Industrial Flight and Black Workers

Divya Bhagia

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Abstract

Employment to population rate differential between black and white low-skill men has been exacerbating over time in the United States. In this paper, I assess the role of declining labor demand in the manufacturing sector in explaining this trend. The differential impact for black workers could stem from differences in initial composition (extensive margin) or due to differential responses to labor demand shocks of similar intensity (intensive margin). I build a model of local labor markets with search frictions and imperfect regional mobility and show that, two groups of workers can have very distinct responses to similar shocks due to differences in the parameters governing the extent of these frictions. I infer the parameters of the model from employment, and population responses of both groups to changes in manufacturing wages in local labor markets. I find that labor demand shocks in manufacturing are able to explain one-third of the total increase in the differential. Initial composition plays no role in driving this differential and it is mainly being driven by differences in extent of search frictions. While I find that black workers have higher estimated costs of relocating, differences in population responses do not contribute significantly to exacerbating the aggregate differential.

"The standard explanation for slow black economic progress in the North emphasizes two demand-side forces: a weakening of the American manufacturing sector after 1960 and racism in northern labor markets. European migrants who settled in U.S. cities circa 1900 enjoyed four or five decades of American manufacturing ascendancy. Black arrivals in the 1940s benefited from only a decade or two of plentiful bluecollar positions before American manufacturing was eclipsed by global competition." — *Leah Platt Boustan, Competition in the Promised Land Black: Migrants in Northern Cities and Labor Markets, 2017*

1 Introduction

There are large differentials in labor market outcomes of black and white men in the United States. A plausible number for the male wage differential after controlling for other factors is around 10 percent (Lang and Lehmann, 2012). While most of the literature focusses on the wage-differential, the differences in employment are even more stark. In 2018, 11% of all working age white men were not employed while this number was slightly more than double for black men. [1] While differences in skill do play a role in explaining this large magnitude, the employment differential still exists even within narrowly defined education categories and is even larger for low-skill men [2]. Figure 1 plots the black-white employment to population ratio differential from the Current Population Survey (CPS) for years 1964-2018 for men without any college education after adjusting for age, marital status, education and state of residence. This differential has doubled over the last half a century, increasing between 1970-2000 and remaining constant thereafter.

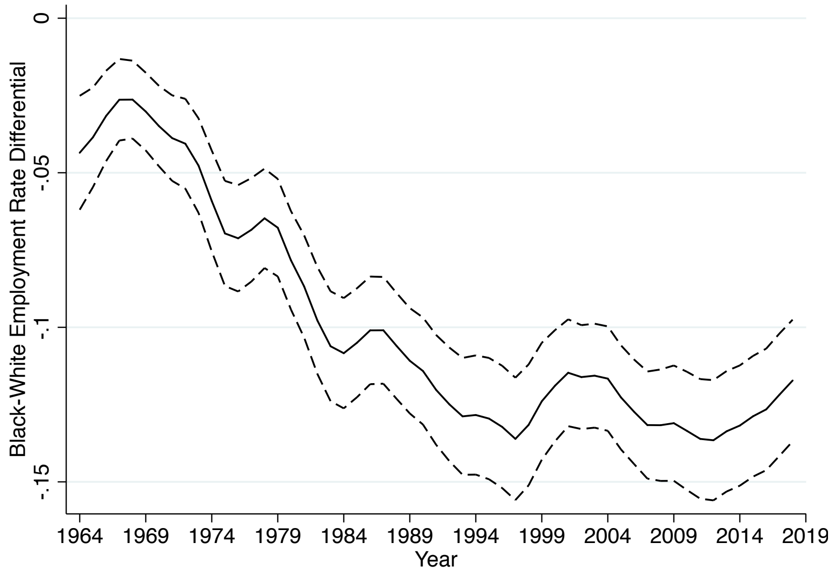
This is surprising given the racial progress in aftermath of the Civil Rights movement that led to improvements in school quality for African-American individuals in the United States. Moreover, as Figure 2 reveals, there is substantial cross-sectional variation in employment to population ratio differentials across the United States. The employment to population ratio differential for low-skill men in states that comprised the former Rust Belt was 1.7 times that of in the states that comprised the Sun Belt in 2018. [3]

[1] All statistics in the introduction are computed using Current Population Survey (CPS) March Supplement data unless otherwise stated. Working age men are defined as men between the ages of 25-54 who are not in the armed forces and do not include incarcerated individuals.

[2] I will refer to low-skill individuals as individuals who have no college education.

[3] Rust Belt includes the states of New York, Pennsylvania, West Virginia, Ohio, Indiana, Michigan,

Figure 1: Employment Rate Differential for Low-Skill Men (1964-2018)



This figure was constructed using data from Current Population Survey (CPS) March Supplement for years 1964-2018. The sample consists of all working-age men without any college education. The solid line plots the coefficient on the black dummy from a weighted regression of a employed dummy on the black dummy while controlling for age, marital status, education category and state of residence. The dashed lines represent 95% confidence interval.

This is in line with the anecdotal evidence suggesting increasing black-poverty in former industrial hubs. In this paper, I quantify the role of persistent negative shocks to the manufacturing sector in exacerbating employment to population ratio differentials for low-skill men.

Over the last five decades the manufacturing sector in the United States has contracted drastically. As Figure 3 shows that the share of employment in manufacturing has declined from 0.32 at the end of World War II to 0.09 by 2010 and manufacturing jobs per working age population has also been declining since 1970s. Contraction of the manufacturing sector represents a severe deterioration of employment opportunities for low-skill men. This is because in 1970, more than half of all manufacturing workers were low-skill men, and more than one-third of all low-skill men worked in manufacturing. Finally, given that manufacturing activity has always been highly clustered in a few regions in the United States, there is a considerable variation in which local labor markets

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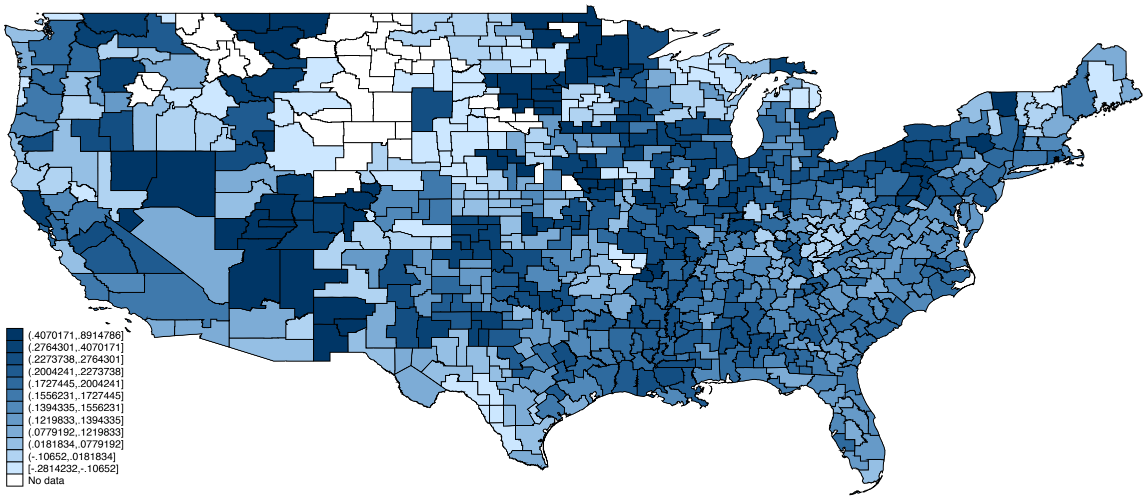
Illinois, Iowa and Wisconsin. While Sun Belt includes the states of Alabama, Arizona, Arkansas, California, Colorado, Florida, Georgia, Kansas, Louisiana, Mississippi, Nevada, New Mexico, North Carolina, Oklahoma, South Carolina, Texas, Tennessee and Utah.

Figure 2: Employment to Population Rate Racial Differentials in 2000 by Commuting Zones



Boundaries depict 741 commuting zones. Employment to population rate ratios are calculated from the U.S. Census for the year 2000. Sample excludes 19 commuting zones in Alaska and Hawaii and 40 other commuting zones that didn't have a black low skill male in the year 2000.

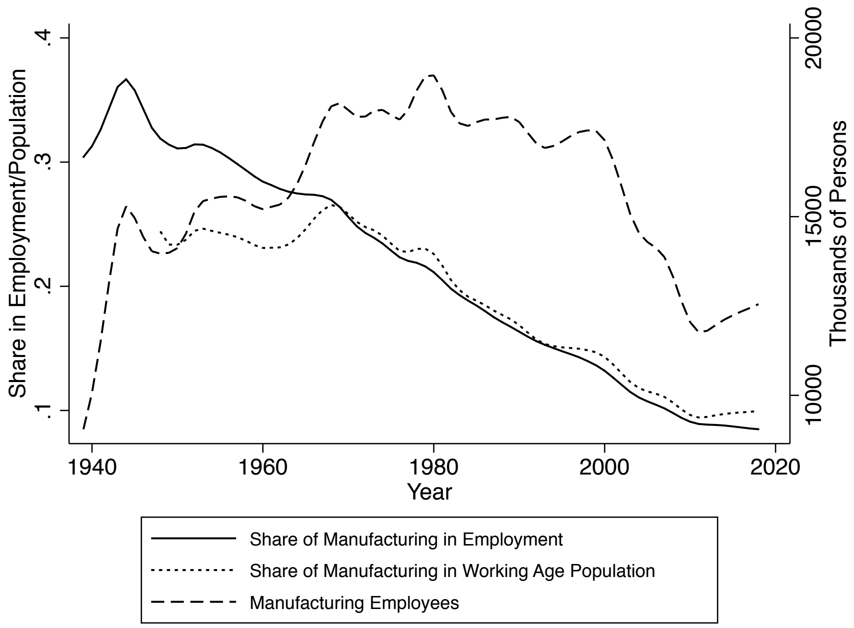
were affected by this decline.

But why would negative shocks to the manufacturing sector have a differential impact across black and white workers? Consider the following hypothetical situation, it's the 1980s and automakers are facing sluggish sales and increasing foreign competition. This pushes General Motors to close it's Cadillac plant in Detroit, displacing 4500 workers. Does this impact black workers more or white workers? It depends on who worked at this particular plant but it also depends on which group of workers can find the next job either in Detroit or somewhere else conditional on being displaced. So differences in impact could stem either from differential intensity of shocks (extensive margin) or due to differences in responses to shocks (intensive margin).

Recent literature on local labor market effects of trade makes it clear that shocks to one sector can have long-run effects on aggregate labor market outcomes in presence of imperfect sectoral and regional mobility. [4] While the predominant focus in this literature is to explain wage-adjustment, there is a consensus that non-wage margins are equally important. Kim and Vogel (2018) explicitly incorporate a labor/leisure tradeoff

[4]See Autor et al. (2013), Kovak (2013), Dix-Carneiro and Kovak (2015) etc.

Figure 3: Long Term Evolution of Manufacturing Industry (1939-2018)



This figure is created by using three series provided by the U.S. Bureau of Labor Statistics - MANEMP, PAYEMS and LNU00000060. MANEMP contains all employees in manufacturing. PAYEMS is a measure of the number of U.S. workers in the economy that excludes proprietors, private household employees, unpaid volunteers, farm employees, and the unincorporated self-employed. Both of these, the MANEMP and PAYEMS are seasonally adjusted. The LNU00000060 contains the civilian noninstitutional population between the ages of 25-54 years. The share of manufacturing in employment is defined as the ratio of MANEMP over PAYEMS and the share of manufacturing in the working age populations is defined as the ratio of MANEMP over LNU00000060. Only observations for the month of January are used for each year. Data was downloaded directly from the St. Louis Federal Reserve's economic data website.

and search frictions to incorporate non-employment in a trade framework. Taking this reasoning one step ahead, then it is obvious that if two groups of workers differ either in the magnitude of their sectoral or regional mobility or the extent of their search frictions, then employment responses to the same shock can be distinct across two groups.

To motivate my empirical strategy, I build a two-sector model of local labor markets with search frictions, imperfect regional mobility and heterogenous groups of workers. The model exposits that local labor market responses of employment to population ratio to a shock to the manufacturing sector can differ across the two groups due to differences in initial composition in manufacturing, elasticity of probability of finding a job with respect to labor market tightness, and propensity to relocate across local labor markets. Further, the model implies that these parameters can be recovered by regressing log changes in employment and population on log changes in manufacturing wages in each local labor market separately for both groups of workers. In order to not confound manufacturing labor demand shocks with other shocks to labor demand, I use a shift-share instrument for manufacturing wages.

The decline of the manufacturing sector has accompanied the process of economic growth in most developed nations. The theoretical literature on structural transformation emphasizes two key mechanisms that can lead to reallocation of activity across sectors: income effects and price effects. [5] In one class of models, income effects propagating structural change arise by assuming non-homotheticity of preferences even under uniform technological progress across sectors (Echevarria, 1997; Kongsamut et al., 2001; Boppart; Foellmi and Zweimller, 2008). While in another class of models, structural change can be accomplished by either incorporating differential technological progress across sectors ((Ngai and Pissarides, 2007)) or differential skill intensity across sectors (Acemoglu and Guerrieri, 2008; Caselli and Coleman, 2001). There is also growing empirical evidence in the context of the U.S. showing that increasing imports from low wage countries such as China (Autor et al., 2013; Pierce and Schott, 2016) and technological progress (Acemoglu and Restrepo, 2017) has led to a decline in manufacturing jobs in the the recent years. For the purpose of this paper, I think of a negative shock to manufacturing as a decline in labor productivity which directly feeds into wages and affects employment.

Related Literature There is an extensive literature on black-white wage and employment differentials, particularly for men. [6] The key findings from the literature are that there is a large raw wage differential between black and white men and much of this differential can be explained by the differences in the skills that they bring to the labor market but despite that a substantial unexplained wage differential exists (O'Neill, 1990; Neal and Johnson, 1996; Rodgers and Spriggs, 1996; Carneiro et al., 2005; Black et al., 2009). Much less attention has been paid to racial employment and unemployment differentials even though they are more dramatic and very little of these can be accounted for by education or other characteristics (Stratton, 1993; Neal and Johnson, 1996; Ritter and Taylor, 2011). It has also been documented that the unexplained wage differential (Lang and Manove, 2011; Bjerk, 2007) and unemployment differentials (Johnson and Neal, 1998) are larger for blue collar workers or workers with low levels of education. [7]

[5]See Herrendorf et al. (2013) for a recent and comprehensive review of the literature on structural transformation.

[6]See Lang and Lehmann (2012) for a review.

[7]However, it is likely that the differential among low-skill workers is understated, because such com-

In addition, black men also face longer unemployment durations (Bowlus and Eckstein, 2002) and lower exit rates from unemployment (DellaVigna and Paserman, 2005). Given this evidence, it seems plausible that the extent of labor market frictions for blue-collar black and white workers could be significantly different. It is also plausible that black men might have lower mobility rates across regions given the pre-existing wealth gap or other environmental factors, leading to spatial mismatch between black workers and jobs (Boustan and Margo, 2013).

In the literature on black-white labor market differentials, it is common to attribute a portion of the wage differential to observables and try to explain the rest with theories of labor market discrimination. But this becomes challenging when one starts looking at trends over time. As Figure 1 shows that the employment differential for low-skill men has been increasing overtime but racial prejudice as measured by implicit association tests and other self-reported measures has been declining steadily. In this paper, I argue that perhaps interactions of changing economic environment with certain elements reflecting pre-market or labor market disadvantage could go a step further in explaining the evolution of labor market differentials over time.

Outline The rest of the paper is organized as follows. Section 2 presents a model of local labor markets which clarifies the economic forces and enables me to derive the main estimating equation which is described in Section 3. Section 4 describes the data. Section 5 presents the main empirical results. Section 6 concludes. Proofs for propositions, and details on data construction can be found in the Appendix A, and B, respectively.

2 A Model of Labor Market Frictions

This section presents a model of local labor markets with search frictions and imperfect labor mobility to exposit the potential effects of a negative shock to labor demand in the manufacturing sector on employment to population ratio differentials between low-skill black and white men. In this model, workers belonging to different groups exogenously differ in their composition across sectors and in their elasticities that govern labor market frictions. There are no productivity differences across or between groups of workers. Also

parisons are conditioned on labor force participation, and low-skill black men are more likely to be not in the labor force or in prison (Chandra, 2000).

there is no labor market discrimination in the traditional sense such that two workers with similar productivity get paid similar wages. The differences in labor market frictions can be interpreted to reflect pre-market and labor market disadvantage, which will lead to disparate outcomes in the equilibrium.

2.1 Model Setup

The economy consists of L local labor markets indexed by l, G groups of workers indexed by g and two sectors (manufacturing and non-manufacturing), indexed by $s = m, n$. Each worker of group g in local labor market l once hired works either in the manufacturing sector or in the non-manufacturing sector depending on the exogenous probability π^l_{mlg}. If the worker ends up working in the manufacturing sector, their productivity is given by A^Y_{ml}. Whereas productivity of a worker in the non-manufacturing sector is given by A^Y_{nl}. Each local labor market is a small open economy and the price of all goods are exogenously determined in the world market. In addition, price of final good is normalized to 1. Search is directed, such that workers choose where to live and firms post vacancies V_{lg} in each market.

2.1.1 Matching in Labor Markets

Once the workers have chosen where to live, the number of matches in each market lg are determined by the following Cobb-Douglas matching function.

$$L_{lg} = A^M_{lg} V^{\alpha_g}_{lg} P^{1-\alpha_g}_{lg} \qquad \text{where} \quad \alpha_g \in (0,1)$$

and P_{lg} is the number of workers of group g looking for a job in local labor market l. A^M_{lg} is the productivity of matching technology which is allowed to differ across groups and local labor markets. Probability of finding a job which is analogous to employment-population ratio is given by

$$p_{lg} = \frac{L_{lg}}{P_{lg}} = A^M_{lg} \left(\frac{V_{lg}}{P_{lg}}\right)^{\alpha_g} = A^M_{lg} \theta^{\alpha_g}_{lg}$$

θ_{lg} denoting the ratio of vacancies to total population can be interpreted as labor market thickness. Workers of different groups, differ in their elasticity (α_g) of probability of finding a job with respect to labor market thickness. Intuitively, employment of a group with a higher value of α_g is more likely to see employment losses in tighter markets and vice versa.

Assuming free entry, firms post vacancies until profits from a new vacancy are zero, such that

$$(A^Y_{lg} - w_{lg})\frac{L_{lg}}{V_{lg}} = F_{lg}$$

where F_{lg} is the cost of posting each vacancy, A^Y_{lg} is the average productivity, and w_{lg} are the average wages of workers belonging to group g in labor market l. The average productivity in each local market for group g workers can be written as,

$$A^Y_{lg} = \pi^l_{mlg} p_m A^Y_{ml} + \pi^l_{nlg} p_n A^Y_{nl}$$

where p_m, and p_n are prices of manufacturing, and non-manufacturing goods, respectively. Wages are determined by Nash-bargaining after the match takes place, implying that $w_{sl} = \beta_l A^Y_{sl}$, where β_l is the worker's bargaining power. The probability of finding a job in each market in the equilibrium then can be written as

$$p_{lg} = c_{lg}(w_{lg})^{\frac{\alpha_g}{1-\alpha_g}} \tag{1}$$

where $c_{lg} = (A^M_{lg})^{\frac{1}{1-\alpha_g}} \left(\frac{1-\beta_l}{\beta_l F_{lg}}\right)^{\frac{\alpha_g}{1-\alpha_g}}$.

2.1.2 Worker's Location Choice

Worker i chooses where to live based on wages, probability of finding employment in each local labor market and an idiosyncratic preference for location. In particular,

$$l^* = \underset{l}{\text{argmax}}\{p_{lg} w_{lg} \varepsilon_l(i)\}$$

where $\varepsilon_l(i)$ is distributed Fréchet with $F_g(\varepsilon) = exp(-\varepsilon^{-\sigma_g})$ where $\sigma_g > 0$. A high value of σ_g implies less variability in the draws, which means that the group with a higher value of σ has lower costs of migration. As shown in the Appendix, the Fréchet assumption implies that the population of each group g in local labor market l is given by

$$P_{lg} = \frac{\tilde{c}_{lg} w_{lg}^{\frac{\sigma_g}{1-\alpha_g}}}{\sum_l \tilde{c}_{lg} w_{lg}^{\frac{\sigma_g}{1-\alpha_g}}} P_g \tag{2}$$

where $\tilde{c}_{lg} = c_{lg}^{\sigma_g}$ and P_g is total population of group g.

2.2 Comparative Statics

In this section, I derive implications of a shock to the manufacturing sector in form of shocks to labor productivity ($d \ln w_{ml} \neq 0$) for employment and population in local labor markets. Shocks to $d \ln w_{ml}$ can be thought of as trade shocks or shocks to demand for products in the manufacturing sector working through p_m or as technology shocks working through A^Y_{ml}. Proofs for all the propositions can be found in the Appendix A.

Proposition 1 *In equilibrium, the impact of a shock to the manufacturing sector on employment and population of group g in local labor market l is given by*

$$d \ln L_{lg} = \frac{\alpha_g}{1-\alpha_g} \pi^w_{mlg} d \ln w_{ml} + d \ln P_{lg} \tag{3}$$

$$d \ln P_{lg} = \frac{\sigma_g}{1-\alpha_g} \pi^w_{mlg} d \ln w_{ml} - \frac{\sigma_g}{1-\alpha_g} \sum_l \pi^p_{lg} \pi^w_{mlg} d \ln w_{ml} \tag{4}$$

where π^w_{mlg} is the share of manufacturing in the wage bill and $\pi^p_{lg} = \frac{P_{lg}}{P_g}$.

Proposition 1 highlights that if there is a negative shock to labor demand in the manufacturing sector ($d \ln w_{ml} < 0$) then employment for any group in a local labor market will decline. The magnitude of this decline varies across local labor markets due to differences in intensity of the shock and initial composition across sectors. Even within local labor markets the magnitude of decline varies across groups of workers due to differences in their shares of wages in manufacturing as well as due to differences in their elasticities. In particular, a negative shock to labor productivity in the manufacturing sector leads to a decline in the overall labor productivity depending on the share of manufacturing in the local economy. Lower labor productivity leads to firms posting less vacancies in these markets leading to tighter labor markets. Whichever group has a higher elasticity (α_g) of probability of finding a job with respect to labor market tightness will see more of a decline.

On the other hand, tighter markets and lower wages resulting from the shock will also impact the location decision of workers. Specifically, workers will respond to lower wages and reduced likelihood of finding a job in their local labor markets by moving to other local labor markets. However, it is not necessary that every labor market where manufacturing wages has declined will experience population decay. This is because whether there is a net inflow or outflow depends on relative magnitudes of shock in other local labor markets as captured by the second term in the Eq. (4). Similar to changes in employment, the magnitude will vary across local labor markets and across groups even within the same local labor markets. Even with similar intensity of shock and composition, workers belonging to the group with higher σ_g (lower migration costs) will be more prone relocating. Also note, that the elasticity of the matching function α_g is important even for population responses as individuals consider the probability of finding employment in their location decisions.

2.3 Aggregation

From Proposition 1, we know how employment to population ratios in local labor markets respond to a negative shock to the manufacturing sector which we can use to generate predictions for aggregate employment to population ratios,

Proposition 2 *In equilibrium, the impact of a shock to the manufacturing sector on aggregate employment to population of group g is given by*

$$d\ln\frac{L_g}{P_g} = \sum_l \underbrace{\left[\underbrace{\pi^l_{lg}\frac{\alpha_g}{1-\alpha_g}}_{\textit{Employment Response}} - \underbrace{(\pi^p_{lg} - \pi^l_{lg})\frac{\sigma_g}{1-\alpha_g}}_{\textit{Population Response}} \right]}_{\textit{Intensive Margin}} \underbrace{\pi^w_{mlg} d\ln w_{ml}}_{\textit{Extensive Margin}} \tag{5}$$

where $\pi^l_{lg} = \frac{L_{lg}}{L_g}$.

Proposition 2 nicely captures the main intuition of the paper that the aggregate effect on employment to population ratios depends on both, the intensive and the extensive margin. In particular, black workers could have fared worse due to declining manufacturing sector if they were highly concentrated in locations that had steep declines in manufacturing wages, this is the extensive margin. However, the impact also depends on how employment of black and white workers responds to a shock of similar magnitude. This intensive margin depends on the magnitude of search frictions and population responses. Population movements dampen the effect of the shock as long as the labor market of origin is on average tighter than rest of the economy.

3 Empirical Specification

Proposition 1, gives me reduced form estimating equations that I can take to the data and estimate the parameters. In particular, I estimate the following discrete-time counterparts of equations from Proposition 1

$$\Delta \ln \frac{L_{lg}}{P_{lg}} = \mu_g^e + \beta_g \pi_{mlg}^w \Delta \ln w_{ml} + \epsilon_{lg}^e \tag{6}$$

$$\Delta \ln P_{lg} = \mu_g^p + \gamma_g \pi_{mlg}^w \Delta \ln w_{ml} + \epsilon_{lg}^p \tag{7}$$

Where $\beta_g = \frac{\alpha_g}{1-\alpha_g}$ and $\gamma_g = \frac{\sigma_g}{1-\alpha_g}$. In the above equations, $\Delta \ln x_{lg}$ represents log-changes in variable x in local labor market l for group g over 1970-2000. And ϵ_{lg} captures other unobserved shocks. The model in equations (6-7) can be readily estimated using OLS. However it is possible that changes in manufacturing wages are correlated with the unobserved shocks leading to biased estimates.

Since I want to identify changes in manufacturing wages that are due to the shocks to labor demand in the manufacturing sector as implied by the model, I estimate equations (6-7) using instrumental variable regression. I use a ‘shift-share’ instrument for $\pi_{mlg}^w \Delta \ln w_{ml}$. The data and the instrument are described more in detail in the next section. The main identifying assumption is that the initial sub-industry composition within manufacturing is uncorrelated to other shocks or trends for each group in the subsequent decades.

4 Data

In this section, I describe the data used in the empirical analysis, provide descriptive statistics, and also describe the construction of the instrument.

4.1 Employment, Population and Wages

I use the Census Integrated Public Use Micro Samples (Ruggles et al. 2004) for the years 1950, 1970, and 2000 to measure changes in employment, population and manufacturing wages. The sample is restricted to low-skill working age men, in particular, men between ages 25-54 who are not in the armed force, do not reside in institutionalized group quarters and have no college education. I study changes in outcomes over 1970-2000 at the level of Commuting Zones originally developed by Tolbert and Sizer (1996), who used county-level commuting data from 1990 Census data to create 741 clusters of counties that are characterized by strong commuting ties within Commuting Zones, and weak commuting ties across Commuting Zones. [8] The final sample is restricted to 363 of these Commuting Zones which had at 100 low skill black men in 1970 and 2000 and had at least 1 manufacturing employee in 1950. [9]

For construction of wages, I consider the annual earnings of full-year workers defined as individuals who worked at least 40 weeks in the previous year. Wages are constructed as the ratio of annual earnings over total hours worked, where total hours are calculated assuming a 40-hour week. This choice is driven by the fact that the usual hours worked variable is unavailable for 1970. Also weeks worked for 1970 are intervalled and hence I use mid-points of intervals for that year. All wages are converted to constant 1999 dollars. Further, I exclude individuals with wages less that $5.15 which was the federal minimum wage in 1999.

According to the model, wages capture marginal productivity of workers but realistically marginal productivity differs across workers depending on their age, race, education and marital status. Therefore, the variation in manufacturing wages across years and commuting zones could be due to compositional changes in addition to due to shocks to manufacturing sector. For instance, even within low-skill workers if high school graduates

[8]These have been popularized in the literature by Autor and Dorn (2013) and Autor, Dorn, and Hanson (2013).

[9]Results are similar with a larger sample when using the instrument with 1970 shares instead of 1950.

are more likely to be employed in manufacturing than high school dropouts in 2000 than in 1970, then we might see an increase in average manufacturing wages even when it is possible that wages for both high school dropouts and high school graduates in manufacturing declined over this period.

To circumvent this problem, throughout the paper I use composition adjusted wages. In particular, for each commuting zone and year I predict counterfactual wages where the counterfactual is to assume that each local labor market in each year had the same composition in manufacturing as the aggregate economy averaged over the whole period. Using composition adjusted wages helps me to capture the variation across commuting zones and over time that is not simply due to differences in composition of workers but reflects marginal productivity more closely. More details on construction of composition adjusted wages can be found in Appendix B.

4.2 Descriptive Statistics

Table 1 presents the total change in composition adjusted manufacturing wages from 1970 to 2000 in the first row. Wages in manufacturing have gone down from $17.83 in 1970 to $15.87 in 2000 after accounting for changes in cohort, race, and educational attainment composition in the sector. This represents a change of around 11% over three decades. The next two rows show the change in employment to population rate for white and black men, respectively.

Table 1: Employment-Population Ratios and Manufacturing Wages over 1970-2000

	1970	2000	% Change
Manufacturing Wages	17.83	15.87	10.99%
Employment/Population: White Men	0.91	0.81	10.98%
Employment/Population: Black Men	0.85	0.64	24.70%
Employment/Population: Differential	0.06	0.15	150%

Notes: This table presents average composition adjusted wages in manufacturing as well as aggregate employment to population ratios. The sample is restricted to white and black men between ages 25-54 who are not in the armed force, do not reside in institutionalized group quarters and have no college education. Wage calculation also excludes workers who worked less than 40 weeks in the last year or whose wages are below minimum wage. Wages are expressed in constant 1999 dollars.

Employment to population rate for low-skill white men has fallen from 0.91 to 0.81, hence leading to a decline of 0.1 for the statistic. What is surprising, and was a motivation for this paper is the decline of around 0.21 in the employment to population ratio for black low-skill men from 0.85 to 0.64. The change in the ratio for black men is almost double of that of white men, thus taking the racial differential in this statistic from 0.06 to 0.15. The magnitude of this decline is large, for every 1 white men who was employed in 1970 but is now not employed, there are 2 black men who have exit employment.

Figure 4a presents fitted lines of changes in employment to population ratio on changes in manufacturing wages for black and white men separately along with a scatter plot of the differential for a few commuting zones with big cities. Both of the fitted lines are upward sloping demonstrating that places with greater declines in manufacturing wages have lost more in employment per population for both groups. However, the line is steeper for black men which suggests that even in places with similar declines in manufacturing wages, employment for black men has fallen by more thus leading to a greater differential in places with larger declines in manufacturing wages. One possible candidate for this pattern would be if black men employed in manufacturing were more likely to be in locations that were hit worse. I will argue later that this channel is insignificant in magnitude.

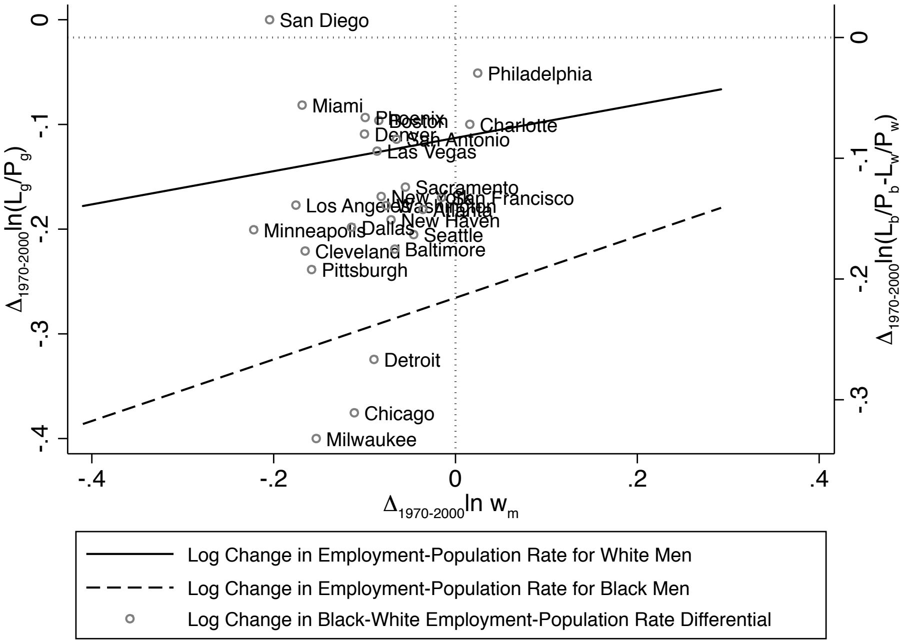
Figure 4b presents an analogous figure to figure 4a for changes in population. In particular, figure 4b presents fitted lines of changes in population on changes in manufacturing wages for both groups along with a scatter plot of the relative population change for a few commuting zones. The upward sloping lines suggest that both groups of workers have lost more population in areas with declines in manufacturing wages. Then changes in population could be a mitigating factor when thinking about how much of local employment losses translate into aggregate employment.

4.3 Shift-Share Instrument

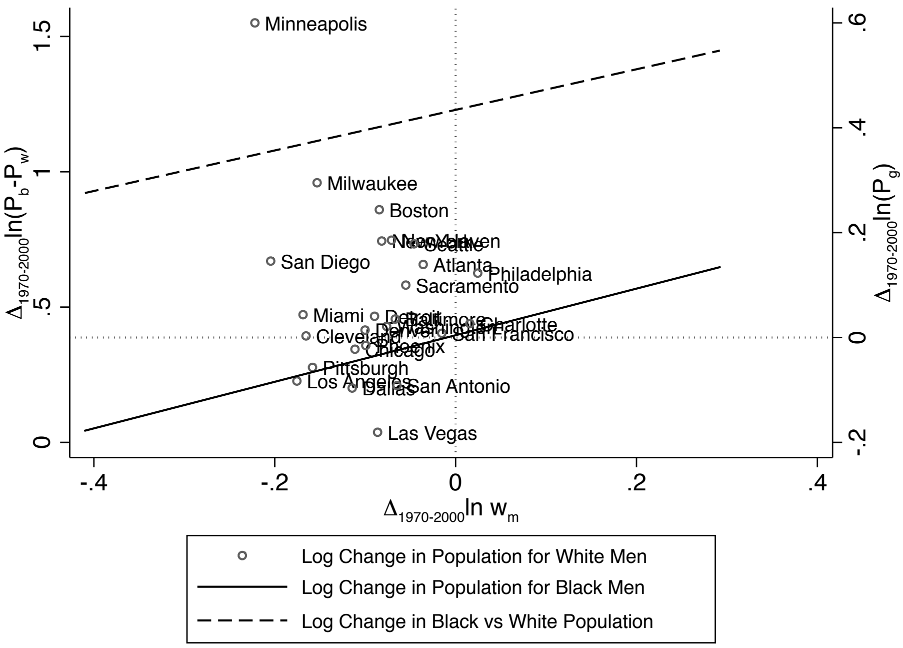
I use the following 'shift-share' instrument to instrument for $\pi^w_{mlg}\Delta \ln w_{ml}$ in the empirical analysis,

$$i_l = \sum_{k \in m} \pi_{kl0} \times \Delta \ln w_{kl}$$

Figure 4: Relationship between the Change in Manufacturing Wages and Employment and Population



(a) Employment



(b) Population

This Figure presents a scatter of changes in employment-population ratios and population in local labor markets for black vs white workers against changes in manufacturing wages. The fitted lines present these changes separately for black and white workers. The sample consists of 611 commuting zones which had at least one black male tin 1970 and 2000.

where π_{klg} is the share of employment in sub-industry k within manufacturing in 1950 and $\Delta \ln w_{kl}$ is a measure of wage growth in sub-industry k in the aggregate economy over 1970-2000. To be able to construct this instrument I first construct a balanced panel of sub-industries within manufacturing for years 1950, 1970 and 2000. More details on construction of the panel for manufacturing sub-industries can be found in Appendix B. For the measure of wage growth in sub-industry k, $\Delta \ln w_{kl}$, I again predict composition adjusted wages for each industry in 1970 and 2000.

Figure 5 shows the first stage relationship between the changes in manufacturing share weighted wages and the instrument for white workers in figure 5a and for black workers in figure 5b. As the figure demonstrates the instrument based on sub-industry composition within manufacturing and national wage growth rates does a good job of capturing variation in changes in manufacturing wages across commuting zones. The F-stat for the regressions is 42.7 and 38.12 for white and black men, respectively.

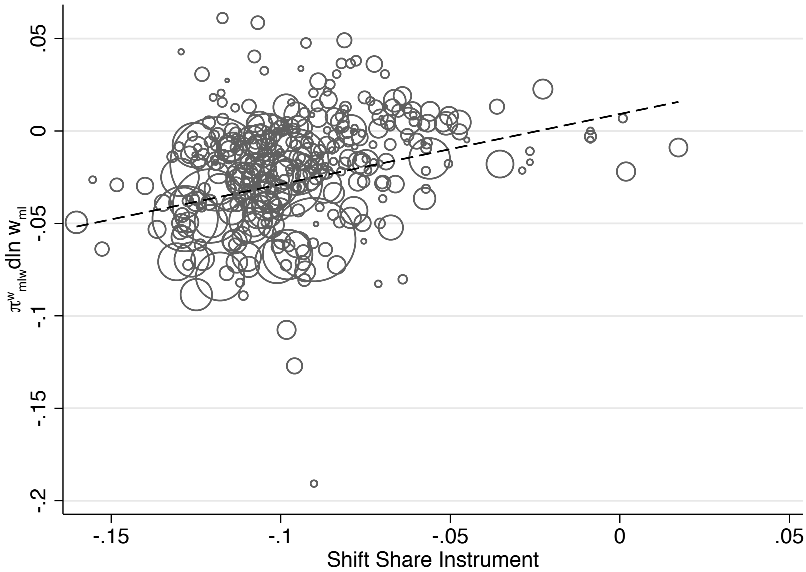
5 Results

In this section, I present reduced-form and IV results from the above specification and elucidate their implications for aggregate statistics. All regressions are weighted by group-specific start of decade population and report robust standard errors clustered at state-level.

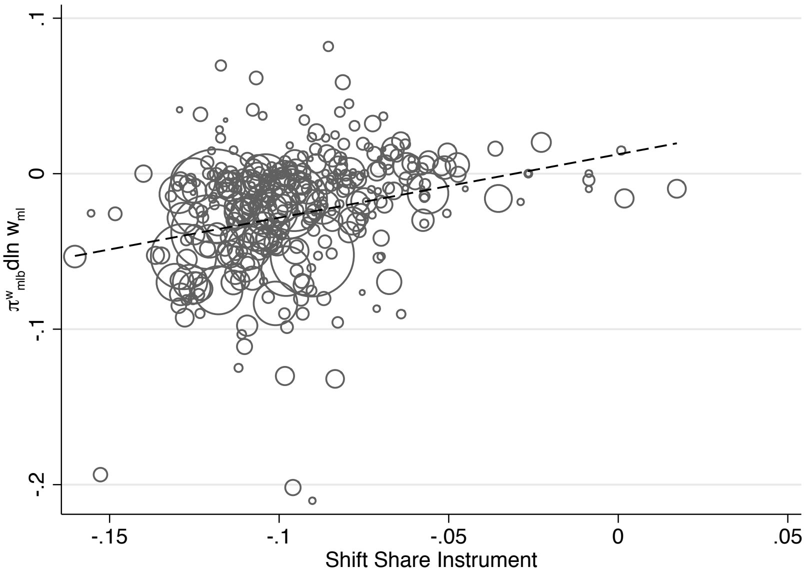
5.1 Reduced Form Results

Table 2 provides a preliminary view of how employment and population have changed differently in commuting zones with higher declines in manufacturing wages. For both, black and white low skill men, the direction of the correlation coefficients is as predicted by the model. Two patterns are notable. First, as shown in column 1, there is a positive correlation between employment and manufacturing wage changes weighted by manufacturing employment in a commuting zone even after accounting for changes in population. This implies that commuting zones that faced greater wage losses in manufacturing on an average have lost more in employment per population vis-à-vis other commuting zones. Secondly, manufacturing wage losses are correlated with urban decay and movement of population out of affected commuting zones.

Figure 5: First Stage Relationship between the Change in Manufacturing Wages and the Instrument



(a) White Low-Skill Men



(b) Black Low-Skill Men

This Figure presents a scatter and fitted line plot from a weighted commuting zone level of regression of the shift-share instrument, i_l on weighted change in manufacturing wages ($\pi^w_{mlg} d \ln w_{ml}$) for white and black men in (a) and (b), respectively. The size of the circle reflects the size of working age population in 1970. The sample consists of 363 commuting zones that had at least a population of 100 black low skill men in both 1970 and 2000 and had at least one manufacturing black employee in 1950. The $F - stat$ of the regression is 42.7 and 38.12 for white and black men, respectively.

What is worth noting is that the magnitude of both these effects differs across black and white men. Specifically, the correlation between manufacturing wage changes and changes employment is much stronger and only significant for black men. While the correlation between manufacturing wage changes and changes population is stronger for white men. The extent that reallocation across local labor markets are potential mitigators in response to negative shocks, weaker responses by black men suggest a potential role for differences in ability to mitigate shocks by race. Also note that the empirical exercise accounts for different shares of workers in manufacturing across commuting zones, so the difference in magnitude of coefficients captures a differential response to a shock of similar magnitude.

Table 2: Reduced Form Results

	Employment/Population	Population
	(1)	(2)
	Panel A: White Low-Skill Men	
$\pi^{w}_{mlw} d\ln w_{ml}$	0.303	3.195***
	(0.183)	(0.929)
R-Squared	0.033	0.060
No. of Observations	363	363
	Panel B: Black Low-Skill Men	
$\pi^{w}_{mlb} d\ln w_{ml}$	1.198***	2.778***
	(0.197)	(0.867)
R-Squared	0.094	0.058
No. of Observations	363	363

Notes: The table presents reduced form estimates from specification in Equations (6-7). The sample consists of 363 commuting zones that had at least a population of 100 black low skill men in both 1970 and 2000 and had at least one manufacturing black employee in 1950. Robust standard errors clustered at state-level are presented in the parenthesis. *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

5.2 Instrumental Variable Estimates

The main IV results are presented in Table 3 and the coefficients have the same direction as the reduced form results but substantially different magnitudes for population responses. But now the interpretation of the coefficients is causal. Once again, the population responses are slightly larger for white men and the coefficient on employment-population responses for white men is economically and statistically insignificant.

To make sense of the magnitudes, one has to consider the initial share of manufacturing in the total wage bill. The average share of manufacturing for black and white men in 1970 was 0.30 and 0.33, respectively. In which case, for a labor market that saw an 11% decline in manufacturing wages which was the average total change in manufacturing wages over this period as shown in Table 1, the coefficient of 1.66 in Column 1 of Panel B of Table 3, represents a decline of around 5.5% in the employment-population ratio for black men. A 5.5% decline would predict that the black employment-population ratio falls from 0.85 in 1970 to 0.8 in 2000, thus increasing the racial differential from 0.06 to around 0.1 which is still below the actual differential of 0.15 in 2000.

Table 3: Instrumental Variable Estimates

	Employment/Population	Population
	(1)	(2)
	Panel A: White Low-Skill Men	
$\pi^{w}_{mlw} d \ln w_{ml}$	0.153	11.34**
	(0.675)	(4.943)
RMSE	0.043	0.393
No. of Observations	363	363
	Panel B: Black Low-Skill Men	
$\pi^{w}_{mlb} d \ln w_{ml}$	1.663*	10.56**
	(0.928)	(4.620)
RMSE	0.111	0.402
No. of Observations	363	363

Notes: The table presents instrumental variable estimates from specification in Equations (6-7). The sample consists of 363 commuting zones that had at least a population of 100 black low skill men in both 1970 and 2000 and had at least one manufacturing black employee in 1950. Robust standard errors clustered at state-level are presented in the parenthesis. *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

5.3 Aggregation and Decomposition

The previous section presented a naive aggregation exercise to interpret the magnitude of the coefficients, however it fails to account for heterogeneity in shocks and composition across local labor markets as well as the share of each market in the aggregate economy. From Proposition 2, we know that the heterogeneity across local labor markets needs to be accounted for to get aggregate prediction for employment to population ratios. Hence, I plug in the IV coefficients from the previous section, relevant shares and changes in manufacturing wages for different local labor markets in Eq. (5) to get the predicted change in employment to population ratios. The coefficients and implied parameters are presented in Table 4. The magnitude of decline in black-white differential that is explained by negative shocks to the manufacturing sector, now falls from 0.4 to 0.3. This suggests that labor markets that saw greater negative effects in employment-population ratio for black men had a smaller share in black employment.

Eq. (5) also allows me to decompose the differences in impact between extensive and intensive margin and to also further investigate the role of population movements in the intensive margin. To decompose the role of intensive and extensive margin, I re-estimate Eq. (5) for black workers assuming that they have the same distribution across locations of share in manufacturing as white workers. I find that none of the differential increase can be explained by geographical differences in initial composition in manufacturing. This implies that, it is not differential intensity of shocks but in fact differential responses to shocks of similar magnitude that drive the racial differential.

Table 4: Parameters

β_w	γ_w	α_w	σ_w	β_b	γ_b	α_b	σ_b
0.15	11.34	0.13	9.86	1.66	10.56	0.62	4.01

Notes: The table presents estimated parameters from the instrumental variable regression in Table 3 (β_g, γ_g) and uses those to estimate the parameters of the model (α_g, σ_g).

As shown in Table 4, the estimated elasticity of the local matching function (α) for white workers is 0.13 and for black workers is 0.62. This implies, that local black employment is four-times as sensitive to local labor demand shocks than white employment. On the other hand, the migration elasticity (σ), for white workers is more than double that for black workers which is around 4. To further decompose the role of search frictions and migration responses in the intensive margin, I run two counterfactuals. I first re-estimate Eq. (5) for both races assuming that both groups have same level search frictions and then again repeat the exercise but while assuming that they have the same migration elasticity. The population responses actually play a very small role in mitigating the shock for both groups and hence have no bite in explaining the differential. This is because, the second term in equation Eq. (5) is weighted by $(\pi^p_{lg} - \pi^l_{lg})$ and hence, population responses only matter if there are local labor markets that are sufficiently insulated from the shock and provide employment opportunities to movers.

6 Conclusion

In this paper, I revisit one of the common explanations for worsening labor market outcomes for black men beginning 1970s, the decline of the manufacturing sector. First formally proposed by Wilson (1987), this explanation has found empirical support from studies that find that black workers were disproportionately affected by decreases in labor demand during these decades (Bound and Holzer, 2000). I first document the response of employment by race to local labor demand shocks and quantify their role in contributing to the aggregate outcomes. I find that, negative shocks to the manufacturing sector explain around one-third of the total decline in black-white employment to population rate differential between 1970-2000.

Further, I explore whether this effect was driven by black workers being heavily represented in manufacturing, especially in labor markets that were hit harder. I find that geographical differences in initial composition play no role in explaining the disproportional effect. This suggests that local labor market outcomes for black workers respond differently than white workers to shocks of similar intensity. I propose that a possible reason for this could be due to differences in the propensity to re-skill and find the next job or to relocate to another labor market. I build a model of local labor markets with search frictions and imperfect labor mobility that captures both of these mechanisms.

The model allows me to quantify the role of search frictions within markets and propensity to relocate across markets in driving aggregate outcomes. I am able to decompose the two, by looking at population responses, in addition to employment responses. I find that, black workers are way less likely to migrate in response to local shocks, however this plays a little role for explaining the decline in the aggregate statistic. 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 which was most likely not true for low-skill workers in these decades.

In future work, I would like to further decompose the role of search frictions. In particular, I am incorporating imperfect sectoral mobility in my framework and trying to answer how much of what is captured by the elasticity of the matching function can be explained by differences in reallocation across sectors and what remains unexplained. Knowing the sources of what drives differential responses to shocks by race is important for informing policies aimed at achieving racial equality.

Appendix

A Proofs and Derivations

This sections provides proofs and derivations for the model laid out in section 2.

A.1 Derivation of Local Population

Worker i's location decision is as follows

$$l^* = \underset{l}{\text{argmax}}\{p_{lg}w_{lg}\varepsilon_l(i)\}$$

denote $u_{lg} = p_{lg}w_{lg}$. Probability of choosing local labor market l' is given by

$$\begin{aligned}
\frac{P_{l'g}}{P_g} &= \mathbb{E}_{\varepsilon_{l'}}[\Pr(u_{l'g}\varepsilon_{l'} > u_{lg}\varepsilon_l) \quad \forall l \neq l'] \\
&= \int_0^\infty \exp\left[-\sum_{l\neq l'}\left(\frac{u_{l'g}\varepsilon_{l'}}{u_{lg}}\right)^{-\sigma_g}\right] f(\varepsilon_l')d\varepsilon_l' \\
&= \int_0^\infty \exp\left[-\left(u_{l'g}^{-\sigma_g}\sum_{l\neq l'}u_{lg}^{\sigma_g}+1\right)\varepsilon_{l'}^{-\sigma_g}\right]\sigma_g\varepsilon^{-\sigma_g-1}d\varepsilon_l' \\
&= \frac{u_{l'g}^{\sigma_g}}{\sum_l u_{lg}^{\sigma_g}}
\end{aligned}$$

Derivation uses the fact that if ε is distributed Fréchet with $H(\varepsilon) = exp(-T\varepsilon^{-\sigma})$, then $h(\varepsilon) = \sigma T\varepsilon^{\sigma-1}\exp(-\varepsilon^{\sigma})$. Now plugging in $u_{lg} = c_{lg}(w_{lg})^{\frac{1}{1-\alpha_g}}$ from Fig. 4a, gives us Fig. 4b.

$$P_{lg} = \frac{\tilde{c}_{lg}w_{lg}^{\frac{\sigma_g}{1-\alpha_g}}}{\sum_l \tilde{c}_{lg}w_{lg}^{\frac{\sigma_g}{1-\alpha_g}}}P_g \tag{4b}$$

where $\tilde{c}_{lg} = c_{lg}^{\sigma_g}$.

A.2 Proof of Proposition 1

Let's say there is a shock to marginal productivity of labor in the manufacturing sector in form of $d\ln w_{ml} \neq 0$. Then taking logs and differentiating $w_{lg} = \pi^l_{mlg} w_{ml} + (1 - \pi^l_{mlg}) w_{nl}$ gives us,

$$\begin{aligned} d\ln w_{lg} =& \frac{L_{mlg} \times w_{mlg}}{L_{lg} \times w_{lg}} d\ln w_{ml} \\ =& \pi^w_{mlg} d\ln w_{ml} \end{aligned}$$

Now taking logs and differentiating the expression in expression Fig. 4a gives us Eq. (3)

$$\begin{aligned} d\ln p_{lg} = d\ln L_{lg} - d\ln P_{lg} &= \frac{\alpha_g}{1-\alpha_g} d\ln w_{lg} \\ &= \frac{\alpha_g}{1-\alpha_g} \pi^w_{mlg} d\ln w_{ml} \end{aligned}$$

Similarly taking logs and differentiating the expression in equation Fig. 4b gives us Eq. (4).

$$\begin{aligned} d\ln P_{lg} =& \frac{\sigma_g}{1-\alpha_g} d\ln w_{lg} - \frac{\sigma_g}{1-\alpha_g} \sum_l \pi^p_{lg} d\ln w_{lg} \\ =& \frac{\sigma_g}{1-\alpha_g} \pi^w_{mlg} d\ln w_{ml} - \frac{\sigma_g}{1-\alpha_g} \sum_l \pi^p_{lg} \pi^w_{mlg} d\ln w_{ml} \end{aligned} \tag{4}$$

where $\pi^p_{lg} = \frac{P_{lg}}{P_g}$.

A.3 Proof of Proposition 2

Over all employment in the economy of each group is the sum of employment across all labor markets.

$$\frac{L_g}{P_g} = \frac{\sum_l L_{lg}}{P_g}$$

Taking logs and differentiating the above expression, we get

$$d \ln \frac{L_g}{P_g} = \sum_l \pi_{lg}^l d \ln L_{lg}$$

where $\pi_{lg}^l = \frac{L_{lg}}{L_g}$. Now plugging in expressions for $d \ln L_{lg}$ and $d \ln P_{lg}$ from equations (3-4) we get Proposition 2.

B Data

This sections provides additional details about data construction.

B.1 Composition Adjusted Wages

To construct composition adjusted wages for manufacturing at the commuting zone-year level, I limit the sample to black and white low skill men employed in manufacturing. Then for each commuting zone and year I run the following individual level regression

$$w_i = \beta_0^{lt} + \beta_b^{lt} Black_i + \beta_m^{lt} Married_i + \beta_a^{lt} age_i + \sum_{e=1}^{6} \beta_e^{lt} E_i^e + \varepsilon_i$$

where $Black_i$ is a dummy variable that takes value 1 if individual i's race is African-American and zero otherwise. $Married_i$ is a dummy variable that takes value 1 if the individual is married and zero otherwise. E^es represent dummy variables for six education categories, nursery school, grade 5-8, grade 9, grade 10, grade 11, and grade 12. The excluded category is no schooling. Coefficients from these regressions give prices attached to each of the composition characteristic for each year t and commuting zone l. With classical OLS assumptions on the error term, we can write average manufacturing in lt as,

$$w_m^{lt} = \beta_0^{lt} + \beta_b^{lt} s_b^{lt} + \beta_m^{lt} s_m^{lt} + \beta_a^{lt} \bar{a}^{lt} + \sum_{e=1}^{6} \beta_e^{lt} s_e^{lt}$$

where s_b^{lt}, s_m^{lt} and s_e^{lt} represent the share of black workers, married workers and workers with education e in manufacturing for year t in commuting zone l. $\bar{a}^{lt}$ denotes the average age. Now the counterfactual that I want to run is to able to get a measure of wages in each year and commuting zone assuming that the composition hasn't changed. To get this I use the coefficients from the above regression and predict wages assuming that the composition in each year and commuting zone is the same as of the aggregate economy averaged over the 1970-2000 period. In particular, wages used in the empirical analysis throughout the paper are predicted as follows

$$w_{mlt} = \beta_0^{lt} + \beta_b^{lt} s_b + \beta_m^{lt} s_m + \beta_a^{lt} a + \sum_{e=1}^{6} \beta_e^{lt} E_i^e$$

where variables without the lt superscript represent corresponding variables for the aggregate economy averaged over the 1970-2000.[10]

B.2 Panel of Manufacturing Sub-Industries

The United States Census records 3-digit codes for workers' industries but the industry classification system gets redefined for every decennial Census. Hence the codes are not directly comparable across years, however Census Bureau also provides IND1990 classification that classifies industries from all years since 1950 into the 1990 Census Bureau industrial classification providing a consistent long-term classification of industries. However, this classification still does not provide a balanced panel of sub-industries. For instance, metal forgings and stampings is recorded as a sub-industry under manufacturing for every year after 1960 but is unavailable for 1950. Similarly, leather tanning and finishing is a sub-industry until 1990 but ceases to exist after.

To ensure a consistent panel of sub-industries, I construct a new classification with 52 manufacturing sub-industries by simply aggregating IND1990 industries.

[10] $s_b = 0.095, s_m = 0.79, \bar{a} = 38.6, s_1 = 0.0177, s_2 = 0.1147, s_3 = 0.0506, s_4 = 0.0648, s_5 = 0.0581, s_6 = 0.6113$

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