Understanding the Racial Employment Gap: The Role of Sectoral Shifts[†]

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Abstract

Employment outcomes of 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 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 explain around one-fifth of the total exacerbation in the employment-to-population ratio differential between Black and White men over 1970–2010. Out-migration from harder-hit markets, while large, does not mitigate the impact of negative labor demand shifts. We also find that most of the predicted change in the employment differential is due to differential response rather than differential exposure to shifts across two groups.

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JEL Classification: R12, J15, J21, J60

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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 Figure 1 shows, employment rates for both groups of workers declined during this period; however, the decline for Black men was more pronounced. One proposed explanation for this phenomenon is that sectoral reallocation of economic activity over this period was especially detrimental for Black men.[1] 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 differs by race, say, due to differences in ability to move away from affected sectors or locations.

In this paper, we quantify the extent to which sectoral reallocation can explain the divergence in employment outcomes of Black and White men over 1970–2010.[2] In addition, we assess the degree to which this effect is driven by differences in exposure vs. differences in adjustment to sectoral shifts across two groups of workers. 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-to-population ratio and population with respect to local labor demand shifts. We then provide a framework that enables us to aggregate the local employment responses while accounting for population movements across locations and investigate the contribution of various margins of adjustment.

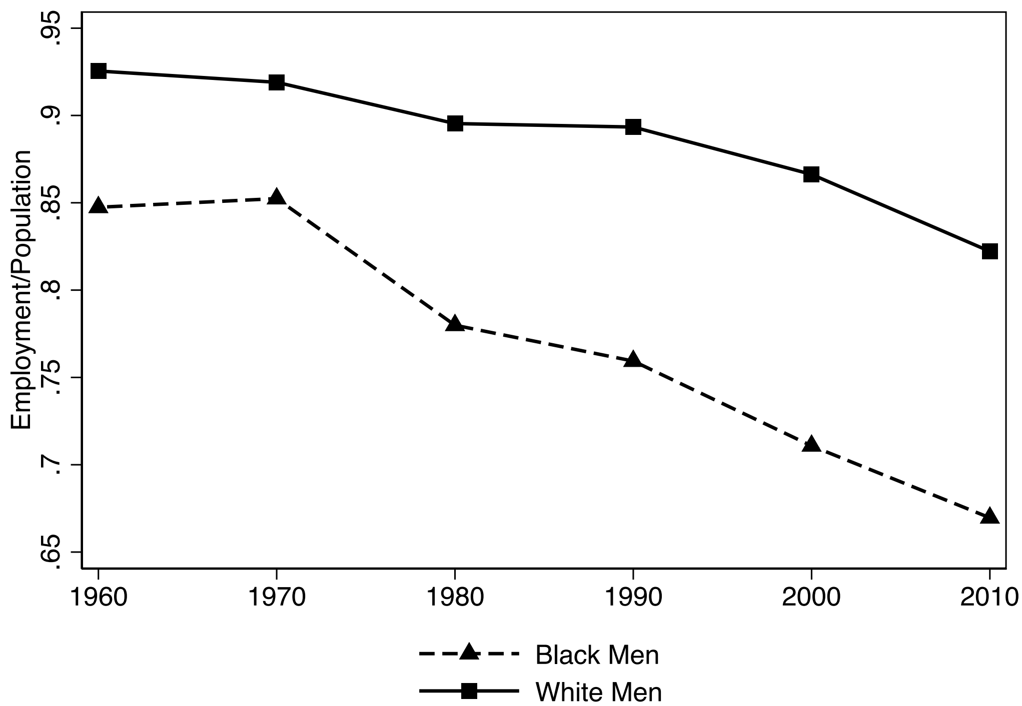
We use data from the Census Integrated Public Use Micro Samples (IPUMS) and measure changes in our outcome variables over 1970–2010 at the level of commuting zones (CZs). To measure changes in local labor demand, we create a *shift-share* measure by combining local employment shares by sectors in 1960 and national changes in sectoral employment over 1970–2010.[3] We document that the local employment-to-population ratio as well as

[1]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. Also, see Boustan (2017) for a recent discussion.

[2]We focus on employment as a share of the total population for each group to avoid selection problems involved with analyzing other outcomes such as wages due to differences in non-participation across groups and over time.

[3]In our main empirical results, we use long-differences over 1970-2010, but we also explore the results

Figure 1: Employment-to-Population Ratios for Black and White Men



Notes: Data are from the United States Census, accessed through Integrated Public Use Micro Samples (IPUMS) (Ruggles et al., 2021). Employment and population is 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.

population vary positively with local labor demand shifts for both groups of workers. In our preferred estimates, we find an elasticity of 0.23 for Black men relative to 0.09 for White men for the employment-to-population ratio. We find substantial population responses; the estimated elasticity of population for both Black and White workers is around 0.7 in our preferred specification. This is in line with the previous literature that finds sizable population responses to shifts in local labor demand (Blanchard and Katz, 1992; Glaeser et al., 1995; Amior and Manning, 2018).

The large population responses highlight the importance of accounting for such movements when considering the aggregate impact of sectoral shifts on employment. In order to do so, one needs to impose some structure on how shifts in labor demand in one region

using other specifications such as panel regressions where sectoral employment changes are allowed to vary for each decade in the sample.

affect the population in other regions. To this end, we set up a stylized model of local labor markets that incorporates matching frictions within markets and mobility frictions across markets. The model implies that changes in the local employment-to-population ratio and population in response to local demand shifts depend on parameters that govern these frictions, which can vary across different groups of workers. Hence, the parameters of the model can be inferred from our estimated elasticities. Further, we show that aggregating these local responses implies that the change in aggregate employment depends on how employment changes *within* local markets and how population adjusts *across* markets for each group. The contribution of both of these margins of adjustment to the aggregate employment gap 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 elasticities with our framework, we find that sectoral reallocation can explain around 20% of the increase in the Black-White employment gap on aggregate. We find that a 2.8 percentage point decrease in the employment-population ratio for Black workers can be attributed to sectoral shifts. While sectoral shifts can explain only a 1.4 percentage point decrease in the employment-population ratio for White workers. This is because, while the population responses across labor markets play out similarly for both groups of workers, the decrease in employment within labor markets for Black men is more than twice that of White men. Furthermore, we provide an intuitive and comprehensive decomposition for understanding these effects and apply it to our sample data. Our findings indicate that the increase in the Black-White employment gap due to sectoral shifts results from the greater responsiveness of Black workers to local labor demand shifts rather than a higher concentration of these shifts in areas or sectors with a higher share of Black workers.

This paper is the first to our knowledge to provide a framework to formally aggregate local effects and decompose the overall response into differential exposure vs. differential response by group in the context of the Black-White employment gap. Existing empirical studies exploit variation across regions in exposure to sectoral shifts and document that employment for Black men changes more relative to White men in response to changes in local labor demand (Bound and Holzer, 2000; Batistich and Bond, 2019; Gould, 2020). While these studies provide robust evidence at the local level on how different racial groups are affected by changes in labor demand, a growing literature spanning the macro, labor, trade, and urban fields has shown that cross-regional estimates are only informative about aggregate responses under specific assumptions.[4] Our work builds on this growing literature and we argue that fully evaluating the effects of local labor demand shocks in the aggregate requires accounting explicitly for migration responses as well as regional employment composition, which we take into account in our framework.

Our analysis indicates that sectoral shifts that played out differently across different regions explain a nontrivial portion of the widening in the Black-White employment gap since 1970. An extensive literature on the wage gap between Black and White workers has traditionally attributed a portion of this differential to observable characteristics of workers and explained the remainder through theories of labor market discrimination.[5] 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 Blacks 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.

The rest of the paper is structured as follows. Section 2 presents our empirical analysis. In this section, we provide details on the methodology we use to estimate the relationship between local labor demand shifts and employment and population outcomes as well as the associated data sources we use to do so. We also provide detailed robustness checks of our main empirical results. In Section 3, we outline a model of labor market frictions and regional mobility that delivers key predictions about how employment and population respond to changes in labor demand for different groups. We show how the parameters

[4]See Chodorow-Reich (2020) for a recent review in the context of the macroeconomics literature. See Adão et al. (2021) for a detailed discussion on recovering the general equilibrium effects of economic shocks from cross-regional estimates.

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

in the model can be recovered from our estimates in the previous section. Section 4 derives a framework based on this model to analyze the aggregate effect of local labor demand shifts on the employment-to-population ratio gap between Black and White workers and decomposes the relevant margins of adjustment. Section 5 provides a discussion of the importance of such a framework as well as suggestions to researchers interested in aggregating local responses to labor demand shifts. Section 6 concludes.

2 Data and Empirical Analysis

In this section we first describe the data used in our analysis. We then outline how we measure local labor demand shifts and present their geographical distribution. Next, we document employment and population responses to local labor demand shifts separately for Black and White men over the period of our analysis. Finally, we discuss several robustness checks of our main empirical results and show that our main conclusions remain intact.

2.1 Data Description

We study changes in local employment and population in response to changes in local labor demand from 1970–2010 separately for Black and White men. Over this period employment outcomes of Black and White men diverged considerably.[6] For the purpose of our analysis, we need a measure of changes in labor demand over this period at the level of local labor markets. To construct this measure, we use local employment shares by sectors in 1960 and national changes in sectoral employment composition over 1970–2010.[7] In our main analysis, we use long differences from 1970–2010 to estimate the elasticity of changes in local employment and population to changes in local labor demand in order to avoid conflating short- and long-run responses (Jaeger et al., 2018).[8]

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

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

[8]As robustness, we also consider changes over each decade in our sample and present the results from panel regressions where both the outcome variables and the local labor demand shifts are allowed to vary by decade in section Section 2.4.

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.[9] Census data is particularly suited to our analysis as it's 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.[10]

We measure all outcomes based on 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. [11] Our main sample includes 336 commuting zones. 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. Since we restrict our sample on employment counts for Black men, the commuting zone in our sample are on an average larger and have a higher share of employment in manufacturing. However, the average commuting zones in our sample is comparable to the average commuting zone in the United States in terms of employment and wages.

2.2 Measurement of Local Labor Demand Shifts

We are interested in quantifying how local employment and population respond to changes in local labor demand. However, shifts in labor demand are not directly observable.

[9]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.

[10]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/.

[11]We show in Section 2.4 that our estimates are not sensitive to the choice of this cutoff.

Table 1: Summary Statistics for Commuting Zones

	All		Sample	
	1970	2010	1970	2010
	(1)	(2)	(3)	(4)
Log of 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 of Wages: Black Men	9.87	9.70	9.78	9.76
Log of 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. 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.

Therefore we use employment shares by sectors in 1960 and national changes in sectoral employment over 1970–2010 to create a proxy for these shifts. In particular, we construct a proxy for changes in local labor demand, denoted by ΔA_{cg}, as follows:

$$\Delta A_{cg} = \sum_{s} \frac{L_{csg,1960}}{L_{cg,1960}} \cdot \left(\ln\left(\frac{L_{-c,s,2010}}{P_{2010}}\right) - \ln\left(\frac{L_{-c,s,1970}}{P_{1970}}\right) \right) \tag{1}$$

Here, $L_{csg,1960}$ represents employment in commuting zone c for group g in sector s in 1960 and $L_{cg,1960}$ represents employment in commuting zone c for group g in 1960. The expression $\ln\left(\frac{L_{-c,s,2010}}{P_{2010}}\right) - \ln\left(\frac{L_{-c,s,1970}}{P_{1970}}\right)$ denotes the leave-one-out growth rate of employment in sector s for commuting zone c over the time period 1970–2010. The leave-one-out growth rate for commuting czone c is constructed by aggregating sectoral employment in all commuting zones besides c in both the beginning and ending years in our sample, dividing by the total population in the appropriate year, and computing the growth rate between these two periods.[12]

[12]We scale by the total population in each year in order to account for the fact that the total level of employment tends to increase over time and we intend to capture net changes in labor demand.

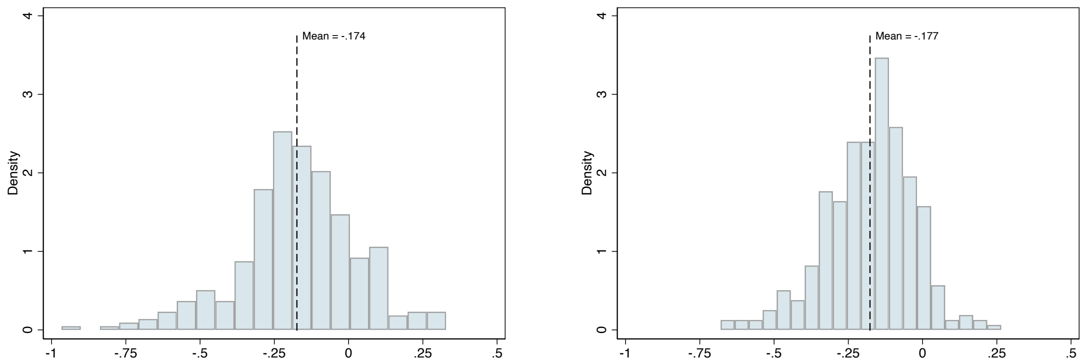
Our measured demand shifts will be more negative in locations with a larger initial share of employment in declining industries. Also, note that we allow the employment shares that determine the weight each sector gets in the overall measure to be race-specific. Suppose for instance, that the demand 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 shift will be more negative for Black workers in that location. In other words, our proxy implicitly takes into account differential initial sectoral composition of Black and White workers.

To construct our measure of local labor demand shifts, we obtain data on total sectoral employment as well as sectoral employment shares within commuting zones. We use time-consistent industry codes from IPUMS and classify industries into 71 broad categories.[13] Figure 2 shows the distribution of local labor demand shifts 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. 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 Fig. 3. It is apparent that there is a higher concentration of large, negative labor demand shifts 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 U.S. represents a large change in employment demand during the time period under consideration and therefore appears prominently in these measures.

[13] 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. Appendix Figures A1 and A2 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. Both sets of industry crosswalks are available upon request.

Figure 2: Distribution of Local Labor Demand Shifts



(i) Black Men

(ii) White Men

Notes: Figure shows the histogram for 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 Eq. (1).

2.3 Employment and Population Responses

We estimate the following equations to measure the elasticity of local employment and population with respect to local labor demand shifts:

$$\Delta \ln l_{cg} = \alpha^l + \beta^l \text{Black}_g + \gamma^l \Delta A_{cg} + \delta^l \Delta A_{cg} \times \text{Black}_g + \zeta^l X_{cg} + \varepsilon^l_{cg} \tag{2}$$

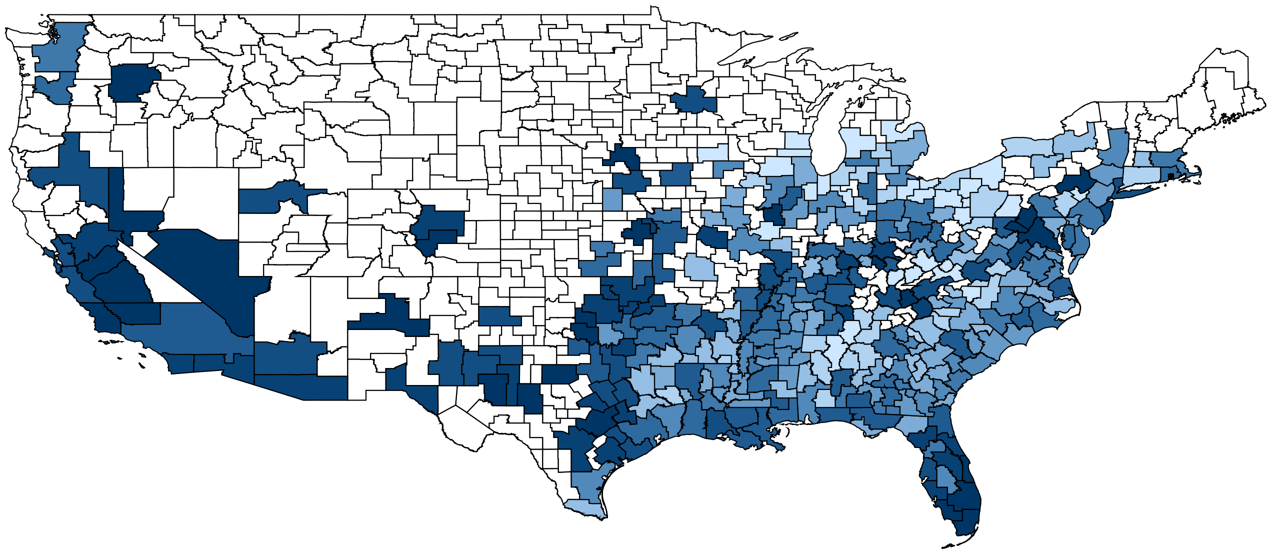
$$\Delta \ln P_{cg} = \alpha^P + \beta^P \text{Black}_g + \gamma^P \Delta A_{cg} + \delta^P \Delta A_{cg} \times \text{Black}_g + \zeta^P X_{cg} + \varepsilon^P_{cg} \tag{3}$$

In these equations, $\Delta \ln l_{cg}$ represents the log change in employment-to-population ratio for group g in commuting zone c from 1970 to 2010 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. X_{cg} contains controls that capture the potential effects of demographic composition across commuting zones and may also vary across groups.

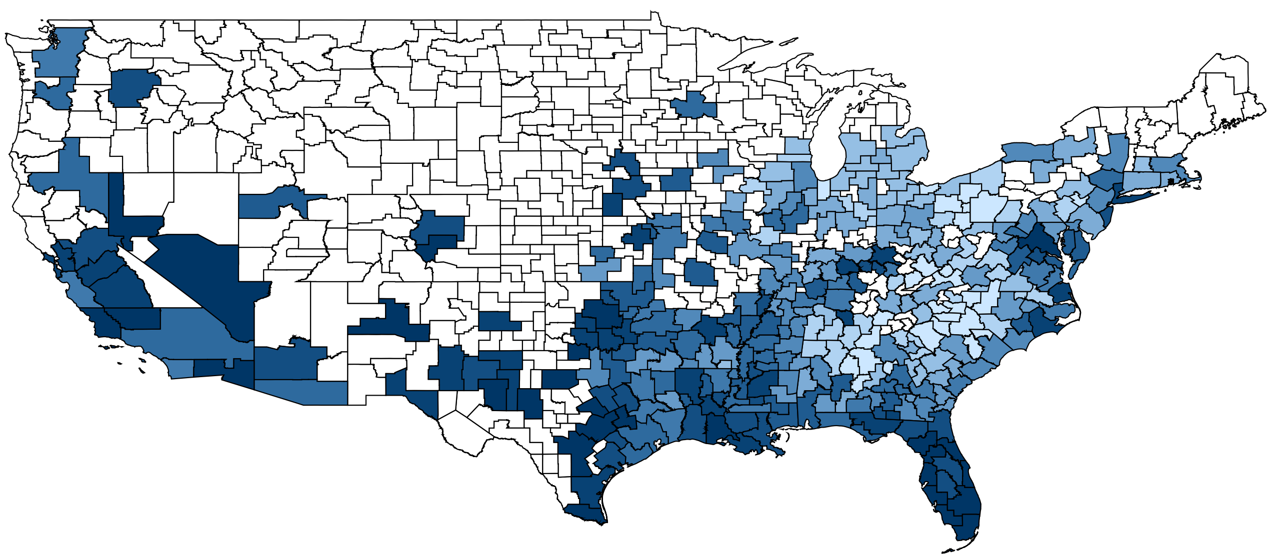
We are interested in capturing the degree to which different regions and groups of workers were differentially exposed to changes in sectoral labor demand. Our proxies for

Figure 3: Geographical Exposure to Sectoral Shifts

(i) Black Men



(ii) White Men



Notes: Maps show the geographic distribution of our proxy for local labor demand shifts across the commuting zones in our sample 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 Eq. (1). Darker shaded areas represent lower values and lighter shaded areas represent higher values. Areas that are not shaded are not included in our sample, as we only include commuting zones that had at least 200 noninstitutionalized civilian Black men between the ages of 25-55 who were employed in 1960. Our sample accounted for 89% of total employment in 2010.

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

	(1)	(2)	(3)	(4)	(5)
			Employment		
Constant	-0.10***	-0.10***	-0.11***	0.04	-0.11***
	(0.01)	(0.01)	(0.02)	(0.04)	(0.02)
Black	-0.12***	-0.13***	-0.13***	-0.26***	-0.12***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)
ΔA_{cg}	0.14***	0.12***	0.09	0.06	0.13
	(0.04)	(0.04)	(0.06)	(0.05)	(0.13)
ΔA_{cg} × Black	0.14**	0.14**	0.14*	0.14**	0.12
	(0.06)	(0.05)	(0.08)	(0.06)	(0.12)
R-Squared	0.24	0.26	0.35	0.37	0.67
Observations	672	672	672	672	672
			Population		
Constant	0.62***	0.57***	0.56***	0.86***	0.49***
	(0.10)	(0.11)	(0.09)	(0.24)	(0.13)
Black	0.40***	0.39***	0.39***	0.10	0.42***
	(0.09)	(0.08)	(0.08)	(0.20)	(0.12)
ΔA_{cg}	1.00**	0.88**	0.69**	0.81**	0.27
	(0.37)	(0.37)	(0.32)	(0.36)	(0.69)
ΔA_{cg} × Black	-0.06	-0.01	0.00	-0.17	0.05
	(0.35)	(0.34)	(0.29)	(0.32)	(0.44)
R-Squared	0.25	0.26	0.43	0.43	0.74
Observations	672	672	672	672	672
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. Table reports results from pooled linear regressions of log differences in employment-to-population ratio 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 Eq. (1). Additional controls include the share of the foreign-born population in 1970 as well as the share of the instituitionalized 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.$^{*}p \leq 0.10$;$^{**}p \leq 0.05$;$^{***}p \leq 0.01$

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. However, it is unclear whether the initial educational composition across commuting zones is more likely to reflect trends in labor supply or labor demand from 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. Hence, we present our results after controlling for educational composition, but we argue that the results without these controls better represent the changes in labor demand we intend to capture. We also 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 below in Section 2.4.4.

Table 2 shows the results of estimating Eqs. (2) and (3). We obtain statistically significant and economically meaningful estimates of the degree to which changes in employment rates and population shares over 1970–2010 vary with local demand shifts. In general, positive changes in local demand induce positive responses in both employment rates and population shares. The results imply that local employment of Black men during this time period was more sensitive to changes in local labor demand than that of White men. Estimates imply that in response to the measured labor demand shifts, for an average commuting zone in our sample, the employment-to-population ratio for Black men decreased by 3.4 percentage points relative to a 1.5 percentage point decrease for White men. 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 for ΔA_{cg} in the population change regression diminishes considerably for White workers. We suspect that there is low statistical power associated with this coefficient due to the fact that 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. In our proceeding analysis, we use the estimates from Column (3) as 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.

2.4 Robustness Checks

We conduct several different robustness checks of our main empirical results in Table 2. We explore the robustness of our results to different empirical strategies and sample selection criteria. Additionally, we run different 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 additional details.

2.4.1 Employment and Population Responses: Panel Regression

In addition to taking long differences in employment rates and population over 1970–2010, 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. That is, we estimate the following equations:

$$\Delta \ln l_{cg,t} = \eta^l + \theta^l \text{Black}_{g,t} + \iota^l \Delta A_{cg,t} + \kappa^l \Delta A_{cg,t} \times \text{Black}_{g,t} + \lambda^l X_{cg,t} + \nu^l_{cg,t} \tag{4}$$

$$\Delta \ln P_{cg,t} = \eta^P + \theta^P \text{Black}_{g,t} + \iota^P \Delta A_{cg,t} + \kappa^P \Delta A_{cg,t} \times \text{Black}_{g,t} + \lambda^P X_{cg,t} + \nu^P_{cg,t} \tag{5}$$

In these equations, the time subscript t indexes decades. For instance, $\Delta \ln l_{cg,1980}$ denotes the log change in the employment-to-population ratio for group g in commuting zone c over 1970-1980. In constructing the proxies for shifts in labor demand, we use lagged shares of sector employment as well as leave-one-out growth rates, as in our long difference specifications above.[14] Shift-share proxies $\Delta A_{cg,t}$ are constructed as follows:

$$\Delta A_{cg,t} = \sum_s \frac{L_{csg,t-1}}{L_{cg,t-1}} \cdot \left(\ln\left(\frac{L_{-c,s,t}}{P_t}\right) - \ln\left(\frac{L_{-c,s,t-1}}{P_{t-1}}\right)\right) \tag{6}$$

Table 3 contains the results of estimating Eqs. (4) and (5). In all specifications, we include decade-fixed effects to control for any time trends in employment rates or population changes. As in the long difference results above, the coefficient estimates are stable across different controls as well as different levels of fixed effects. 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 also explore the implications of two additional specifications. We run a separate regression for each decade in our sample and display the results in Appendix Table A7. We also run panel regression specifications where we include lags of our measures of shift-share proxies as suggested by Jaeger et al. (2018) to account for lingering effects of sectoral shifts. We display the results for the latter in Appendix Table A8.

2.4.2 Different Employment Cutoffs

In our 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

[14] Our sample for the panel specifications includes 315 commuting zones instead of 336, as we exclude commuting zones with less than 200 black men in any of the years we use to calculate the industry shares in our shift-share measure $\Delta A_{cg,t}$. Specifically, these years are 1960, 1970, 1980, and 1990.

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

	(1)	(2)	(3)	(4)	(5)
Black Employment	0.34***	0.33***	0.31***	0.30***	0.35***
	(0.07)	(0.07)	(0.08)	(0.08)	(0.12)
R-Squared	0.06	0.06	0.09	0.09	0.21
Observations	1260	1260	1260	1260	1260
White Employment	0.20***	0.22***	0.24***	0.24***	0.24***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)
R-Squared	0.40	0.41	0.44	0.44	0.50
Observations	1260	1260	1260	1260	1260
Black Population	0.74***	0.66***	0.63***	0.60***	0.38
	(0.16)	(0.17)	(0.17)	(0.17)	(0.29)
R-Squared	0.08	0.09	0.16	0.18	0.33
Observations	1260	1260	1260	1260	1260
White Population	0.94***	0.93***	0.59***	0.59***	0.43***
	(0.25)	(0.25)	(0.13)	(0.14)	(0.15)
R-Squared	0.38	0.38	0.56	0.58	0.75
Observations	1260	1260	1260	1260	1260
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, 1990, 2000, and 2010. Table reports results from panel regressions of log differences in employment-to-population ratio 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 Eq. (6). Additional controls include the share of the foreign-born population as well as the share of the institutionalized population for each group in each decade. 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 each decade. Robust standard errors clustered at the state level are in parentheses. $^{*}p \leq 0.10$; $^{**}p \leq 0.05$; $^{***}p \leq 0.01$

of our main 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 use either 100 or 300 as the employment cutoff in each of our estimation strategies.

Tables A1 and A2 display these results for our main estimation strategy. Comparing these results to Table 2, we can see that our long difference estimates are not very sensitive to the choice of employment cutoff. The same holds true for our panel regression estimation strategy. Tables A3 and A4 display the results from using employment cutoffs of 100 or 300, respectively, in our panel regression specifications. Comparing these results to Table 3, we can see that the coefficients for changes in employment rates are almost exactly the same. They are similar in magnitude and stable across specifications. This is true for the coefficients on changes in population to a lesser extent. Coefficients are mildly sensitive to the choice of cutoff, but differences in magnitudes are quantitatively small. Moreover, the same qualitative patterns hold across specifications in the robustness checks as in the main results. We conclude that our results are not very sensitive to sample selection in terms of our choice of commuting zone-level employment cutoff for Black men.

2.4.3 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: i). finer industrial classifications allow for more variation in the data and ii). broader industrial classifications are more likely to be consistent across years due to re-classification by the Census. However, our estimates may be sensitive to the specific choice of industrial classification scheme.

We therefore present our results using 33 broad industry categories for our long difference and panel estimation strategies in Tables A5 and A6, respectively. We obtain very similar estimates in both qualitative and quantitative terms as in our main estimates. The exception is the coefficients on changes in population for our broad industrial classification (see the bottom panel of A5). In columns (3) and (4), the coefficients on ΔA_{cg} lose their statistical significance and are lower in magnitude. However, the main takeaway from these estimates is the same: we do not find large differences in population response across Black vs. White workers over this time horizon. Moreover, we would expect the 71 sub-industries used in our main analysis to be a better source of variation than these broad 33 industries.

Therefore, we conclude that our choice of industrial classification scheme is appropriate.

2.4.4 Bartik Diagnostics

We also perform several 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 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 in aggregate and by group in Appendix C.5.1. As can be seen from the tables, the industries *Textile mill products and apparel* and *Metal industries manufacturing* have the largest Rotemberg weights. However, neither of their weights are above 50%, indicating that they do not drive a majority of the variation in our shift-share proxies of labor demand. Additionally, they show up in the tables for both Black and White workers, indicating that they are important in driving the shock variation for both groups. Given that we are interested in estimating the differential response for these groups, we do not view these large Rotemberg weights as a major concern for our results. Moreover, Rotemberg weights are smaller and more uniform in size for the other industries in our analysis.

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 regression specifications and industry shares $\pi_{csg,1960} \equiv L_{csg,1960}/L_{cg,1960}$ in 1960 across commuting zones. We do so for the industries with the ten largest Rotemberg weights for each group. As discussed above, industry shares are group specific, where $\pi_{csB,1960}$ denotes the share of employment among Black men of industry s in commuting zone c in 1960 and $\pi_{csW,1960}$ denotes the share of employment among White men of industry s in commuting zone c in 1960. Correlation tables are displayed in Section C.5.2.

From these tables, we can see that the correlations between our control variables and key industries that drive the variation in our shift-share proxies are very weak. With the exception of the *Metal and coal mining* industry in the case of White men and the *Lumber and wood products, except furniture* industry in the case of Black men, correlations are below 0.4 in all cases and even lower in most. These controls are meant to capture differences in labor supply across local labor markets that could have also influenced the widening of the employment rate gap between White and Black men over this time horizon. Our identifying assumption is that industry shares $\pi_{csg,1960}$ are as-good-as randomly assigned across commuting zones in 1960. Low correlations between our control variables and industry shares support this assumption.

2.5 Summary of Empirical Results

In sum, our results suggest that Black men have a higher elasticity of employment to changes in local labor demand. We can also see that both Black and White men out-migrate 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.

3 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. The model is based on Kim and Vogel (2021) and allows us to characterize the relationship between local labor demand and employment outcomes for different racial groups. We show that structural parameters of our model can be inferred from the elasticities estimated in the previous section.

3.1 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}.[15] Workers choose a location based on their expected

[15]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.

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, $\theta_{cg} \equiv V_{cg}/L_{cg}$. Hence, markets are effectively indexed by location-group pairs cg. Both firms and workers are risk neutral.

3.1.1 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 3.4, the parameter κ_g governs the elasticity of labor supply across labor markets and can be interpreted as capturing costs of moving across locations.

3.1.2 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:

$$(A_{cg} - w_{cg}) q_{cg} = F_{cg} \tag{7}$$

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.

3.1.3 Matching and Wage Setting

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

$$L_{cg} = m(V_{cg}, P_{cg}) = \gamma_{cg} V_{cg}^{\alpha_g} P_{cg}^{1-\alpha_g} \tag{8}$$

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

Finally, we will assume that wages are determined by Nash Bargaining such that:

$$w_{cg} = \omega_{cg} A_{cg} \tag{9}$$

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

3.2 Equilibrium Outcomes

We now discuss the derivation of the equilibrium. From Eqs. (7) to (9) 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,

$$l_{cg}^{*} = \gamma_{cg}\theta_{cg}^{*\alpha_g} = \gamma_{cg}\left[\frac{(1-\omega_{cg})\gamma_{cg}}{F_{cg}}\right]^{\frac{\alpha_g}{1-\alpha_g}} A_{cg}^{\frac{\alpha_g}{1-\alpha_g}} \tag{10}$$

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 work in location c is given by:*

$$\frac{P^*_{cg}}{P_g} = \frac{\tilde{c}_{cg} A_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}}}{\sum_c \tilde{c}_{cg} A_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}}} \tag{11}$$

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}.

3.3 Comparative Statics

We next derive comparative statics to illustrate how changes in local labor demand 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 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.

Proposition 2. *For some variable x_{cg}, denote $\hat{x}_{cg} = \partial \ln x_{cg}$. The equilibrium responses of employment rates $\hat{l}^*_{cg}$ and population shares $\hat{P}^*_{cg}$ to changes in local labor demand $\hat{A}_{cg}$ are given by*

$$\hat{l}^*_{cg} = \frac{\alpha_g}{1-\alpha_g}\hat{A}_{cg} \tag{12}$$

$$\hat{P}^*_{cg} = \frac{1}{\kappa_g(1-\alpha_g)}\left(\hat{A}_{cg} - \sum_c \pi^p_{cg}\hat{A}_{cg}\right) \tag{13}$$

where $\pi^p_{cg} = P^*_{cg}/P_g$.

Equation 12 shows that if a market cg experiences a negative labor demand shock, employment 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 employment declines depends on the parameter α_g, such that groups with higher α_g experience larger drops in employment for a given shock to labor demand. 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 13 shows that in response to a negative shock to labor demand, we expect to see out-migration of workers as they decide to search for better employment opportunities in other areas. This happens so long as the shock in market cg is more negative than the shock in the average market (the second term in the parentheses). 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.

3.4 Structural Parameters

The equations we estimated in Section 2 are the empirical counterparts of Eqs. (12) and (13) and allow us to recover the structural parameters of the model from the estimated elasticities.[16] Table 4 shows the estimates for the structural parameters implied by our results. We can see that α_B is more than double 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 prospects of Black men over this time horizon were much more sensitive

[16] Recall that we constructed proxies for labor demand shifts $\hat{A}_{cg}$ using the following formula $\Delta A_{cg} = \sum_s (L_{csg,1960}/L_{cg,1960}) \cdot (\ln(L_{s,2000}) - \ln(L_{s,1970}))$. One concern with this measure could be that the change in sectoral employment differs in magnitude from the change in sectoral labor demand. However, our proxies will still capture the variation in local labor demand due to sectoral shifts under the condition that the degree to which employment varies with labor demand is the same across sectors.

Table 4: Structural Parameters

Parameter	Explanation	Estimate	SE
α_B	Match Elasticity: Black men	0.17	(0.041)
α_W	Match Elasticity: White men	0.05	(0.046)
κ_B	Mobility Costs: Black men	4.29	(0.041)
κ_W	Mobility Costs: White men	2.09	(0.046)

Notes: Estimates are for parameters of the model as implied by estimated elasticities reported in Table 2. Standard errors (SE) are computed using the delta method.

to labor demand shifts to local areas. We can also see that since $\kappa_B > \kappa_W$, mobility costs to re-location are higher for Black workers than for White workers.[17]

4 Aggregation and Decomposition

As we mentioned before, it is not possible to directly infer what happens to aggregate statistics from the local responses documented in the previous section. Our estimates suggest that there are large movements in local employment in response to labor demand shifts, however, workers also out-migrate from harder hit areas. The impact on the aggregate depends on the extent to which population responses are able to mitigate the employment responses. Additionally, the size of harder hit areas relative to the rest of the economy also determines the contribution of local demand shifts to aggregate employment. The next proposition formally states this idea.

Proposition 3. *The change in aggregate employment for group g, L_g, in response to shifts in local labor demand can be written as follows:*

$$\hat{L}_g = \frac{\alpha_g}{1-\alpha_g}\sum_c \pi_{cg}\hat{A}_{cg} - \frac{1}{\kappa_g(1-\alpha_g)}\sum_c \left(\frac{l_g - l_{cg}}{l_{cg}}\right)\pi_{cg}\hat{A}_{cg} \tag{14}$$

From this proposition, we can see that the change in aggregate employment for each group can be written as the sum of two terms — the first term captures the *employment* response while the second captures the *population* response. The magnitude of the employ-

[17] Suppose instead that workers' decision choices were based only on wages in a local area, rather than on wages and employment probabilities. Then, the mobility cost parameter κ_g would be $1/\beta_{2g}$.

ment response for group g depends on the overall intensity of the shock for that group, the weighted average of $\hat{A}_{cg}$, and the responsiveness of group g's local employment to changes in local labor demand captured by α_g. Note that, the intensity of a negative shock can be higher for one group if local shifts are more negative for this group in all locations or most affected locations have a higher share of employment for that group.[18]

Workers can mitigate the impact of negative shifts by moving away from affected areas. The second term in Eq. (14) illustrates that population responses can mitigate employment responses only to the extent that there are locations with very different employment opportunities. For instance, if all locations were identical in terms of probability of finding employment, such that $l_{cg} = l_g$, workers moving from one location to another won't gain much and we would see that the contribution of the population response to aggregate employment would be zero. The population response, in addition, also depends on the elasticities governing the extent of labor market frictions, α_g and κ_g.

4.1 Aggregation Exercise

We now combine estimates of the structural parameters presented in Table 4 with data on regional employment shares in 1970 and our measure of $\hat{A}_{cg}$ 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 as well as the predicted changes in the employment-to-population ratio for Black and White men from 1970–2010.

From Table 5, we can see that our measured labor demand shifts capture little of the decline in the employment-to-population ratio for both groups and can only increase a portion of the increase in the gap between Black and White workers. We can see that from 1970–2010, the employment-to-population ratio fell from 85.7 to 68.1 for Black workers and from 93 to 82.6 for White workers in our sample commuting zones. Our measured shifts account for a decrease of 2.8 and 1.4 percentage points for Black and White workers, respectively. Consequently, sectoral reallocation helps us explain 1.5 percentage points of the total 7.3 percentage point increase in the Black-White employment gap. So are able to explain about one-fifth of the total exacerbation in the Black-White gap.

[18]Given the way we measure $\hat{A}_{cg}$, the reason shifts are different across locations is due to initial sectoral composition. So differences in intensity of shifts in this framework result from differences in initial composition of employment across sectors and locations.

Table 5: Actual and Predicted Changes in Employment-to-Population Ratios

	Employment-to-Population Ratio			Log change (1970-2010)	
	1970	2010	Predicted	Actual	Predicted
	(1)	(2)	(3)	(4)	(5)
Black Men	85.7	68.1	82.9	-0.231	-0.034
White Men	93.0	82.6	91.6	-0.119	-0.015
Gap: Black-White	-7.2	-14.5	-8.7	-0.112	-0.019

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 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-to-population ratio. Column (4) shows the log difference between the values in Columns (2) and (1), while Column (5) shows the log difference between the values in Columns (3) and (1). The last row shows the difference between the values in the preceding two rows.

While the results reported above pertain to the aggregation exercise using our preferred estimates from column (3) of Table 2. Appendix C.6 presents results from an analogous exercise for estimates from different specifications in Table 2 and Table 3. Overall across different specifications we explain around 10-20% of the increase in the Black-White gap.

4.2 Decomposition Exercise

In order to further understand what forces are driving changes in the employment-to-population ratio, we next decompose the aggregate change in employment separately into the population and employment response. We find that population responses for both groups have no effect on mitigating the impact of sectoral shifts. This is because population responses even if huge in magnitude only help mitigate shocks if the shocks are limited to a few markets and workers can relocate to other markets.

Next, we investigate what accounts for the larger employment response of Black workers. Conceptually, it may stem from two sources: greater exposure to labor demand shifts or a larger response to a similar set of shifts. In order to formalize the contributions of these margins, we present results from the following two decompositions:

(i). $$\hat{L}_B - \hat{L}_W = \sum_c \pi_{cB}\hat{A}_{cB} \underbrace{\left(\frac{\alpha_B}{1-\alpha_B} - \frac{\alpha_W}{1-\alpha_W}\right)}_{\text{Differential Response}} + \tfrac{\alpha_W}{1-\alpha_W} \underbrace{\sum_c \left(\pi_{cB}\hat{A}_{cB} - \pi_{cW}\hat{A}_{cW}\right)}_{\text{Differential Exposure}}$$

$$\text{(ii).}\ \hat{L}_B - \hat{L}_W = \sum_c \pi_{cW}\hat{A}_{cW} \underbrace{\left(\frac{\alpha_B}{1-\alpha_B} - \frac{\alpha_W}{1-\alpha_W}\right)}_{\text{Differential Response}} + \frac{\alpha_B}{1-\alpha_B} \underbrace{\sum_c \left(\pi_{cB}\hat{A}_{cB} - \pi_{cW}\hat{A}_{cW}\right)}_{\text{Differential Exposure}}$$

These equations show two similar ways of breaking down the evolution of the employment gap.[19] In each, we can see that changes in the employment gap between Black and White workers may be attributed to either a higher response of a certain group to a given set of labor demand shifts *(Differential Response)* or a higher incidence of labor demand shifts for a certain group of workers *(Differential Exposure)*. Notice that the Differential Response term depends on the structural parameters that govern the responsiveness of employment for each group to changes in labor demand. The Differential Exposure term depends on the average size of labor demand shifts experienced by each group as well as the composition of employment across regions for each group.

Table 6: Differential Response vs. Differential Exposure

	Differential Response (1)	Differential Exposure (2)
(i)	-0.021	0.002
(ii)	-0.024	0.004

Table 6 shows the results of this exercise. In each case, we can see that the Differential Response term dominates the Differential Exposure term in magnitude (note that the only difference between (i) and (ii) are the weights used). Hence, what explains the employment response across groups is the fact that for Black workers, employment drops by much more after a local labor demand shock of a given magnitude. We do not find much evidence that local labor demand shifts were simply more heavily concentrated in areas that had a higher composition of Black employment.

5 Discussion

In this section, we highlight the importance of accounting for population responses when aggregating local employment responses. Not doing so would lead to overestimating

[19]These equations can be derived by writing out Eq. (14) separately for Black and White workers and taking the difference.

the impact of a set of economic shocks on aggregate employment, depending on the extent to which population responses mitigate the impact of these shocks. The extent of overestimation will depend on whether changes in local employment-to-population ratios or local employment is the dependent variable. To illustrate this, consider the following. Let $\hat{x}$ denote the log change in outcome x following some shock(s) to the fundamentals of the economy. Then, for group g in location c, the log change in employment, $\hat{L}_{cg}$, is given by the sum of the log change in employment-to-population ratio, $\hat{l}_{cg}$, and population, $\hat{P}_{cg}$:

$$\hat{L}_{cg} = \hat{l}_{cg} + \hat{P}_{cg}$$

Next, the log change in aggregate employment for group g, $\hat{L}_g$, can be written as:

$$\hat{L}_g = \sum_c \pi_{cg} \hat{L}_{cg}$$

where $\pi_{cg} = L_{cg}/L_g$ is the employment share in location c for group g. Furthermore, changes in population for group g in location c can be written as a sum of two components:

$$\hat{P}_{cg} = \hat{P}^{PE}_{cg} + \hat{P}^{GE}_{cg}$$

Here $\hat{P}^{PE}_{cg}$ is the Partial Equilibrium (PE) term that represents changes in population that are in response to shocks affecting location c. On the other hand, $\hat{P}^{GE}_{cg}$ is the General Equilibrium (GE) term capturing changes in population in location c that are due to shocks in other locations. This term arises because shocks to other location induce migration responses into or out of location c. Separately regressing log changes in employment-to-population ratio and population on shocks at the local level recovers $\hat{l}_{cg}$ and $\hat{P}^{PE}_{cg}$, respectively. Regressing log changes in local employment on shocks at the local level recovers $\hat{L}_{cg} = \hat{l}_{cg} + \hat{P}^{PE}_{cg}$.[20] Note that neither approach estimates the $\hat{P}^{GE}_{cg}$ term, which is a crucial component in the aggregate group response.

In our approach, we impose additional structure on population movements in order to express $\hat{P}^{GE}_{cg}$ as a function of the estimated elasticities from our local regressions and the observed shocks.[21] This enables us to back out the aggregate impact of sectoral shifts.

[20] This is a version of the so-called "missing intercept" problem — local regressions are unable to recover aggregate general equilibrium impact of a shock when regions are spatially correlated. See Adão et al. (2021) for a brief discussion of different approaches to deal with this problem.

[21] In particular, according to our model $\hat{P}^{PE}_{cg} = \beta_{2g}\hat{A}_{cg}$ and $\hat{P}^{GE}_{cg} = -\beta_{2g}\sum_{l'} \pi^{p}_{cg}\hat{A}_{c'g}$, see Eq. (13).

Without this additional structure, one has two options for aggregating local responses: (1) estimate and sum up $\hat{l}_{cg}$ across locations or (2) estimate and sum up $\hat{L}_{cg}$ across locations. We emphasize that while both of these will lead us to inexact conclusions about the aggregate impact, the former is better than the latter. This is because changes in local employment-to-population ratios capture changes in employment net of population movements. Although, this approach still ignores the indirect adjustment in the likelihood of finding employment in a region due to shocks in other regions.

However, estimating and aggregating changes in local employment (instead of the local employment *rate*) results in erroneously finding a very large aggregate elasticity of employment with respect to shocks. This is because that procedure incorporates the partial equilibrium population term, $\hat{P}^{PE}_{cg}$, while ignoring the general equilibrium term, $\hat{P}^{GE}_{cg}$. In other words, population (and hence employment) in more negatively affected regions is allowed to decline while ignoring that this would lead to an increase in population (and hence employment) in less affected regions.[22] Therefore our suggestion for other researchers interested in aggregating employment changes from local responses is to use employment-to-population ratios and acknowledge the estimates as upper bounds on true employment effects.

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-to-population ratio for Black men and White men, and little of the evolution of the employment-to-population ratios for these groups individually over this period. Mirroring other results in the literature, we find that employment for Black workers is 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 overrepresented. In future work, we plan to

[22]One exception to this would be if individuals moving to other locations do not find jobs upon moving. However, this is ruled out empirically by our estimated positive elasticity of employment-to-population ratios with respect to local labor demand shocks.

further investigate what gives rise to these differential responses across groups.

Our results show that sectoral shifts were a somewhat important factor behind the decrease in Black relative to White employment 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 and fail to account for why both Black and White workers experienced such a big decline in their employment-to-population 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

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

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

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.

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

Taking the log of Eq. (10) we get,

$$\ln l_{cg}^* = \ln(c_{cg}/\omega_{cg}) + \frac{\alpha_g}{1-\alpha_g} \ln A_{cg}$$

Now if we total differentiate this expression, we get

$$\frac{\partial l_{cg}^*}{l_{cg}^*} = \frac{\alpha_g}{1-\alpha_g} \frac{\partial A_{cg}}{A_{cg}} \rightarrow \hat{l}_{cg}^* = \frac{\alpha_g}{1-\alpha_g} \hat{A}_{cg}$$

Similarly, taking the log of Eq. (11) we get,

$$\ln P_{cg}^* = \ln \tilde{c}_{cg} + \frac{1}{\kappa_g(1-\alpha_g)} \ln A_{cg} - \ln \left[\sum_c \tilde{c}_{cg} A_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}} \right]$$

Now again if we total differentiate this expression, we get

$$\hat{P}_{cg}^* = \frac{1}{\kappa_g(1-\alpha_g)} \hat{A}_{cg} - \frac{1}{\sum_c \tilde{c}_{cg} A_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}}} \cdot \frac{1}{\kappa_g(1-\alpha_g)} \sum_c \tilde{c}_{cg} A_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}} \frac{\partial A_{cg}}{A_{cg}}$$

Since $\frac{P_{cg}^*}{P_g} = \frac{\tilde{c}_{cg} A_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}}}{\sum_c \tilde{c}_{cg} A_{cg}^{\frac{1}{\kappa_g(1-\alpha_g)}}}$, we can write the above expression as,

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

where $\pi_{cg}^p = P_{cg}^*/P_g$. □

A.3 Proof of Proposition 3

Proof. First note that, $L_g = \sum_c L_{cg}$ so we can write $\hat{L}_g = \sum_c \pi_{cg} \hat{L}_{cg}$. Since $l_{cg} = L_{cg}/P_{cg}$, we have

$$\hat{L}_g^* = \sum_c \pi_{cg}(\hat{l}_{cg} + \hat{P}_{cg})$$

Now if we plug in the expressions from Proposition 2, we get

$$\hat{L}_g^* = \frac{\alpha_g}{1-\alpha_g} \sum_c \pi_{cg} \hat{A}_{cg} - \frac{1}{\kappa_g(1-\alpha_g)} \sum_c (\pi_{cg}^p - \pi_{cg}) \hat{A}_{cg}$$

Note that,

$$(\pi_{cg}^p - \pi_{cg}) = \pi_{cg} \left(\frac{P_{cg}}{P_g} \cdot \frac{L_g}{L_{cg}} - 1 \right) = \pi_{cg} \left(\frac{l_g}{l_{cg}} - 1 \right)$$

$\square$

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 A1: Industry Level Shifts

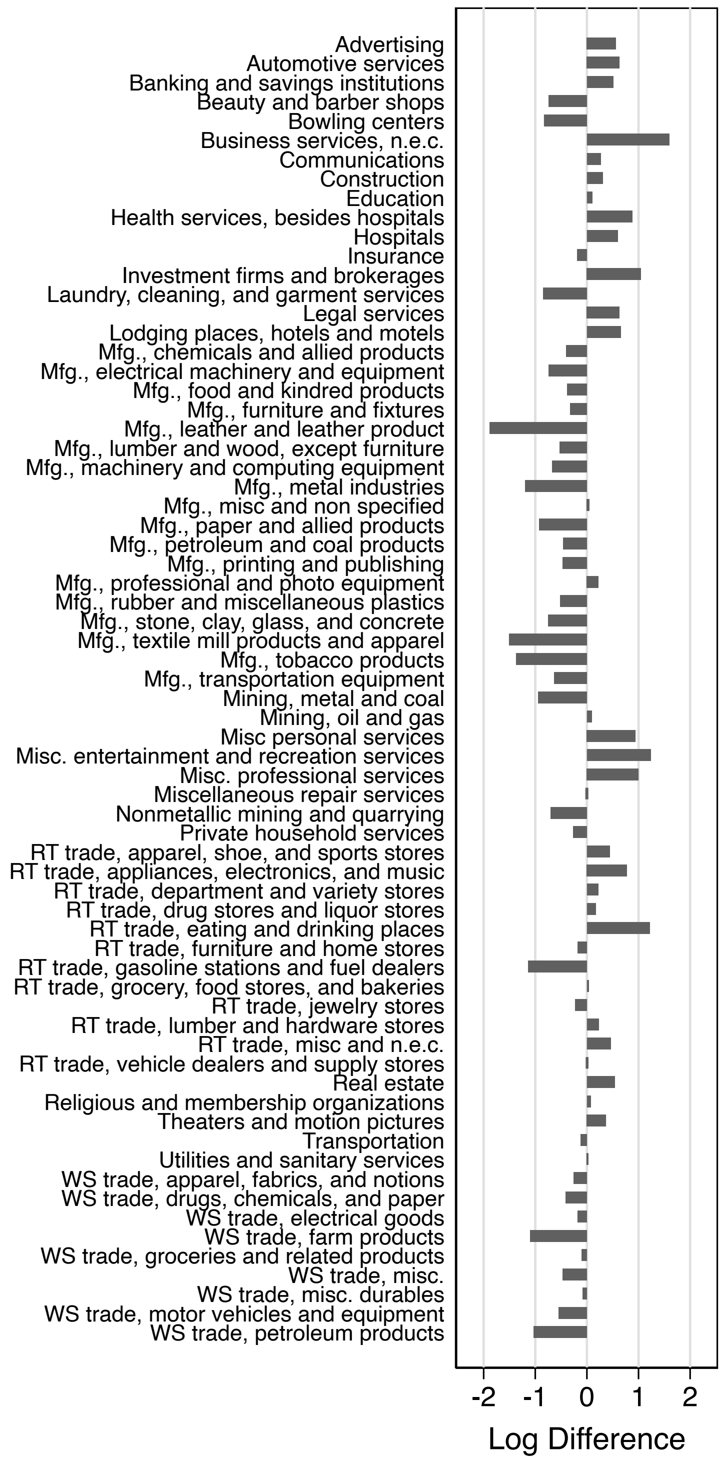
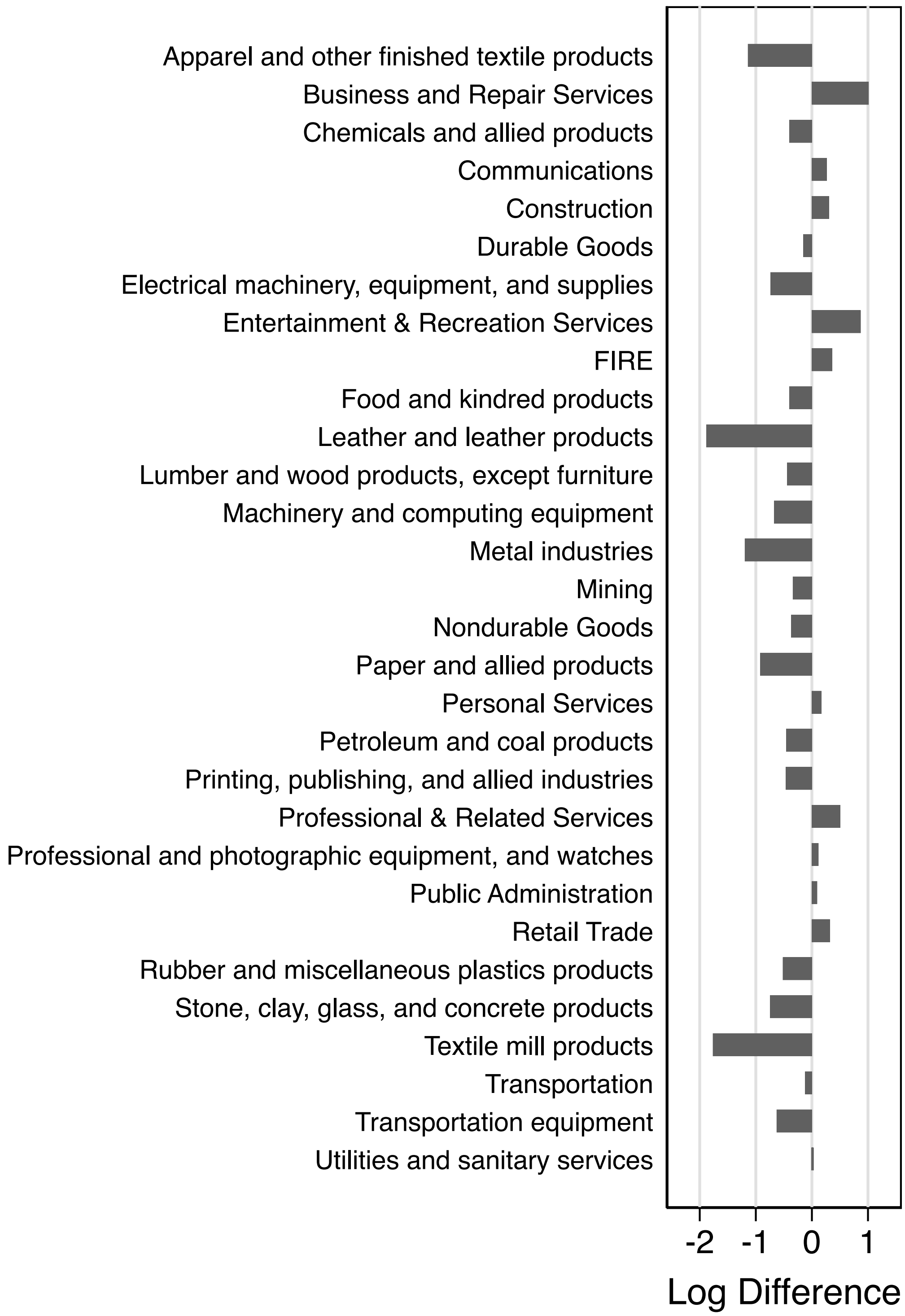


Figure A2: Industry Level Shifts, Broad Industries



C Robustness

C.1 Robustness to Different Employment Cutoffs

Table A1: Employment and Population Responses, Long Differenes, Cutoff = 100

	(1)	(2)	(3)	(4)	(5)
			Employment		
Constant	-0.10***	-0.10***	-0.11***	0.05	-0.12***
	(0.01)	(0.01)	(0.01)	(0.06)	(0.03)
Black	-0.12***	-0.13***	-0.13***	-0.28***	-0.12***
	(0.02)	(0.02)	(0.02)	(0.05)	(0.04)
ΔA_{cg}	0.15***	0.13***	0.11	0.12*	0.07
	(0.04)	(0.03)	(0.07)	(0.07)	(0.19)
ΔA_{cg} × Black	0.12	0.13*	0.11	0.07	0.14
	(0.08)	(0.07)	(0.09)	(0.08)	(0.17)
Observations	768	768	768	768	768
			Population		
Constant	0.56***	0.46***	0.55***	0.63**	0.53***
	(0.09)	(0.11)	(0.08)	(0.26)	(0.19)
Black	0.34***	0.36***	0.32***	0.22	0.32*
	(0.10)	(0.08)	(0.09)	(0.18)	(0.18)
ΔA_{cg}	0.80**	0.65*	0.90***	1.08***	0.60
	(0.34)	(0.34)	(0.31)	(0.34)	(0.97)
ΔA_{cg} × Black	-0.08	-0.02	-0.11	-0.30	-0.21
	(0.32)	(0.32)	(0.29)	(0.32)	(0.61)
Observations	768	768	768	768	768
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 100 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-to-population ratio 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 Eq. (1). Additional controls include the share of the foreign-born population in 1970 as well as the share of the instituitionalized 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 A2: Employment and Population Responses, Long Differenes, Cutoff = 300

	(1)	(2)	(3)	(4)	(5)
			Employment		
Constant	-0.10***	-0.10***	-0.13***	0.00	-0.11***
	(0.01)	(0.01)	(0.02)	(0.04)	(0.02)
Black	-0.13***	-0.14***	-0.13***	-0.24***	-0.12***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
ΔA_{cg}	0.13***	0.11***	0.07	0.03	0.08
	(0.04)	(0.04)	(0.06)	(0.05)	(0.12)
ΔA_{cg} × Black	0.14**	0.14**	0.14*	0.15**	0.15
	(0.06)	(0.06)	(0.07)	(0.07)	(0.11)
Observations	612	612	612	612	612
			Population		
Constant	0.62***	0.59***	0.61***	0.83***	0.44***
	(0.11)	(0.11)	(0.08)	(0.25)	(0.13)
Black	0.36***	0.36***	0.36***	0.17	0.38***
	(0.08)	(0.08)	(0.08)	(0.21)	(0.11)
ΔA_{cg}	1.01**	0.94**	0.68**	0.70*	0.02
	(0.41)	(0.41)	(0.34)	(0.36)	(0.63)
ΔA_{cg} × Black	-0.14	-0.12	-0.09	-0.14	-0.03
	(0.37)	(0.36)	(0.29)	(0.33)	(0.39)
Observations	612	612	612	612	612
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 300 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-to-population ratio 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 Eq. (1). Additional controls include the share of the foreign-born population in 1970 as well as the share of the instituitionalized 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 A3: Employment and Population Responses, Panel Regressions, Cutoff = 100

	(1)	(2)	(3)	(4)	(5)
Black Employment	0.33***	0.31***	0.29***	0.29***	0.28**
	(0.09)	(0.09)	(0.10)	(0.10)	(0.13)
Observations	1424	1424	1424	1424	1424
White Employment	0.20***	0.21***	0.23***	0.22***	0.22***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)
Observations	1424	1424	1424	1424	1424
Black Population	0.65***	0.56***	0.57***	0.54***	0.36
	(0.19)	(0.20)	(0.18)	(0.18)	(0.29)
Observations	1424	1424	1424	1424	1424
White Population	0.85***	0.82***	0.57***	0.58***	0.44***
	(0.22)	(0.21)	(0.12)	(0.12)	(0.14)
Observations	1424	1424	1424	1424	1424
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
Number of Observations	1,260	1,260	1,260	1,260	1,260

Notes: Sample is restricted to commuting zones that had at least 100 noninstitutionalized civilian Black men between the ages of 25-55 employed in all years 1960, 1970, 1980, 1990, 2000, and 2010. Table reports results from panel regressions of log differences in employment-to-population ratio 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 Eq. (6). Additional controls include the share of the foreign-born population as well as the share of the instituitionalized population for each group in each decade. 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 each decade. Robust standard errors clustered at the state level are in parentheses.$^{*}p \leq 0.10$;$^{**}p \leq 0.05$;$^{***}p \leq 0.01$

Table A4: Employment and Population Responses, Panel Regressions, Cutoff = 300

	(1)	(2)	(3)	(4)	(5)
Black Employment	0.34***	0.32***	0.27***	0.27***	0.36***
	(0.07)	(0.07)	(0.09)	(0.09)	(0.13)
Observations	1144	1144	1144	1144	1144
White Employment	0.20***	0.21***	0.24***	0.23***	0.24***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)
Observations	1144	1144	1144	1144	1144
Black Population	0.67***	0.59***	0.51**	0.48**	0.27
	(0.20)	(0.21)	(0.21)	(0.21)	(0.34)
Observations	1144	1144	1144	1144	1144
White Population	1.00***	1.01***	0.60***	0.60***	0.42**
	(0.29)	(0.29)	(0.13)	(0.12)	(0.17)
Observations	1144	1144	1144	1144	1144
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
Number of Observations	1,260	1,260	1,260	1,260	1,260

Notes: Sample is restricted to commuting zones that had at least 300 noninstitutionalized civilian Black men between the ages of 25-55 employed in all years 1960, 1970, 1980, 1990, 2000, and 2010. Table reports results from panel regressions of log differences in employment-to-population ratio 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 Eq. (6). Additional controls include the share of the foreign-born population as well as the share of the instituitionalized population for each group in each decade. 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 each decade. 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 *Robustness: Broad Industrial Composition*

Table A5: Employment and Population Responses, Long Differences, Broad Industries

	(1)	(2)	(3)	(4)	(5)
			Employment		
Constant	-0.12***	-0.11***	-0.12***	0.04	-0.12***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.01)
Black	-0.13***	-0.15***	-0.14***	-0.28***	-0.13***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)
ΔA_{cg}	0.11***	0.11***	0.05	0.03	0.12
	(0.03)	(0.03)	(0.05)	(0.05)	(0.12)
ΔA_{cg} × Black	0.16***	0.15***	0.15**	0.14***	0.14*
	(0.05)	(0.05)	(0.06)	(0.05)	(0.08)
Observations	672	672	672	672	672
			Population		
Constant	0.52***	0.46***	0.48***	0.80***	0.42***
	(0.07)	(0.08)	(0.07)	(0.22)	(0.08)
Black	0.37***	0.36***	0.37***	0.08	0.40***
	(0.06)	(0.06)	(0.06)	(0.18)	(0.09)
ΔA_{cg}	0.84**	0.76**	0.50	0.55	-0.25
	(0.38)	(0.37)	(0.33)	(0.34)	(0.58)
ΔA_{cg} × Black	-0.34	-0.32	-0.22	-0.32	-0.13
	(0.35)	(0.34)	(0.28)	(0.30)	(0.35)
Observations	672	672	672	672	672
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. Table reports results from pooled linear regressions of log differences in employment-to-population ratio 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 Eq. (1). Additional controls include the share of the foreign-born population in 1970 as well as the share of the instituitionalized 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 A6: Employment and Population Responses, Panel Regressions, Broad Industries

	(1)	(2)	(3)	(4)	(5)
Black Employment	0.38***	0.37***	0.33***	0.32***	0.43***
	(0.07)	(0.07)	(0.09)	(0.09)	(0.14)
Observations	1260	1260	1260	1260	1260
White Employment	0.25***	0.26***	0.30***	0.30***	0.35***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)
Observations	1260	1260	1260	1260	1260
Black Population	0.67***	0.59***	0.61***	0.60***	0.35
	(0.16)	(0.16)	(0.14)	(0.15)	(0.29)
Observations	1260	1260	1260	1260	1260
White Population	1.10***	1.08***	0.71***	0.72***	0.63***
	(0.29)	(0.28)	(0.15)	(0.13)	(0.18)
Observations	1260	1260	1260	1260	1260
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
Number of Observations	1,260	1,260	1,260	1,260	1,260

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, 1990, 2000, and 2010. Table reports results from panel regressions of log differences in employment-to-population ratio 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 Eq. (6). Additional controls include the share of the foreign-born population as well as the share of the instituitionalized population for each group in each decade. 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 each decade. 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 Separate Decades

We are interested in understanding whether specific decades in the range 1970–2010 are driving our results. Therefore, we display results where we run our long difference specifications separately by decade in Table A7. We use lagged industry shares corresponding to each decade. For instance, the regression using outcomes from 1980-90 uses industry shares in 1970. As can be seen in the table, estimates are similar for the years 1970-80 and 1980-90, while the decade 2000-2010 appears to display larger elasticities.

It is important to note that the variation in these specifications is not necessarily the same as in our main results, which are driven by variation in industry employment changes over the entire period 1970–2010. We therefore capture which industries grew on net over this time period rather than any decade specific trends in industry employment that would be heavily influenced by business cycle contractions and expansions.

Table A7: Employment and Population Responses, Each Decade Separately

	(1) 1970-80	(2) 1980-90	(3) 1990-2000	(4) 2000-2010
Black Employment	0.22*	0.31***	-0.21	0.62***
	(0.11)	(0.11)	(0.17)	(0.17)
Observations	315	315	315	315
White Employment	0.16***	0.15***	0.05	0.46***
	(0.04)	(0.04)	(0.05)	(0.05)
Observations	315	315	315	315
Black Population	0.35	0.96***	1.24***	0.42*
	(0.43)	(0.20)	(0.19)	(0.22)
Observations	315	315	315	315
White Population	1.53***	1.59***	0.47***	0.63***
	(0.27)	(0.18)	(0.08)	(0.13)
Observations	315	315	315	315

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. Additional controls include the share of the foreign-born population in 1970 as well as the share of the instituitionalized population for each group in 1970. $^{*}p \leq 0.10$;$^{**}p \leq 0.05$;$^{***}p \leq 0.01$

C.4 *Panel Regressions Including Lags of Independent Variable*

Table A8: Employment and Population Responses, Panel Regressions with Lags

	(1)	(2)	(3)	(4)	(5)
Black Employment	0.39***	0.37***	0.32***	0.32***	0.32**
	(0.07)	(0.07)	(0.08)	(0.08)	(0.14)
Observations	1260	1260	1260	1260	1260
White Employment	0.24***	0.25***	0.25***	0.24***	0.22***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)
Observations	1260	1260	1260	1260	1260
Black Population	0.58***	0.54***	0.58***	0.55***	0.48*
	(0.17)	(0.18)	(0.17)	(0.17)	(0.28)
Observations	1260	1260	1260	1260	1260
White Population	0.85***	0.86***	0.59***	0.59***	0.41**
	(0.22)	(0.22)	(0.13)	(0.14)	(0.15)
Observations	1260	1260	1260	1260	1260
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
Number of Observations	1,260	1,260	1,260	1,260	1,260

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, 1990, 2000, and 2010. Table reports results from panel regressions of log differences in employment-to-population ratio and population on our measure of local labor demand shifts. In addition, lagged labor demand shifts for each decade are also included in the regressions. 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 Eq. (6). Additional controls include the share of the foreign-born population as well as the share of the instituitionalized population for each group in each decade. 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 each decade. Robust standard errors clustered at the state level are in parentheses.$^{*}p \leq 0.10$;$^{**}p \leq 0.05$;$^{***}p \leq 0.01$

C.5 *Bartik Diagnostic Checks*

C.5.1 *Rotemberg Weights*

Table A9: Industries with the Largest Rotemberg Weights: White Workers

Industry Name	α_k	α_k (Residualized)
Textile mill products and apparel	0.383	0.384
Metal industries manufacturing	0.230	0.230
Metal and coal mining	0.097	0.098
Construction	0.046	0.049
Transportation equipment	0.033	0.032
Machinery and computing equipment	0.027	0.025
Paper and allied products	0.027	0.026
Gasoline service stations and fuel dealers	0.024	0.022
Lumber and wood products, except furniture	0.018	0.017
Business services, n.e.c.	0.017	0.018

Notes: Table shows the industries with the ten largest Rotemberg weights for shift-share proxies of labor demand with respect to White men over 1970–2010. 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 specifically for White men $L_{csW,1960}/L_{cW,1960}$ in 1960. The (Residualized) column contains the results when we first residualize both our shift-share proxies $\hat{A}_{cW}$ and our outcome variables with respect to controls before computing the Rotemberg weights.

Table A10: Industries with the Largest Rotemberg Weights: Black Workers

Industry Name	α_k	α_k (Residualized)
Metal industries manufacturing	0.446	0.446
Metal and coal mining	0.126	0.127
Lumber and wood products, except furniture	0.109	0.108
Textile mill products and apparel	0.053	0.052
Eating and drinking places	0.035	0.036
Construction	0.033	0.035
Gasoline service stations and fuel dealers	0.026	0.025
Transportation equipment	0.023	0.022
Food and kindred products	0.014	0.014
Machinery and computing equipment	0.014	0.014

Notes: Table shows the industries with the ten largest Rotemberg weights for shift-share proxies of labor demand with respect to Black men over 1970–2010. 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 specifically for Black men $L_{csB,1960}/L_{cB,1960}$ in 1960. The (Residualized) column contains the results when we first residualize both our shift-share proxies $\hat{A}_{cB}$ and our outcome variables with respect to controls before computing the Rotemberg weights.

Table A11: Industries with the Largest Rotemberg Weights

Industry Name	α_k	α_k (Residualized)
Metal industries manufacturing	0.375	0.375
Textile mill products and apparel	0.179	0.179
Metal and coal mining	0.147	0.148
Construction	0.052	0.052
Lumber and wood products, except furniture	0.050	0.051
Transportation equipment	0.031	0.030
Gasoline service stations and fuel dealers	0.022	0.023
Machinery and computing equipment	0.019	0.019
Paper and allied products	0.018	0.019
Eating and drinking places	0.016	0.016

Notes: Table shows the industries with the ten largest Rotemberg weights for shift-share proxies of labor demand over 1970–2010. 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. The (Residualized) column contains the results when we first residualize both our shift-share proxies $\hat{A}_{cg}$ and our outcome variables with respect to controls before computing the Rotemberg weights. As in our main specifications, we stack groups and include group specific dummy variables.

C.5.2 Correlation of Industry Shares with Controls

Table A12: Correlates with Industry Shares: White Workers

Industry Name	Foreign	Inst.	HS	College
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

Notes: Table contains the correlation between industry shares specifically for White men $L_{csW,1960}/L_{cW,1960}$ in 1960 and our control variables. We choose the 10 industries that have the largest Rotemberg weights. 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 instituitionalized population for White men in 1970. HS refers to the share of the population who are high school dropouts for White men. College refers to the share of the population with a college degree for White men in 1970.

Table A13: Correlates with Industry Shares: Black Workers

Industry Name	Foreign	Inst.	HS	College
Metal industries manufacturing	0.059	-0.157	-0.312	-0.269
Metal and coal mining	-0.119	-0.105	-0.163	-0.177
Lumber and wood products, except furniture	-0.304	0.445	0.739	0.540
Textile mill products and apparel	-0.096	0.011	0.232	0.139
Eating and drinking places	0.191	-0.126	-0.288	-0.221
Construction	0.086	0.031	0.176	0.155
Gasoline service stations and fuel dealers	-0.100	-0.014	0.099	0.048
Transportation equipment	0.166	-0.118	-0.160	-0.063
Food and kindred products	-0.106	-0.049	0.031	-0.008
Machinery and computing equipment	0.029	-0.133	-0.216	-0.199

Notes: Table contains the correlation between industry shares specifically for Black men $L_{csB,1960}/L_{cB,1960}$ in 1960 and our control variables. We choose the 10 industries that have the largest Rotemberg weights. 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 instituitionalized population for Black men in 1970. HS refers to the share of the population who are high school dropouts for Black men. College refers to the share of the population with a college degree for Black men in 1970.

C.6 Aggregation Results from Different Specifications

Table A14: Aggregation Results for the Long Specification

	Specification				
	1	2	3	4	5
Black Men	18.13	16.94	14.81	13.19	16.46
White Men	20.16	17.47	12.72	8.60	18.39
Gap	15.98	16.38	17.02	18.05	14.43

Notes: This table presents aggregation results using coefficients from specifications (1)-(5) from Table 2. The first two rows show the percentage of decline in employment for Black and White men explained by our measured sectoral shifts. While the last row presents the percentage of the total increase in the Black-White employment gap explained by these shifts.

Table A15: Aggregation Results for the Panel Specification

	Specification				
	1	2	3	4	5
Black Men	14.84	14.29	13.19	12.89	15.45
White Men	14.09	14.93	16.61	16.17	16.39
Gap	15.62	13.62	9.61	9.46	14.47

Notes: This table presents aggregation results using coefficients from specifications (1)-(5) from Table 3. The first two rows show the percentage of decline in employment for Black and White men explained by our measured sectoral shifts. While the last row presents the percentage of the total increase in the Black-White employment gap explained by these shifts.