\kappa})$.

Plugging in equilibrium values of w_{cg} and l_{cg}, we can find equilibrium expected utility from location c as follows:

$$u_{cg}^* = \omega_{cg}A_{cg} \times \gamma_{cg}\left[\frac{(1-\omega_{cg})\gamma_{cg}}{F_{cg}}\right]^{\frac{\alpha_g}{1-\alpha_g}} A_{cg}^{\frac{\alpha_g}{1-\alpha_g}} = c_{cg}A_{cg}^{\frac{1}{1-\alpha_g}}$$

where $c_{cg} = \omega_{cg}\gamma_{cg}\left[\frac{(1-\omega_{cg})\gamma_{cg}}{F_{cg}}\right]^{\frac{\alpha_g}{1-\alpha_g}}$. Plugging in u_{cg}^* in the expression for $P_{c'g}/P_g$ we get the expression specified in the proposition. □

A.2. Proof of Proposition 2

Proof. Recall that we are denoting $\hat{x}_{cg} = x'_{cg}/x_{cg}$, where x'_{cg} represents the value of a variable in the new equilibrium and x_{cg} represents its value in the current equilibrium. Then from Eq. (7),

$$\hat{l}_{cg} = \frac{l'_{cg}}{l_{cg}} = \frac{\gamma_{cg}\left[\frac{(1-\omega_{cg})\gamma_{cg}}{F_{cg}}\right]^{\frac{\alpha_g}{1-\alpha_g}} A'^{\frac{\alpha_g}{1-\alpha_g}}_{cg}}{\gamma_{cg}\left[\frac{(1-\omega_{cg})\gamma_{cg}}{F_{cg}}\right]^{\frac{\alpha_g}{1-\alpha_g}} A_{cg}^{\frac{\alpha_g}{1-\alpha_g}}} = \hat{A}_{cg}^{\frac{\alpha_g}{1-\alpha_g}}$$

Taking the natural log of the above expression, we obtain Eq. (9).

Similarly, using Eq. (8) and denoting $\beta_g^P = 1/[\kappa_g(1-\alpha_g)]$, we can write:

$$\hat{\pi}_{cg} = \frac{\pi'^P_{cg}}{\pi^P_{cg}} = \frac{\tilde{c}_{cg}(A'_{cg})^{\beta_g^P}}{\tilde{c}_{cg}(A_{cg})^{\beta_g^P}} \cdot \frac{\sum_c \tilde{c}_{cg}(A_{cg})^{\beta_g^P}}{\sum_c \tilde{c}_{cg}(A'_{cg})^{\beta_g^P}}$$

Now note that,

$$\frac{\sum_c \tilde{c}_{cg}(A'_{cg})^{\beta_g^P}}{\sum_c \tilde{c}_{cg}(A_{cg})^{\beta_g^P}} = \sum_c \frac{\tilde{c}_{cg}(A'_{cg})^{\beta_g^P}}{\sum_c \tilde{c}_{cg}(A_{cg})^{\beta_g^P}} \cdot \frac{\tilde{c}_{cg}(A_{cg})^{\beta_g^P}}{\tilde{c}_{cg}(A_{cg})^{\beta_g^P}} = \sum_c \pi_{cg}^P \hat{A}_{cg}^{\beta_g^P}$$

Plugging the above term in the expression for $\hat{\pi}_{cg}$ and noting $\beta_g^P = 1/[\kappa_g(1-\alpha_g)]$, we obtain:

$$\hat{\pi}_{cg} = \frac{\hat{A}_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}}}{\sum_c \pi_{cg}^P \hat{A}_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}}}$$

Equation (10) can be obtained by taking the natural log of the above expression. □

B. Data

We use time-consistent industry codes at the three-digit level from IPUMS contained in the variable `ind1990`. IPUMS constructs these codes from underlying Census Bureau industrial classifications to reflect the same broad set of industries across different samples. Based on these, we classify industries into 71 broad categories. We drop the agricultural sector as well as armed forces. Detailed industry crosswalk files are available upon request.

Figure B.1: Industry-Level Shifts

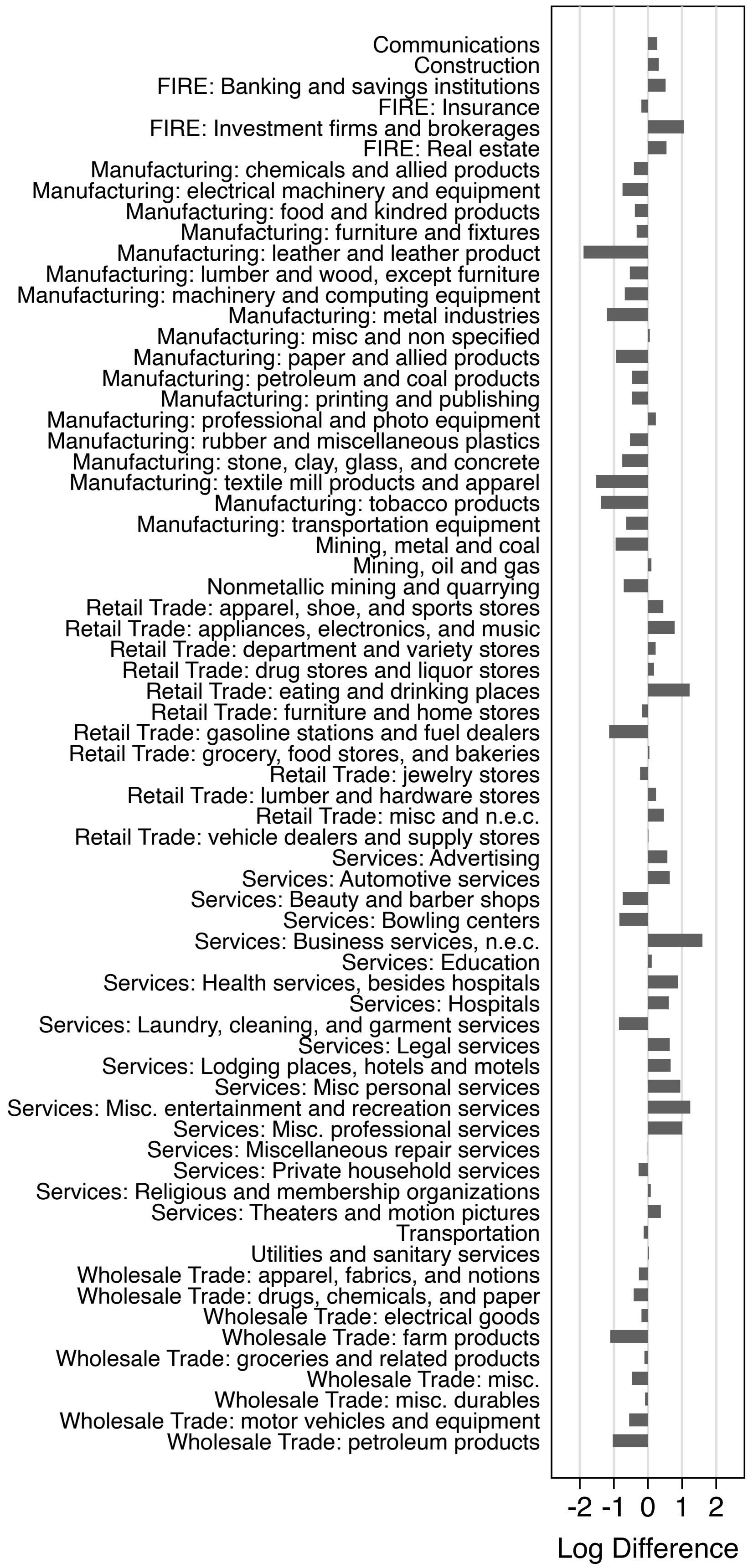
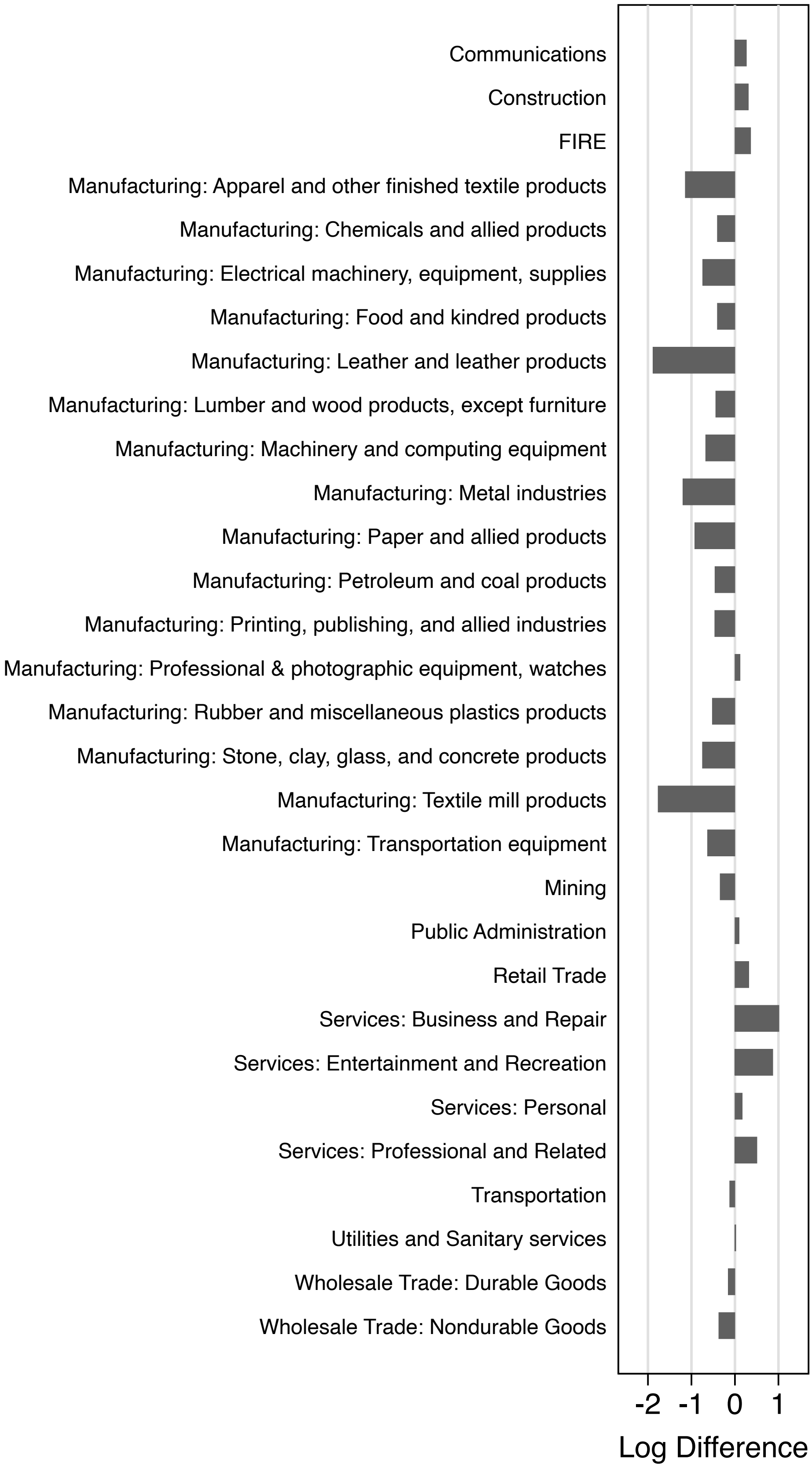


Figure B.2: Industry-Level Shifts, Broad Industries



C. Robustness

C.1. Robustness to Different Employment Cutoffs and Industrial Classification Schemes

Table C.1.1: Robustness of Main Estimates to Sample Cutoff

Sample employment cutoff	100	150	200	250	300
Panel A: Long Difference					
			Employment		
ΔA_{cg}	0.10	0.07	0.08	0.07	0.06
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)
ΔA_{cg} × Black	0.10	0.13	0.14*	0.16**	0.14*
	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)
R-Squared	0.29	0.33	0.36	0.38	0.41
Observations	768	704	672	636	612
			Population		
ΔA_{cg}	0.90***	0.72**	0.67**	0.67**	0.67*
	(0.31)	(0.31)	(0.32)	(0.31)	(0.33)
ΔA_{cg} × Black	-0.11	-0.02	0.01	-0.13	-0.09
	(0.29)	(0.27)	(0.29)	(0.28)	(0.29)
R-Squared	0.34	0.38	0.43	0.44	0.46
Observations	768	704	672	636	612
Panel B: Panel Regression					
			Employment		
$\Delta A_{cg,t}$	0.20***	0.21***	0.20***	0.20***	0.19***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
$\Delta A_{cg,t}$ × Black	0.12	0.12	0.13*	0.09	0.12*
	(0.10)	(0.07)	(0.07)	(0.06)	(0.06)
R-Squared	0.11	0.15	0.15	0.17	0.19
Observations	2848	2624	2520	2376	2288
			Population		
$\Delta A_{cg,t}$	0.62***	0.66***	0.65***	0.60***	0.65***
	(0.17)	(0.18)	(0.17)	(0.17)	(0.17)
$\Delta A_{cg,t}$ × Black	-0.10	-0.06	-0.09	-0.12	-0.21
	(0.25)	(0.24)	(0.23)	(0.23)	(0.25)
R-Squared	0.22	0.26	0.28	0.30	0.30
Observations	2848	2624	2520	2376	2288

Notes: Each column shows the results where the sample has been restricted to commuting zones that had at least a certain number of noninstitutionalized civilian Black men between the ages of 25-55 employed in 1960 (Panel A) and in all years 1960, 1970, 1980, and 1990 (Panel B). Table reports results from pooled linear regressions (Panel A) and panel regressions (Panel B) of log differences in employment rates and population on our measure of local labor demand shifts, which are constructed according to Equation (1). All specifications include additional controls, the share of the foreign-born population and the share of the institutionalized population by group in each time period, as well as state fixed effects. Robust standard errors clustered at the state level are in parentheses.$^{*}p \le 0.10$;$^{**}p \le 0.05$;$^{***}p \le 0.01$

Table C.1.2: Employment and Population Responses, Broad Industries

	(1)	(2)	(3)	(4)	(5)
Panel A: Long Difference					
			Employment		
ΔA_{cg}	0.11***	0.10***	0.04	0.04	0.12
	(0.03)	(0.03)	(0.05)	(0.05)	(0.09)
ΔA_{cg} × Black	0.16***	0.15***	0.15***	0.13**	0.14**
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
R-Squared	0.24	0.27	0.35	0.38	0.67
Observations	672	672	672	672	672
			Population		
ΔA_{cg}	0.84**	0.74*	0.48	0.58**	-0.25
	(0.38)	(0.37)	(0.32)	(0.25)	(0.41)
ΔA_{cg} × Black	-0.34	-0.31	-0.21	-0.25	-0.13
	(0.35)	(0.34)	(0.28)	(0.23)	(0.25)
R-Squared	0.19	0.23	0.41	0.47	0.74
Observations	672	672	672	672	672
Panel B: Panel Regression					
			Employment		
$\Delta A_{cg,t}$	0.25***	0.25***	0.25***	0.25***	0.32***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)
$\Delta A_{cg,t}$ × Black	0.13*	0.12*	0.12*	0.12	0.11*
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)
R-Squared	0.13	0.14	0.15	0.15	0.21
Observations	2520	2520	2520	2520	2520
			Population		
$\Delta A_{cg,t}$	1.10***	0.97***	0.80***	0.81***	0.63***
	(0.29)	(0.28)	(0.19)	(0.17)	(0.16)
$\Delta A_{cg,t}$ × Black	-0.42*	-0.39	-0.30	-0.24	-0.27
	(0.25)	(0.24)	(0.22)	(0.23)	(0.21)
R-Squared	0.20	0.21	0.27	0.31	0.38
Observations	2520	2520	2520	2520	2520
Additional Controls		X	X	X	
Educational Composition				X	
State Fixed Effects			X	X	
CZ Fixed Effects					X

Notes: Sample is restricted to commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 who were employed in 1960 (Panel A) and in all years 1960, 1970, 1980, and 1990 (Panel B). Table reports results from pooled linear regressions (Panel A) and panel regressions (Panel B) of log differences in employment rates and population on our measure of local labor demand shifts, which are constructed according to Equation (1). Additional controls include the share of the foreign-born population and the share of the institutionalized population by group in each time period. Educational composition includes controls for the share of the population who are high school dropouts by group and the share of the population with a college degree by group in each period. Panel regressions include decade fixed effects that are allowed to vary by group. Robust standard errors clustered at the state level are in parentheses.$^{*}p \leq 0.10$;$^{**}\ p \leq 0.05$;$^{***}\ p \leq 0.01$

C.2. Separate Decades, 20-Year Changes, and Lagged Effects

Table C.2.1: Employment and Population Responses, Each Time Period Separately

	Decades				Vicennials	
	1970-1980	1980-1990	1990-2000	2000-2010	1970-1990	1990-2010
			Employment			
$\Delta A_{cg,t}$	-0.02	0.17	0.17***	0.14	0.13**	0.16
	(0.08)	(0.13)	(0.04)	(0.17)	(0.05)	(0.14)
$\Delta A_{cg,t}$ × Black	0.18	0.22**	-0.21	0.37**	0.22**	0.18
	(0.12)	(0.10)	(0.17)	(0.15)	(0.08)	(0.16)
R-Squared	0.33	0.31	0.24	0.21	0.51	0.30
Observations	630	630	630	630	630	630
			Population			
$\Delta A_{cg,t}$	0.83*	0.89**	0.49***	0.63**	1.15**	0.65**
	(0.41)	(0.34)	(0.12)	(0.25)	(0.48)	(0.30)
$\Delta A_{cg,t}$ × Black	-0.59	-0.21	0.78***	-0.32	-0.55	0.05
	(0.70)	(0.35)	(0.19)	(0.34)	(0.53)	(0.30)
R-Squared	0.17	0.35	0.34	0.27	0.34	0.36
Observations	630	630	630	630	630	630

Notes: Sample is restricted to commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 employed in all years 1960, 1970, 1980, and 1990. Table reports results from pooled linear regressions of log differences in employment rates and population on our measure of local labor demand shifts, separately for each time period in our sample. Labor demand shifts for each group are constructed using employment shares of the respective group by sectors and national changes in sectoral employment in the respective time period according to Equation (1). All specifications include additional controls, the share of the foreign-born population and the share of the institutionalized population by group in each time period, as well as state fixed effects. Robust standard errors clustered at the state level are in parentheses.$^{*}p \leq 0.10$;$^{**}p \leq 0.05$;$^{***}p \leq 0.01$

Table C.2.2: Responses to Labor Demand Shifts: Panel Regressions, 20-Year Changes

	(1)	(2)	(3)	(4)	(5)
			Employment		
$\Delta A_{cg,t}$	0.13***	0.13***	0.22***	0.22***	0.31***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.08)
$\Delta A_{cg,t}$ × Black	0.16**	0.15**	0.11	0.10	0.08
	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)
R-Squared	0.23	0.25	0.27	0.27	0.36
Observations	1890	1890	1890	1890	1890
			Population		
$\Delta A_{cg,t}$	1.18***	1.13***	0.84***	0.85***	0.27
	(0.35)	(0.36)	(0.25)	(0.26)	(0.24)
$\Delta A_{cg,t}$ × Black	-0.30	-0.28	-0.18	-0.16	-0.02
	(0.29)	(0.29)	(0.24)	(0.27)	(0.25)
R-Squared	0.29	0.29	0.40	0.44	0.59
Observations	1890	1890	1890	1890	1890
Add. Controls		X	X	X	
Educ. Comp.				X	
State FEs			X	X	
CZ FEs					X
Vicennial FEs	X	X	X	X	X

Notes: Sample is restricted to commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 employed in all years 1960, 1970, 1980, and 1990. Table reports results from panel regressions of log differences in employment rates and population on our measure of local labor demand shifts. Labor demand shifts for each group are constructed using employment shares of the respective group by sectors and national changes in sectoral employment in the respective vicennial (20-year periods) according to Equation (1). Additional controls include the share of the foreign-born population in each vicennial as well as the share of the institutionalized population by group in each vicennial. Educational composition includes controls for the share of the population who are high school dropouts by group in each vicennial as well as the share of the population with a college degree by group in each vicennial. Vicennial fixed effects are allowed to vary by group. Robust standard errors clustered at the state level are in parentheses.$^{*}p \leq 0.10$;$^{**}p \leq 0.05$;$^{***}p \leq 0.01$

Table C.2.3: Responses to Labor Demand Shifts: Panel Regressions, with Lags of $\Delta A_{cg,t}$

	(1)	(2)	(3)	(4)	(5)
			Employment		
$\Delta A_{cg,t}$	0.27***	0.25***	0.29***	0.29***	0.27***
	(0.04)	(0.03)	(0.03)	(0.04)	(0.08)
$\Delta A_{cg,t}$ × Black	0.18*	0.17*	0.15*	0.16*	0.17**
	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)
$\Delta A_{cg,t-1}$	-0.18***	-0.20***	-0.15***	-0.16**	-0.15**
	(0.04)	(0.05)	(0.06)	(0.06)	(0.07)
$\Delta A_{cg,t-1}$ × Black	-0.05	-0.03	-0.07	-0.07	-0.08
	(0.17)	(0.17)	(0.19)	(0.19)	(0.18)
R-Squared	0.13	0.14	0.16	0.16	0.24
Observations	1890	1890	1890	1890	1890
			Population		
$\Delta A_{cg,t}$	0.75***	0.70***	0.58***	0.60***	0.35
	(0.18)	(0.19)	(0.20)	(0.22)	(0.24)
$\Delta A_{cg,t}$ × Black	-0.10	-0.10	-0.05	-0.01	0.00
	(0.22)	(0.21)	(0.22)	(0.25)	(0.21)
$\Delta A_{cg,t-1}$	0.27**	0.23*	0.04	0.03	-0.24*
	(0.12)	(0.13)	(0.12)	(0.13)	(0.13)
$\Delta A_{cg,t-1}$ × Black	0.22	0.24	0.35**	0.35**	0.40**
	(0.15)	(0.15)	(0.15)	(0.15)	(0.17)
R-Squared	0.26	0.26	0.33	0.35	0.50
Observations	1890	1890	1890	1890	1890
Additional Controls		X	X	X	
Educational Composition				X	
State Fixed Effects			X	X	
CZ Fixed Effects					X
Decade Fixed Effects	X	X	X	X	X

Notes: Sample is restricted to commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 employed in all years 1960, 1970, 1980, and 1990. Table reports results from panel regressions of log differences in employment rates and population on our measure of local labor demand shifts. Labor demand shifts for each group are constructed using employment shares of the respective group by sectors and national changes in sectoral employment in the respective decades according to Equation (1). Additional controls include the share of the foreign-born population in each decade as well as the share of the institutionalized population by group in each decade. Educational composition includes controls for the share of the population who are high school dropouts by group in each decade as well as the share of the population with a college degree by group in each decade. Decade fixed effects are allowed to vary by group. Robust standard errors clustered at the state level are in parentheses.$^{*}p \leq 0.10$;$^{**}p \leq 0.05$;$^{***}p \leq 0.01$

C.3. Sub-Samples and Sub-Groups

Table C.3.1: Employment and Population Responses to Labor Demand Shifts over 1970–2010, U.S.-Born Sub-Sample

	(1)	(2)	(3)	(4)	(5)
			Employment		
ΔA_{cg}^{US}	0.12***	0.11***	0.06	0.05	0.07
	(0.04)	(0.03)	(0.06)	(0.05)	(0.09)
ΔA_{cg}^{US} × Black	0.16***	0.16***	0.17**	0.16**	0.17**
	(0.05)	(0.05)	(0.07)	(0.06)	(0.08)
R-Squared	0.26	0.28	0.37	0.38	0.68
Observations	672	672	672	672	672
			Population		
ΔA_{cg}^{US}	0.71**	0.66*	0.51*	0.68**	0.17
	(0.33)	(0.35)	(0.29)	(0.28)	(0.42)
ΔA_{cg}^{US} × Black	0.11	0.12	0.12	-0.04	0.13
	(0.33)	(0.33)	(0.29)	(0.25)	(0.29)
R-Squared	0.23	0.24	0.39	0.45	0.73
Observations	672	672	672	672	672
Add. Controls		X	X	X	
Educ. Comp.				X	
State FEs			X	X	
CZ FEs					X

Notes: Sample is restricted to commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 who were employed in 1960 and includes only individuals who were born in the contiguous United States. Table reports results from pooled linear regressions of log differences in employment rate and population over 1970–2010 on our measure of local labor demand shifts. Labor demand shifts for each group are constructed using employment shares of the respective group by sectors in 1960 and national changes in sectoral employment over 1970–2010 according to Equation (1). Additional controls include the share of the foreign-born population in 1970 as well as the share of the institutionalized population for each group in 1970. Educational composition includes controls for the share of the population who are high school dropouts by group as well as the share of the population with a college degree by group in 1970. Robust standard errors clustered at the state level are in parentheses.$^{*}p \leq 0.10$;$^{**}\ p \leq 0.05$;$^{***}\ p \leq 0.01$

Table C.3.2: Employment and Population Responses to Labor Demand Shifts over 1970–2010, Low-Skill Outcomes

	(1)	(2)	(3)	(4)	(5)
			Employment		
ΔA_{cg}	0.15***	0.14***	0.09	0.09	0.20*
	(0.04)	(0.04)	(0.07)	(0.06)	(0.10)
ΔA_{cg} × Black	0.10*	0.10*	0.11	0.09	0.07
	(0.06)	(0.05)	(0.07)	(0.07)	(0.08)
R-Squared	0.23	0.24	0.33	0.34	0.65
Observations	672	672	672	672	672
			Population		
ΔA_{cg}	1.01**	0.93**	0.65**	0.90***	0.38
	(0.38)	(0.38)	(0.31)	(0.30)	(0.50)
ΔA_{cg} × Black	-0.16	-0.13	-0.06	-0.29	-0.07
	(0.35)	(0.35)	(0.29)	(0.24)	(0.31)
R-Squared	0.26	0.26	0.43	0.49	0.71
Observations	672	672	672	672	672
Add. Controls		X	X	X	
Educ. Comp.				X	
State FEs			X	X	
CZ FEs					X

Notes: Sample is restricted to commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 who were employed in 1960. Table reports results from pooled linear regressions of log differences in employment rate and population over 1970–2010 on our measure of local labor demand shifts. Labor demand shifts for each group are constructed using employment shares of the respective group by sectors in 1960 and national changes in sectoral employment over 1970–2010 according to Equation (1). Additional controls include the share of the foreign-born population in 1970 as well as the share of the institutionalized population for each group in 1970. Educational composition includes controls for the share of the population who are high school dropouts by group as well as the share of the population with a college degree by group in 1970. Robust standard errors clustered at the state level are in parentheses.$^{*}p \leq 0.10$;** $p \leq 0.05$;*** $p \leq 0.01$

C.4. Bartik Diagnostic Checks

Table C.4.1: Industries with the Largest Rotemberg Weights

Industry Name (White Workers)	α_k^W	Industry Name (Black Workers)	α_k^B
Textile mill products and apparel	0.384	Metal industries manufacturing	0.446
Metal industries manufacturing	0.230	Metal and coal mining	0.127
Metal and coal mining	0.098	Lumber and wood products, except furniture	0.108
Construction	0.049	Textile mill products and apparel	0.052
Transportation equipment	0.032	Eating and drinking places	0.036
Machinery and computing equipment	0.025	Construction	0.035
Paper and allied products	0.026	Gasoline service stations and fuel dealers	0.025
Gasoline service stations and fuel dealers	0.022	Transportation equipment	0.022
Lumber and wood products, except furniture	0.017	Food and kindred products	0.014
Business services, n.e.c.	0.018	Machinery and computing equipment	0.014

Notes: Table shows the industries with the ten largest Rotemberg weights for shift-share proxies of labor demand over 1970–2010, separately for each racial group. Rotemberg weights are constructed following the procedure outlined in Goldsmith-Pinkham et al. (2020). We use changes in industry employment (scaled by total population) $\ln\left(\frac{L_{-c,s,2010}}{P_{2010}}\right) - \ln\left(\frac{L_{-c,s,1970}}{P_{1970}}\right)$ and industry shares $L_{csg,1960}/L_{cg,1960}$ in 1960.

Table C.4.2: Correlates with Industry Shares

Industry Name	Foreign	Inst.	HS	College
Panel A: White Workers				
Textile mill products and apparel	-0.173	-0.111	0.212	-0.300
Metal industries manufacturing	0.106	-0.045	-0.030	0.021
Metal and coal mining	-0.115	-0.001	0.442	-0.221
Construction	-0.071	0.001	-0.011	0.026
Transportation equipment	0.128	-0.096	-0.200	0.170
Machinery and computing equipment	0.086	0.037	-0.185	0.172
Paper and allied products	-0.132	0.120	-0.130	-0.184
Gasoline service stations and fuel dealers	-0.307	0.070	0.109	-0.337
Lumber and wood products, except furniture	-0.299	-0.004	0.081	-0.365
Business services, n.e.c.	0.222	-0.089	-0.219	0.339
Panel B: Black Workers				
Metal industries manufacturing	-0.096	0.011	0.232	0.139
Metal and coal mining	0.059	-0.157	-0.312	-0.269
Lumber and wood products, except furniture	-0.119	-0.105	-0.163	-0.177
Textile mill products and apparel	0.086	0.031	0.176	0.155
Eating and drinking places	0.166	-0.118	-0.160	-0.063
Construction	0.029	-0.133	-0.216	-0.199
Gasoline service stations and fuel dealers	-0.120	0.305	0.236	0.223
Transportation equipment	-0.100	-0.014	0.099	0.048
Food and kindred products	-0.304	0.445	0.739	0.540
Machinery and computing equipment	0.239	-0.120	-0.193	-0.114

Notes: Table contains the correlation between industry shares $L_{csg,1960}/L_{cg,1960}$ by group in 1960 and our control variables. We choose the 10 industries that have the largest Rotemberg weights for each group. As in our main specifications, control variables (with the exception of Foreign) are group-specific. Foreign refers to the share of the foreign-born population in 1970. Inst. refers the share of the institutionalized population for each group in 1970. HS refers to the share of the population who are high school dropouts for each group. College refers to the share of the population with a college degree for each group in 1970.

C.5. Aggregation and Counterfactual Results for Different Specifications

Table C.5.1: Counterfactual Results Across Different Specifications, Percentage of Change Explained by Sectoral Shifts

Specification	(1)	(2)	(3)	(4)	(5)
Panel A: Long Difference					
Predicted Change (1970-2010)	13.3	15.0	17.9	15.5	14.3
Counterfactuals					
(1) Shutting Off Migration	17.7	19.1	21.2	18.4	15.8
(2) Identical Shock Exposure					
(a) White Men Exposure	21.6	22.5	24.2	21.1	20.5
(b) Black Men Exposure	18.2	19.0	20.6	18.2	17.7
(3) Identical Response Elasticities					
(a) White Men Elasticities	-6.6	-5.4	-3.8	-3.6	-5.2
(b) Black Men Elasticities	-12.4	-11.3	-9.7	-8.6	-10.2
Panel B: Panel Regression					
Predicted Change (1970-2010)	14.2	13.6	13.5	12.9	15.3
Counterfactuals					
(1) Shutting Off Migration	16.8	15.9	15.5	14.9	16.7
(2) Identical Shock Exposure					
(a) White Men Exposure	13.6	12.7	12.1	11.6	12.8
(b) Black Men Exposure	11.3	10.9	11.1	10.4	13.0
(3) Identical Response Elasticities					
(a) White Men Elasticities	0.9	0.7	0.5	0.5	0.2
(b) Black Men Elasticities	-2.5	-2.1	-1.6	-1.6	-0.7

Notes: Table presents aggregation results using coefficients from specifications (1)-(5) in Tables 2 and 3. Numbers correspond to the percentage of the total change in the employment rate gap explained by sectoral shifts.