Federal Reserve Bank of Cleveland Working Paper Series

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Working Paper No. 26-09

March 2026

Suggested citation: Dicandia, Vittoria. 2026. "Technological Change and Racial Wage Gaps." Working Paper No. 26-09. Federal Reserve Bank of Cleveland. https://doi.org/10.26509/frbc-wp-202609.

Federal Reserve Bank of Cleveland Working Paper Series
ISSN: 2573-7953

Technological Change and Racial Wage Gaps

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Abstract

The wage gap between Black and white Americans narrowed in the 1960s-1970s but stagnated after 1980. This study argues that routine-biased technological change (RBTC) contributed to this stagnation by affecting Black and white male workers differently across the wage distribution. Using new empirical evidence on occupational patterns and wage determinants for these workers, I rationalize these patterns with a novel RBTC theoretical framework. Contrary to expectations, Black workers' employment in routine-intensive occupations increased, while white workers experienced a significant decline. Applying the Oaxaca-RIF decomposition, I show that occupational sorting amplifies wage gaps, particularly at the lower end of the wage distribution. These findings, interpreted through the novel theoretical framework, offer new insights into the mechanisms driving racial wage gaps at the close of the twentieth century.

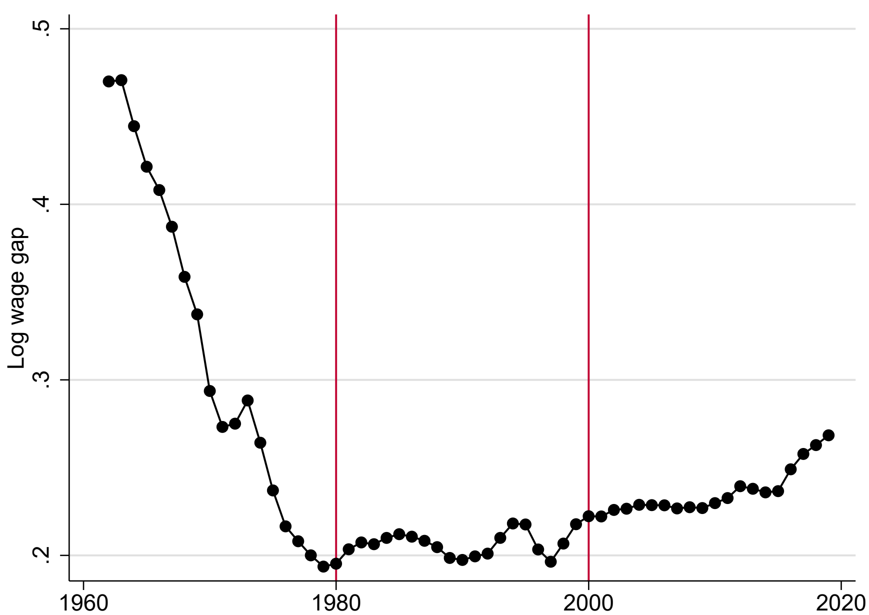
Key words: Technological change, wage differentials
JEL codes: O33, J31

*I thank Kevin Lang and Daniele Paserman for their support and guidance. I would also like to thank Costas Cavounidis, Joshua Goodman, Chiara Margaria, Pascual Restrepo, Silvia Vannutelli, Conrad Miller, seminar participants at Boston University, the University of Rochester, Purdue University, and the University of York, and attendees at APPAM, ASSA, MEA, SOLE, and the Barcelona Summer Forum (Macroeconomics of Labor Markets) for helpful comments and suggestions.

1 Introduction

The Black-white wage gap in the United States narrowed substantially during the 1960s and 1970s, reflecting advances in civil rights protections, gains in educational attainment among Black workers, and broad-based economic growth. By the 1980s, however, this progress largely stalled: Figure 1 shows that the hourly wage gap between Black and white male workers stabilized at roughly 20 percent and remained at this level through the 1990s (trends in mean annual wages are similar, shown in Figure 18). Understanding the causes of this stagnation provides insights into how technological and institutional forces shape labor market differences.

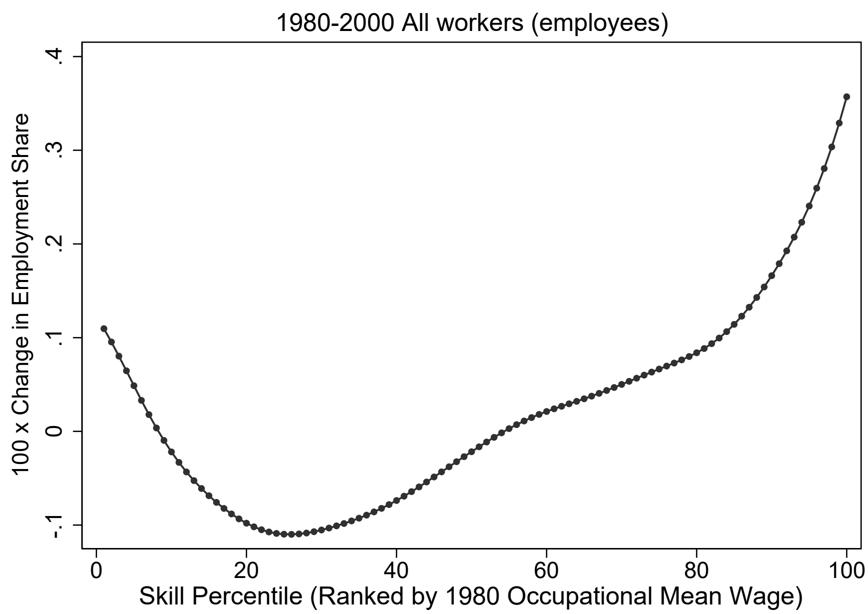
Figure 1: Raw white-Black hourly wage gap



Source: CPS ASEC. Sample: All civilian 20-64 Black and white male workers with non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

This paper investigates the role of routine-biased technological change (RBTC) in shaping the racial wage gap between 1980 and 2000. This focus is motivated by the fact that RBTC was a central and well-documented determinant in the labor market during this period, generating substantial effects on both employment and wages. Technological innovations, particularly the adoption of computers, disproportionately affected occupations that involve routine-intensive tasks, including clerical, operations, and production roles (Autor et al. [2003], Autor and Dorn [2013]). These routine-intensive occupations were concentrated in the lower-middle portion of the wage distribution, and their erosion contributed to labor market polarization: employment expanded at both the low-skill and the high-skill ends while contracting in routine-intensive roles (Figure 2).

Figure 2: Change in employment 1980-2000



Source: IPUMS. Sample: All civilian 20-64 Black and white male workers with non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

The analysis focuses on male workers between 1980 and 2000, a period that predates major trade liberalization shocks such as the China trade expansion, avoids the ef-

fects of the Great Recession, and precedes more recent labor market disruptions, including the COVID-19 pandemic. This window allows for a cleaner assessment of the interaction between technological change and racial wage gaps, as it coincides with a period when routine-biased technological change broadly affected employment and wages, with the strongest effects concentrated in routine-intensive occupations.
Using newly compiled empirical evidence, I document three main patterns. First, Black workers increased their employment share in routine-intensive occupations, whereas white workers moved out of these roles. These shifts are most pronounced among workers with a high school diploma or less and among younger cohorts, and they cannot be explained by demographic differences. The results are robust across multiple sample definitions and specifications.

Second, the wage gap evolved unevenly across the distribution. While the mean hourly wage gap remained largely stagnant, differences decreased in the lower half of the distribution and increased in the upper half. Applying the Oaxaca-RIF decomposition (Firpo et al. [2009]), I show that occupational sorting associated with RBTC contributed to widening racial wage gaps, partially offsetting gains from rising educational attainment and reductions in returns to worker characteristics. These patterns are particularly pronounced in commuting zones with high concentrations of routine-intensive employment, underscoring the role of occupational composition in shaping the racial wage gap.

Third, to provide a theoretical rationale for these empirical patterns, I develop a refined framework for RBTC in which technological change is modeled as a shock that reduces the responsiveness of wages to individual ability in routine-intensive occupations. Moreover, the approach adopted in this paper combines RBTC with statistical discrimination. The model considers a labor market with two types of workers, Black and white, and three occupational sectors: manual (lowest paying), routine (middle paying), and abstract (highest paying). Crucially, firms observe ability signals that are noisier for Black workers than for white workers. This asymmetry generates differences in net movements into and out of routine-intensive occupations for the two groups of workers, mirroring the empirical patterns documented above. By explicitly incorporating workers' heterogeneity and statistical discrimination, the framework extends standard RBTC models (Acemoglu and Autor [2011]) while maintaining consistency with the broader literature on labor market polarization and skill-biased technological change.

This paper contributes to two broad areas of research.

First, it deepens our understanding of wage gaps between demographic groups by providing new evidence on occupational sorting and wage-gap dynamics across the wage distribution. It complements prior work on the evolution of gaps over time and the determinants of Black-white differences. Classic contributions such as Bound and Freeman [1992], Juhn et al. [1991], and Altonji and Blank [1999] document the narrowing of racial wage differentials during the mid-twentieth century and their subsequent stagnation, while studies such as Lang and Lehmann [2012], Fang and Moro [2011], Lundberg and Startz [1983], and Coate and Loury [1993] analyze the role of discrimination and labor market institutions in shaping persistent inequalities.

Some studies instead assess the role of specific anti-discrimination policies, such as the Voting Rights Act (Aneja and Avenancio-Leon [2019]). Others examine the effects of broader economic changes, such as Smith and Welch [1986], who study the rise in educational attainment among African Americans, and Bayer and Charles [2018], who document how racial wage-gap patterns have evolved over time and differ along the wage distribution.

Another strand of this literature focuses, like this paper, on racially neutral economic shocks to explain changes in racial differences. Derenoncourt and Montialoux [2021] show that the extension of the federal minimum wage (the Fair Labor Standards Act of 1966) contributed to narrowing earnings gaps in the 1960s and 1970s. Batistich and Bond [2023], in contrast, examine the Japanese manufacturing trade shock of the mid-1970s and find that Black employment was adversely affected. As in this paper, they employ a spatial empirical strategy, exploiting the variation in initial exposure across labor markets to identify the effects of the shock. Similarly, Miller [2018] studies how job suburbanization affects differences in the labor market across demographic groups, estimating that it explains a substantial share of the decline in Black men's and women's employment rates relative to whites.

Research linking technological change to differences across demographic groups has been relatively limited. A notable exception is Hurst et al. [2024], who develop a task-based framework showing that reductions in the racial skill gap and in taste-based discrimination were offset by rising returns to abstract skills, disproportionately benefiting white workers. This paper complements theirs by focusing on distinct aspects of how RBTC affects wage gaps between demographic groups. It offers a comprehensive view of changes across the entire wage distribution and emphasizes the role of different occupational sorting rather than differences in economy-wide skill use across demographic groups. Importantly, it presents new empirical evidence on divergent occupational patterns between Black and white workers and interprets these findings through a model of RBTC that, while distinct, remains consistent with the broader literature.

This paper also contributes to a second major area of economic research by advancing the study of RBTC in two key ways. First, it introduces an alternative modeling approach in which technological progress affects output's responsiveness to workers' skills rather than employment levels per se. In contrast to the canonical task-replacing models of Autor et al. [2003], where technology substitutes for workers performing routine tasks, this framework emphasizes how technological change modifies the productivity of skills. Two notable exceptions to the traditional task-replacement paradigm are consistent with this approach. Cavounidis et al. [2021] model technology as altering the productivity of individual skills within occupations, enabling both worker reallocation across jobs and substantial changes in skill composition and intensity within existing occupations. Danieli [2026], by contrast, offers an interpretation of technological change closely related to the one presented in this paper, by conceptualizing technological progress as substituting for the skill used by workers in routine occupations rather than replacing the workers themselves. Second, this study explicitly links RBTC to wage gaps between demographic groups. While seminal contributions by Autor et al. [2003], Acemoglu and Autor [2011], and Autor and Dorn [2013] demonstrate how RBTC polarizes labor markets and reshapes wage structures, subsequent research has focused primarily on gender differences (Autor and Price [2013]; Black and Spitz-Oener [2010]) rather than race.

This paper therefore extends the literature by examining how occupational sorting contributes to the stagnation of the racial wage gap, showing that differences in employment shares in routine-intensive occupations by race played a central role. By integrating empirically distinct patterns across the entire wage distribution with a novel theoretical framework of RBTC, the paper offers a richer understanding of how technological change interacts with labor market dynamics for different demographic groups.

Taken together, the empirical findings and theoretical model illustrate how technological change shaped the trajectory of the Black-white wage gap over the final two decades of the twentieth century. These insights deepen our understanding of persistent racial differences and have important implications for policies aimed at fostering more evenly distributed labor market outcomes.

2 Data

I draw on three primary data sources for my analysis: the March Current Population Survey (CPS) from 1972 to 2000, the decennial US Census from 1980 to 2000, and the third edition of the Dictionary of Occupational Titles, published in 1977. The CPS datasets allow me to examine time trends with high (annual) frequency. However, their relatively small sample sizes limit the ability to study the evolution of racial disparities in detail, particularly changes across the wage distribution and geographic variation. To address these limitations, I use the decennial Census data for analyses requiring greater granularity.

Finally, I employ the Dictionary of Occupational Titles to classify occupations according to skill-use intensity and their susceptibility to routine-biased technological change, following its established use in the literature for this purpose.

2.1 March CPS

I use the March Annual Social and Economic Supplements (ASEC) of the Integrated Public Use Microdata Series (IPUMS). These files provide individual-level information on employment, including weeks and hours worked, occupation, and industry, as well as income and demographic characteristics such as race, gender, education, age, and marital status.

The CPS first implemented the 1970 Census occupation codes in 1972. Starting with the 1970 codes is essential because earlier classifications were less detailed and not consistently aligned with later decades, making longitudinal comparisons of occupations unreliable. Because this study requires consistent observation of occupations over time, my sample begins in 1972. I adopt the occupational crosswalk developed by Dorn [2009], which harmonizes the decennial Census classifications into 330 consistent occupational categories.

Income is measured as nominal annual wages and salaries from the previous year and is top-coded to protect the confidentiality of high earners. I address top-coding by substituting values using the dataset created by Larrimore et al. [2008], who constructed cell-mean values by demographic characteristics using restricted-use CPS data. No adjustments are required before 1976, as no top-coded observations are present in those years. To convert nominal values into real terms, I use the FRED 2006 Personal Consumption Expenditures Price Index.

Hourly wages are calculated by dividing annual wage and salary income by the product of reported weeks and hours worked. In earlier years, weeks worked are reported in intervals; following Derenoncourt et al. (2021), I first estimate weekly wages by dividing annual wages by the median of the reported interval and then smooth the resulting values by adding a random number drawn from a uniform distribution. Hourly wages are then computed by dividing these smoothed weekly wages by the number of hours worked in the previous week, which is consistently reported throughout the period.

The main analysis sample includes all Black and white male employees aged 20-64 in both the private and public sectors. I exclude self-employed individuals, unpaid family workers, workers residing in group quarters, agricultural workers, and members of the armed forces. The sample is not restricted to full-time, full-year employees; however, the appendix demonstrates that limiting the sample in this way does not alter the results. All computations employ ASEC individual weights.

2.2 Census

I use the 5 percent 1980 and 2000 samples of the US decennial Census. Like the CPS, the Census provides data on employment (weeks and hours worked, occupation, and industry), annual income, and demographic information such as race, gender, education, age, marital status. Because of its larger sample, the Census provides more detailed geographic information on individuals, including their county of residence. Using this information, I adopt Dorn [2009]'s geographic crosswalk and place all counties in 722 time-consistent commuting zones, geographic units characterized by a common labor market. Commuting zones are defined across the entire country, except for Alaska and Hawaii, which I, therefore, exclude from my sample.

Data on hours and weeks of work for these two samples are provided with non-intervalled measures, making it straightforward to calculate hourly wages by dividing annual wage income by the number of hours and weeks worked the previous year. Lacking a more accurate data source to deal with income top-coding issues, I make an *ad hoc* adjustment by multiplying top-coded annual wages by 1.5.[1]

I use the same sample restriction that I used for the CPS data. All computations use individual weights provided by the Census multiplied by the product of the number of hours and weeks worked (Autor and Dorn [2013]).

2.3 Dictionary of Occupational Titles

I use the occupation-level measures of routine intensity computed by Autor and Dorn [2013]. The data are originally from the Dictionary of Occupational Titles, which is the standard dataset for information on skill use during the period of time under analysis. It provides numerical measures of attitudes, temperaments, and abilities needed to perform a job. The data is at the occupational-title level, but Autor and Dorn [2013] aggregate it to Census-occupation level. In their paper, they define three measures, for manual, routine, and abstract skills, and use the following measure to

[1] Lemieux [2006] multiplies top-coded wages by 1.4, and Autor et al. [2008] multiply them by 1.5. There is a single top income value in 1980, but in 2000, it varies by state. Hence, I make this adjustment uniformly across states in 1980 and by state in 2000.

define the routine intensiveness of occupations:

$$RTI = ln(R) - ln(A) - ln(M) \tag{1}$$

where routine (R) is the mean of variables measuring *ability to work requiring set limits, tolerances, or standards* and *finger dexterity*; abstract (A) is the mean of variables measuring *quantitative reasoning requirements* and *direction, control, and planning of activities*; and manual (M) is defined by the variable measuring *eye, hand, foot coordination.*

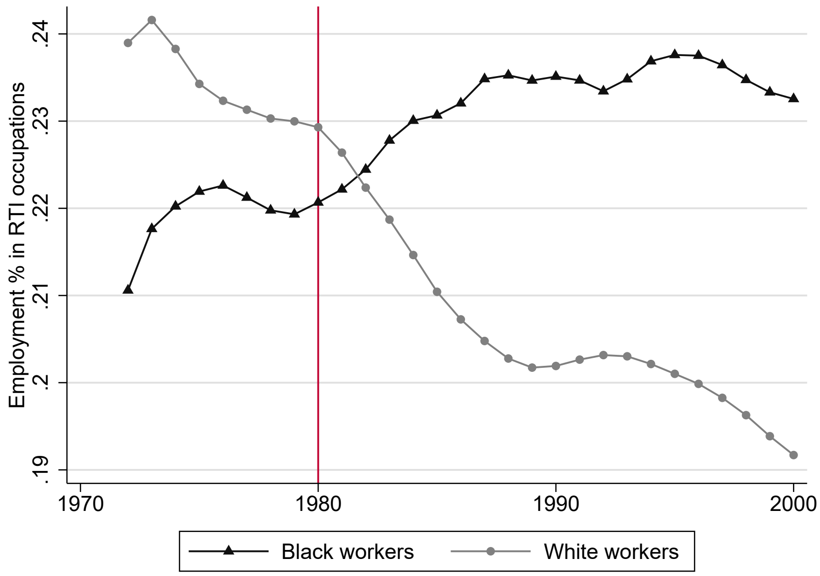
Like them, I use RTI to identify routine-intensive occupations, defined as the top third occupations in terms of RTI.[2] This measure, as well as its individual components, has been used in several studies of RBTC. Using it for my analysis allows for consistency with the existing literature. While there may be concerns about the validity of RTI, they should be less important when it is only used to identify a group of routine-intensive occupations.

3 Employment

Figure 3 shows race-specific employment shares in the top third RTI occupations over time. Black and white workers exhibit opposite patterns: after 1980, we observe a sharp decrease for white workers, and a significant increase for Black workers.

[2]The 10 occupations with the highest RTI scores are: Butchers and meat cutters; Secretaries and stenographers; Payroll and timekeeping clerks; Bank tellers; File clerks; Cashiers; Typists; Pharmacists; Bookkeepers, accounting clerks; Postal clerks, except mail carriers. (Autor and Dorn [2013])

Figure 3: Race-specific employment share of top RTI occupations



Source: CPS. Sample: All civilian 20-64 Black and white male workers with non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

Between 1980 and 2000, the share of white workers employed in the top third RTI occupations fell from 23 percent to 19 percent. This change, although striking, is expected and consistent with the standard RBTC framework, which predicts that workers will shift out of routine-intensive occupations in response to the computerization shock. The same cannot be said for Black workers. Even before 1980, we observe a slight increase in their share of routine-intensive occupations, which, at the time, were viewed as good jobs, with salaries that would place workers broadly in the middle of the wage distribution. After 1980, notwithstanding the declining desirability of routine jobs, Black workers' employment share in RTI occupations increased even more sharply.

These patterns are invariant to sample choice. Perhaps this anomaly reflects the over-representation of Black workers in seasonal and/or part-time jobs.[3] In Figure

[3]Even if that were the case, it would still be a result incompatible with the current consensus

20 I show that these trends hold when I conservatively restrict the sample to individuals who work at least 30 hours per week for a minimum 40 weeks.

Perhaps differences in educational achievement can account for this unexpected finding. It is possible, for instance, that RBTC negatively affected only workers with at least some college education, causing their displacement from routine jobs and some level of replacement from workers with a high school diploma or less. Given the higher college–non-college ratio for white workers, this type of technological shock would be consistent with the patterns shown, although it would still be inconsistent with the standard framework. Still, it would mean that the difference was due to education, not race. Figure 4 addresses this concern by showing that the same trends apply to workers with a high school diploma or less. Thus, for workers with lower educational achievement, there are diverging employment trends between Black and white workers.

on the employment patterns of routine occupations.

Figure 4: Race-education employment share of top RTI occupations

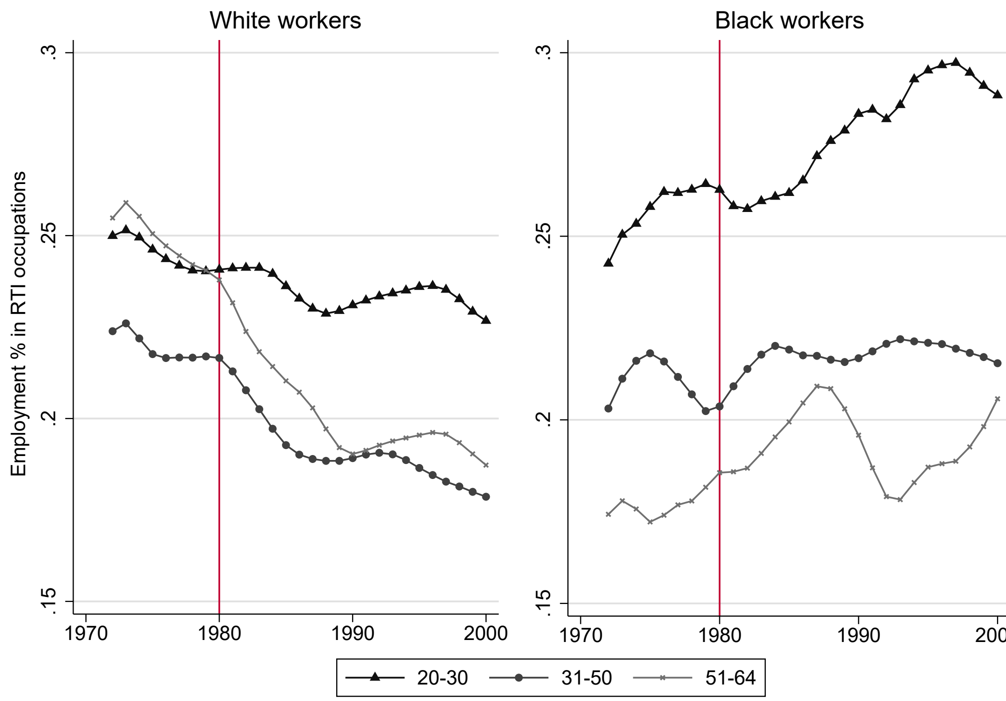
High school diploma or less

Source: CPS. Sample: All civilian 20-64 Black and white workers with high school diploma or less, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

For workers with at least some college education, we only observe differences in the extent to which Black and white workers exit routine-intensive occupations (see Figure 21). Thus, workers with a high school diploma or less drive the diverging patterns. The higher prevalence of these workers among the Black workforce exacerbates observed differences in the overall working population.

Lastly, I look at whether there are differences in the patterns by worker age (and, consequently, experience). I partition workers into three groups: new entrants (age 20-30), prime-age workers (31-50), and those closer to retirement (51-64). Figure 5 shows that workers belonging to different age groups exhibit diverse magnitudes in employment share shifts, but that the racial discrepancies are consistent. For white workers, there is a fall for all age groups, with the extent of the drop being larger the older the age group. For all Black workers there is a rise in their employment share for routine occupations, but younger workers are those with the bigger magnitude.

Figure 5: Race-age group employment share of top RTI occupations



Source: CPS. Sample: All civilian 20-64 Black and white workers, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

This finding helps to address a widespread concern about missing Black men in survey data. In fact, a well-known phenomenon that impacts differently the composition of the Black and white workforce, especially among males, is mass incarceration. The period under analysis in this paper has been characterized by a significant rise in Black males' incarceration rates.[4] The consequent higher rate of missing men in survey data (Sabety and Spitzer [2025]) among the youngest group could have

[4]From about 1 percent of the Black male population in 1980 to roughly 4 percent in 2000(Council [2014]).

potentially been a reason for concern, had we observed a higher decrease in routine jobs employment for this group. Consider an alternative scenario in which the pattern for young Black workers was actually decreasing. The overall increase in routine employment for Black workers could have resulted from survey data sample selection, with a relative over-representation of older workers. While available data do not allow us to determine the types of jobs in which missing men are employed, observing an increase in routine jobs employment for Black workers of all age groups provides suggestive evidence that the reliability of these findings is not threatened by sample selection.

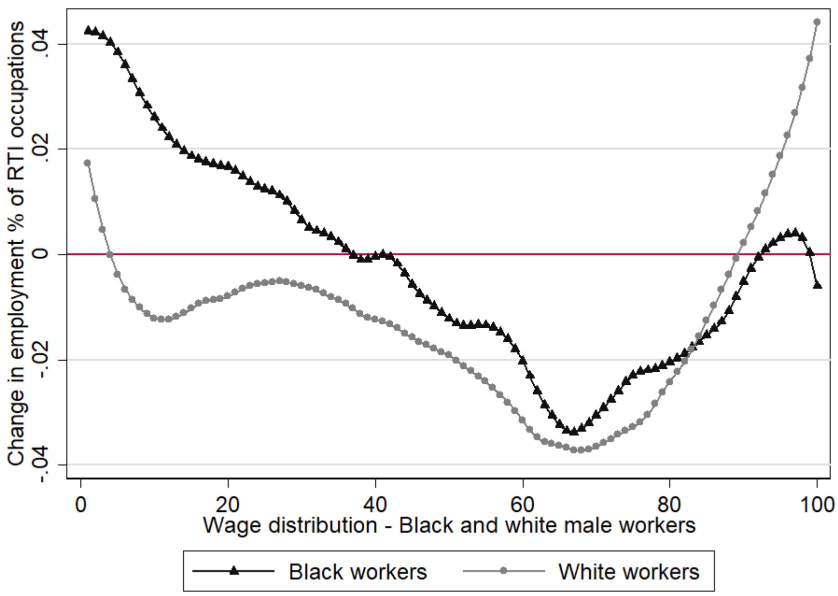
4 Wage gaps

We have seen that between 1980 and 2000 Black and white workers exhibited different employment patterns. In what follows, as advocated by Bayer and Charles [2018], I document how the wage gap has changed along the distribution and relate the changes to the effect of RBTC.

Figure 6 illustrates how Black and white employment in RTI jobs changed at different points along the wage distribution. Employment of white workers in RTI jobs fell at all points in the distribution except jobs in the bottom 3 percent and top 10 percent of the wage distribution.[5] Black workers, instead, increased RTI employment in the bottom part of the distribution, and decreased such employment in the top half. This finding reflects the different patterns observed earlier between high- and low-education workers.

[5]The increase at the top of the distribution reflects employment in law and other high-paying RTI occupations.

Figure 6: 1980-2000 top RTI change over wage distribution



Source: IPUMS. Sample: All civilian 20-64 Black and white male workers, with hourly wage $\geq$ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Wage distribution defined on the entire described sample. Smoothing bandwidth: 0.2.

4.1 Oaxaca-RIF decomposition

I use a Oaxaca-RIF decomposition to better explain how the racial wage gap in 1980 changed along the entire distribution between 1980 and 2000. This approach extends the Oaxaca decomposition to address statistics other than the mean. The standard decomposition is:

$$\Delta \text{Hourly wage}_{W-B} = X_W\beta_W - X_B\beta_B = \underbrace{(X_W - X_B)\beta_W}_{\text{Composition gap}} + \underbrace{X_B(\beta_W - \beta_B)}_{\text{Differential returns gap}} \quad (2)$$

where X is a set of worker's characteristics, the subscript W and B indicate white and Black workers.

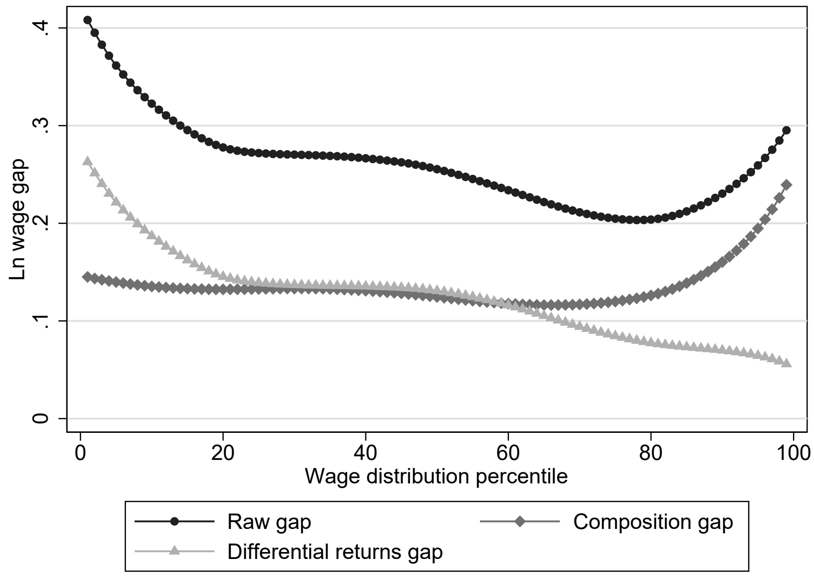
Equation (2) divides the total change in the wage gap into a *composition* element, which captures the difference in characteristics, such as educational achievement or the occupations in which workers are employed, and a *differential returns* element, which captures the racial disparities in the effects of characteristics on earnings. We can further decompose each of the two elements into specific characteristics, in order to, for instance, show the role played by education and occupations separately.

The Oaxaca-RIF method (Firpo et al. [2009]) relies on recentered influence functions (RIF). It involves choosing a baseline group on which the effect of the economic shocks of interest is minimized. The relevant statistics (percentiles of the wage distribution, in this paper) are expressed as the average of the conditional expectation of the RIF given the covariates (Firpo et al. [2018]). A major advantage of this method is that it allows for non-sequential decomposition, as in the standard Oaxaca decomposition.

I control for the following characteristics: demographic - 9 5-year age groups and a dummy for married individuals; education - 4 schooling levels; occupation - 12 categories (Autor and Dorn [2013]); industry - 14 categories (Firpo et al. [2018]) and a dummy indicating employment in the private sector; geography - 4 regions and 3 categories for rural areas, metropolitan areas, and mixed areas. The baseline group consists of white non-married workers, age 40-45, with a high school diploma, employed in mechanical/mining/construction occupations in the construction industry in the private sector, living in the northeastern region of the country and in a non-metropolitan area.

Figure 7 shows that in 1980 the Black-white wage gap was greater at lower percentiles of the wage distribution. This heterogeneity was mainly driven by the differential returns component: in 1980, racial differences in pay were higher for those who were paid less, and these workers tended to have less education. Therefore, it is not surprising that these Black workers would be more highly penalized in the labor market. Of course, these disparities need not reflect only race discrimination.

Figure 7: 1980 white-Black wage gap along wage distribution



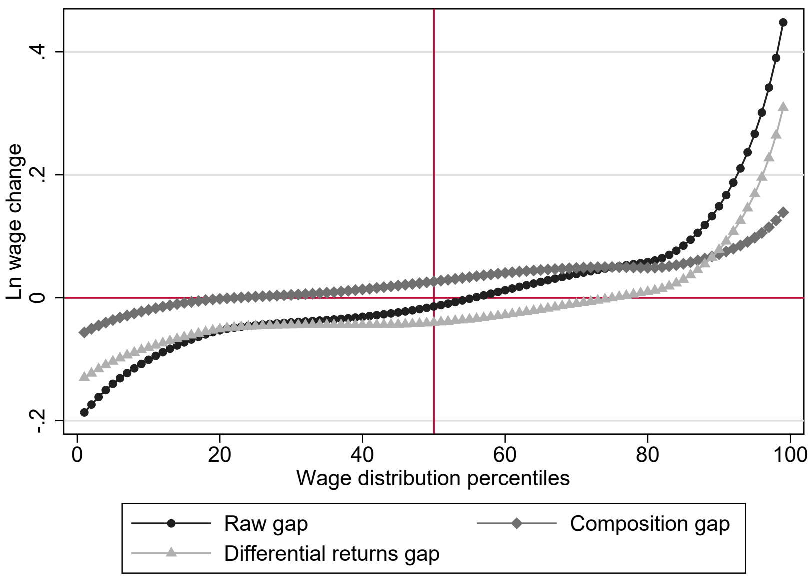
Source: IPUMS. Sample: All civilian 20-64 Black and white male workers, with hourly wage $\geq$ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Race-specific wage distribution. Smoothing bandwidth: 0.4.

Next, I obtain Oaxaca-RIF decompositions for 1980 and 2000 and show how the gaps have changed. This allows me to calculate the changes in the composition and differential returns gaps:

$$\begin{aligned}
&\Delta \text{Hourly wage}^{2000}_{W-B} - \Delta \text{Hourly wage}^{1980}_{W-B} = \\
&\underbrace{(X^{2000}_{W} - X^{2000}_{B})\beta^{2000}_{W} - (X^{1980}_{W} - X^{1980}_{B})\beta^{1980}_{W}}_{\text{Composition gap}} \\
&+ \underbrace{X^{2000}_{B}(\beta^{2000}_{W} - \beta^{2000}{}_{B}) - X^{1980}_{B}(\beta^{1980}_{W} - \beta^{1980}_{B})}_{\text{Differential returns gap}}
\end{aligned} \tag{3}$$

Figure 8 reports the outcome of this exercise. Recall that because it reports a change in the white-Black wage gap, a *negative* coefficient implies a *reduction* in the gap, and vice versa.

Figure 8: 1980-2000 white-Black wage gap change along wage distribution



Source: IPUMS. Sample: All civilian 20-64 Black and white male workers, with hourly wage $\geq$ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Race-specific wage distribution. Smoothing bandwidth: 0.4.

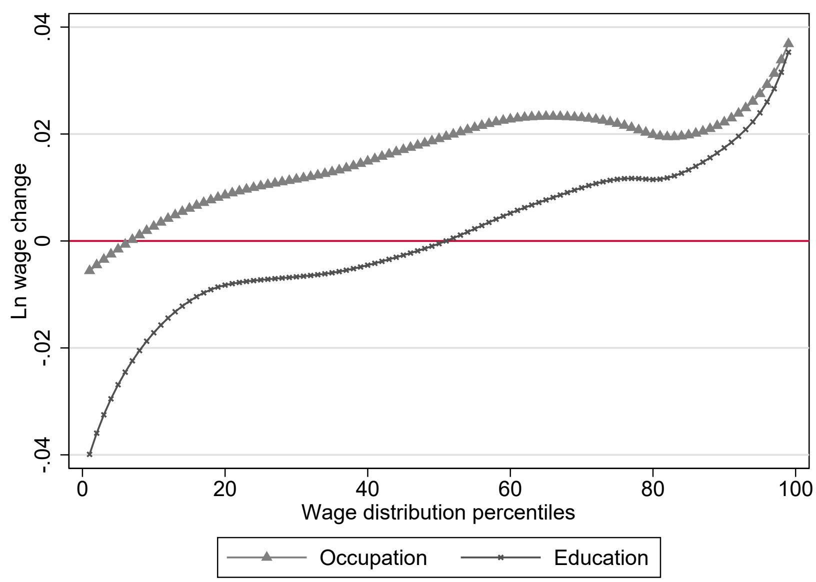
Between 1980 and 2000, the racial wage gap decreased in the bottom half of the distribution and increased in the top half. Consistent with the prior literature, the change in the gap at the median is approximately 0. Strikingly, Figure 8 shows that the composition element does reduce the gap. While throughout most of the wage distribution differential returns declined,[6] the different composition of the Black and white workforce increased the earnings gap.

[6]Given the focus of this paper, I will not devote space to the changes in the top 20 percent of the distribution. The increased gap in this range is consistent with Hurst et al. [2024] and Bayer and Charles [2018], who ascribe it to the increased gap in college graduation and the increased return to abstract skill.

4.2 Detailed Oaxaca-RIF decomposition

In Figure 9 I further decompose the composition change. Here, I show only the education and occupation components, the two major drivers of the change (see Appendix Figure 23 for all components).

Figure 9: 1980-2000 white-Black detailed *composition* change



Source: IPUMS. Sample: All civilian 20-64 Black and white male workers, with hourly wage $\geq$ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Race-specific wage distribution. Smoothing bandwidth: 0.4.

The most striking finding is that shifts in the occupational component drive the increase in the wage gap explained by composition change. The education component alone, instead, would decrease earnings disparities in the bottom half of the distribution, consistent with the increase in Black educational attainment. However, in the top half of the distribution, the education component increases the gap (although less so than the occupational component), consistent with the increase in the college graduation gap between Black and white men.

From equation (3), we know that the change in the occupational component is itself a combination of two changes: the change in the return to each occupation group and the change in the difference in occupations held by white and Black workers.

$$\underbrace{(X_W^{2000}-X_B^{2000})\beta_W^{2000}-(X_W^{1980}-X_B^{1980})\beta_W^{1980}}_{\text{Composition gap}}=$$
$$\underbrace{[(X_W^{2000}-X_B^{2000})-(X_W^{1980}-X_B^{1980})]\beta_W^{2000}}_{\text{Change in sorting differences}}-\underbrace{(\beta_W^{2000}-\beta_W^{1980})(X_W^{1980}-X_B^{1980})}_{\text{Change in occupational returns}}$$

Figure 10 shows each component's effect. I show findings separately for each occupational group included in the Oaxaca decomposition specifications. Groups labeled "A" are those in which abstract skill is the most important one, those labeled "R" mostly involve the use routine skills, and those labeled "M" are jobs that require the use of manual skills most of all.

Changes in the occupations held by Black and white workers drive the 1980-2000 difference in occupational returns. Interestingly, the only group for which changes in occupational sorting lead to a notable increase in the wage gap is clerical jobs, which are the most routine-intensive ones. Overall, Figure 10 shows important shifts in returns to occupations over the observed period. Black workers were penalized by these changes, as they were employed in occupations that were more likely to be negatively affected, and did not leave these occupations in sufficient numbers to take advantage of the aftermath of RBTC.

Figure 10: 1980-2000 detailed occupation components

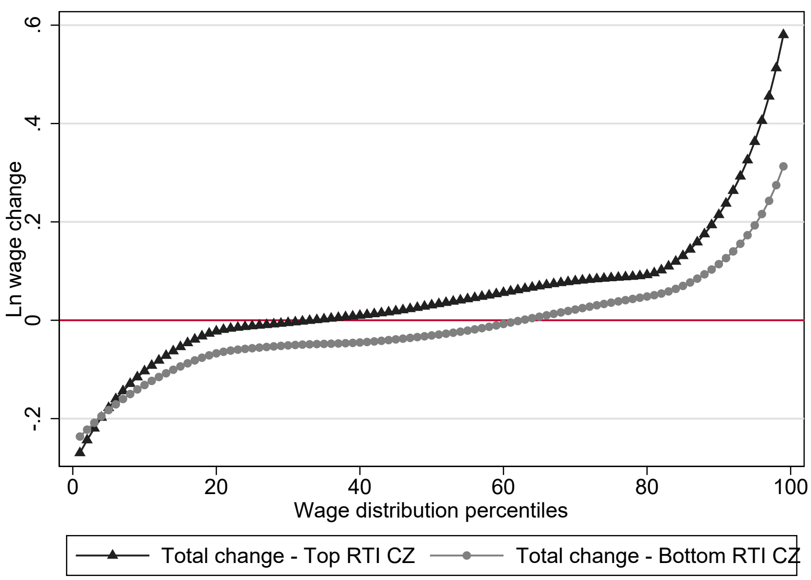
Source: IPUMS. Sample: All civilian 20-64 Black and white male workers, with hourly wage $\geq$ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Race-specific wage distribution. Positive coefficients are equal to an increase in the wage gap

Figure 24 in the appendix shows the detailed decomposition of the differential returns component. Most of the fall in the wage gap explained by this component is driven by the race fixed effect, which can be seen as a proxy (although imperfect) for a decrease in racial discrimination over this time period. The only element that has a contrasting pattern is geography, which by itself would lead to an increase in the differential returns component of the wage gap.

4.3 Spatial analysis

Next, I show whether we observe different convergence patterns for geographical areas that were more or less exposed to RBTC. In fact, given that this shock had effects on employment sorting and occupational returns, we would expect to see a narrower convergence in racial wage gaps in labor markets that were affected more by RBTC. As mentioned in the data section, I will use commuting zones (CZ) as the geographic unit of interest, as they identify local labor markets. In the spirit of Autor and Dorn [2013], I split the sample in two: top RTI CZs, which are the top third commuting zones for routine employment share in 1980, and bottom RTI CZs, which are the bottom two-thirds in terms of the same measure.

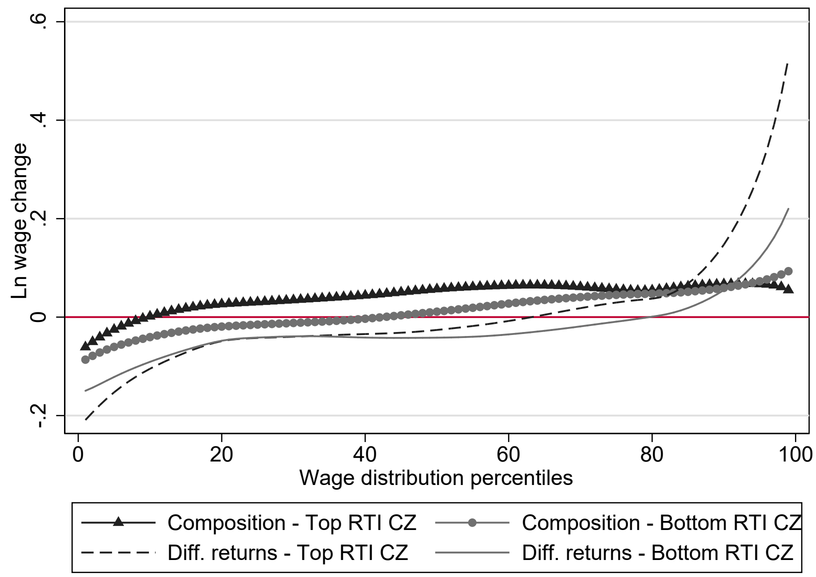
Figure 11: 1980-2000 white-Black wage gap total change by CZ groups



Source: IPUMS. Sample: All civilian 20-64 Black and white male workers, with hourly wage ≥ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Race-specific wage distribution

Figure 11 shows that, indeed, the wage gap narrowed only for the bottom 40 percent of the wage distribution in top routine CZs, while the reduction in the bottom routine CZs affected the bottom 60 percent of the distribution. Figure 12 shows the distribution of the composition and of the differential returns component for the two groups of CZs.

Figure 12: 1980-2000 white-Black wage gap change decomposition by CZ groups



Source: IPUMS. Sample: All civilian 20-64 Black and white male workers, with hourly wage ≥ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Race-specific wage distribution. Smoothing bandwidth: 0.4.

We observe that at the bottom of the distribution, the differences in changes for the differential returns component are very slim, and for both the top and the bottom routine CZs this component alone would lead to a reduction in the wage gap for the bottom 60 percent. For the composition element, instead, the difference between the two groups is more significant and in line with our priors: in CZs that were more affected by RBTC, the change in the composition element thwarts wage gap convergence, while in less affected CZs this change contributes to the narrowing of the wage gap observed in the bottom half of the distribution.

5 Theoretical framework

I develop a 2-period 3-sector statistical discrimination model to rationalize the empirical findings. The standard model (Acemoglu and Autor [2011]) of RBTC predicts that no group of workers increases its routine-intensive employment, although some may be affected less than others (e.g., men vs. women). However, I show that the interaction of statistical discrimination with RBTC can increase the share of Black workers in routine-intensive occupations.

5.1 Setting - Labor demand

There is a continuum of perfectly competitive employers, each operating in one of three sectors. The matching of employers to sectors is exogenous and time-invariant. Hence, any technological change taking place between the two analyzed periods affects employment through the overall allocation of workers across sectors, ignoring possible firm entry and exit, as well as changes of the sector in which they operate. This simplifies the problem at hand, implying that firms are affected by technological shocks only insofar as the production function is affected, and consequently the type and number of workers they employ.

As is common in the RBTC literature, employment is partitioned into three sectors: manual, routine, and abstract. Manual occupations are the least skill sensitive and abstract the most, with routine occupations in between. Routine jobs involve completing standardized tasks, and, hence, higher ability raises productivity less than in abstract jobs. In equilibrium, the highest-skill workers will be matched with abstract jobs and have the highest wages.

The sector-specific production functions are given by:

$$v_{ij}(\theta_i) = \alpha_j + \beta_j \theta_i \tag{4}$$

where v_{ij} is the value of the output produced by a worker of ability θ_i, and α_j and β_j are sector-specific parameters where β_j captures the sensitivity of output value to individual ability. Denoting the manual, routine, and abstract sectors as M, R, and

A, I assume

$$0 = \beta_M < \beta_R < \beta_A \tag{5}$$

$$\alpha_M > \alpha_R > \alpha_A \tag{6}$$

Condition (2) ensures that the routine sector's productivity is less responsive than the abstract sector's productivity to workers' ability. For simplicity, I assume that the manual sector productivity is independent of workers' ability.

Condition (3) ensures that for some workers it is optimal to be employed in a sector with lower productivity and wages. Consider for instance the case in which $\alpha_M \leq \alpha_R$. Employment in the manual sector will be equal to 0, because for all individuals, regardless of their signal, it will be optimal to work in the routine sector, given the linearity of the wage schedule and the higher return of $w_R(\theta)$ to signals.

5.2 Setting - Labor supply

Workers are endowed with ability $\theta_i \sim \mathcal{N}(\mu, \sigma)$. Note that ability is unidimensional. If there are multiple skills, they can be combined into a single interval scale.

Employers observe a noisy signal of ability given by:

$$s_{ir} = \theta_i + \varepsilon_{ir} \tag{7}$$

where ε_{ir} is a race-specific (Black or white) error and is independently and normally distributed: $\varepsilon_{ir} \sim \mathcal{N}(0, \sigma_r)$. I make the standard assumption that the ability signal is less informative for Black than for white workers, i.e., $\sigma_B > \sigma_W$. For simplicity, I also assume that $\sigma_{\varepsilon B}, \sigma_{\varepsilon W} >= \sigma$.

The distribution of s_{ir} is therefore:

$$s_{ir} \sim \mathcal{N}(\mu, \sigma + \sigma_r) \tag{8}$$

5.3 Equilibrium

Workers choose employment in the sector that maximizes their wage. This implies that the wage in each sector is given by:

$$w_{ij}(s) = E[v_{ij}(\theta|s)] = E[\alpha_j + \beta_j \theta_i | s] = \alpha_j + \beta_j E[\theta_i | s]]$$

and by the standard properties of the bivariate normal distribution:

$$w_i(s) = \alpha_j + \beta_j \left[\left(1 - \frac{\sigma^2}{\sigma^2 + \sigma_r^2}\right) \mu + \frac{\sigma^2}{\sigma^2 + \sigma_r^2} s \right] \tag{9}$$

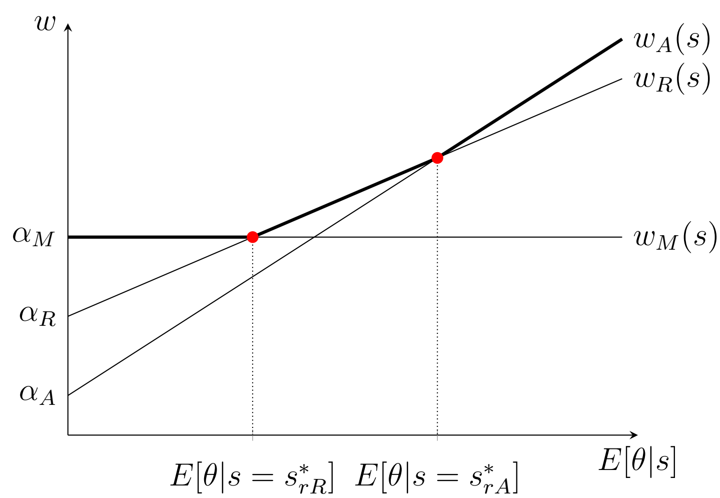
The wage is a weighted average of mean ability, which is not race specific, and of the signal. Because the signal is less precise for Black workers compared to white workers, their wage puts more weight on the mean. Thus, Black and white workers with the same signal will (almost always) receive different wages.

The wage schedule ultimately depends on signal s, and the cutoff values that determine sorting into the three sectors are:

$$\begin{aligned}
& w_M(s^*_{rM}) : \alpha_M \\
& w_R(s^*_{rR}) : \alpha_M = \alpha_R + \beta_R \left[\left(1 - \frac{\sigma^2}{\sigma^2 + \sigma_r^2}\right) \mu + \frac{\sigma^2}{\sigma^2 + \sigma_r^2} s^*_{rR} \right] \\
& w_A(s^*_{rA}) : \alpha_R + \beta_R \left[\left(1 - \frac{\sigma^2}{\sigma^2 + \sigma_r^2}\right) \mu + \frac{\sigma^2}{\sigma^2 + \sigma_r^2} s^*_{rR} \right] \\
& = \alpha_A + \beta_A \left[\left(1 - \frac{\sigma^2}{\sigma^2 + \sigma_r^2}\right) \mu + \frac{\sigma^2}{\sigma^2 + \sigma_r^2} s^*_{rA} \right]
\end{aligned} \tag{10}$$

The equilibrium is depicted in Figure 13, where the thick line indicates the wage schedule in equilibrium:

Figure 13: Labor market equilibrium in period 1



All workers are employed in equilibrium and they are sorted into sectors on the basis of their signal. $E[\theta|s = s^*_{rR}]$, $E[\theta|s = s^*_{rA}]$ are the conditional expectations of ability corresponding to the signal cutoff values indicated in (10).

What are the implications of this equilibrium for racial disparities in terms of employment sorting and wages? Given the wage schedules derived in (10), we can focus on the distribution of signals, rather than the distribution of $E[\theta|s]$. For any given cutoff wage, the racial difference in signal variance implies that the underlying ability signal is also different. Using (10) the relationship between the signals for Black and white workers at a given cutoff is:

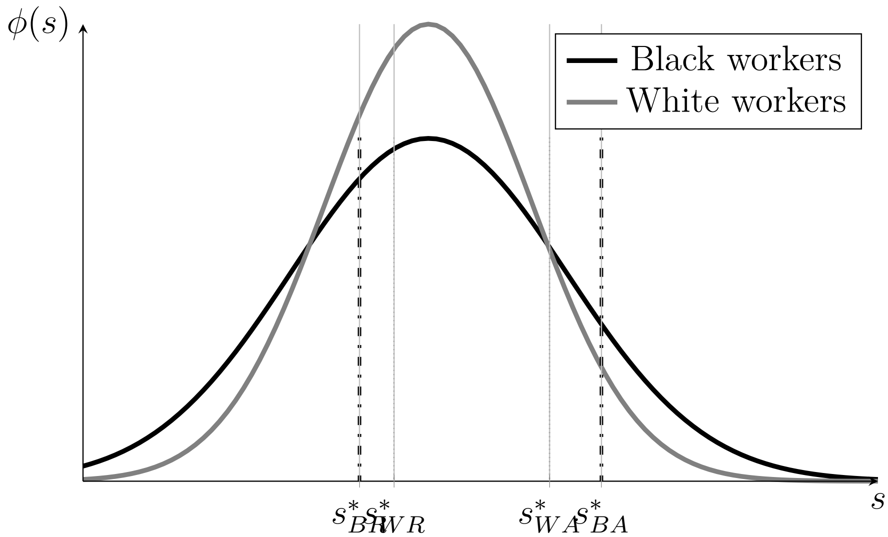
$$s_W = \frac{\sigma_B^2 - \sigma_W^2}{\sigma^2 + \sigma_B^2}\mu + \frac{\sigma^2 + \sigma_W^2}{\sigma^2 + \sigma_B^2} s_B \tag{11}$$

Therefore, for any expected productivity cutoff above the mean, $s^*_B > s^*_W$, while $s^*_B < s^*_W$ for cutoffs below the mean. This is a straightforward consequence of the racial difference in signal noise; because the signal is less precise for Black workers, a given signal implies expected productivity closer to the mean than it would for white workers.

I assume that no sector employs more than half the workforce. Therefore, $E[\theta|s = s^*_{rR}] < \mu$ and $E[\theta|s = s^*_{rA}] > \mu$, and the distance between the two is such that the routine sector's share of employment is below 50 percent.[7] The equilibrium is shown in Figure 14.

[7] In this setting, counterfactually, relative to Black workers, white workers always have a higher proportion of workers in both abstract and manual employment. As noted in the discussion subsection, this concern is easily addressed by allowing μ to be race specific.

Figure 14: Equilibrium in period 1 - workers' signals



Notice that for each cutoff ($E[\theta|s]$) and, therefore, implicitly each wage cutoff, there are different cutoff signals for each group. Cutoffs above the mean require higher signals for Black workers than for white workers, while the opposite is true for cutoffs below the mean. On either side of the mean, the closer the original cutoff is to the center of the distributions, the narrower the gap between the required racial signals.

5.4 Technological change and new equilibrium

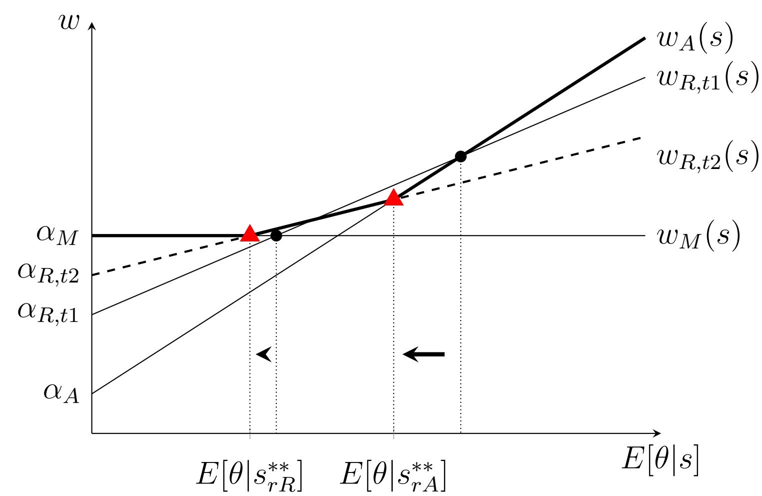
How does RBTC affect this labor market framework? From the empirical analysis, the model should be consistent with 1) an overall contraction of the routine sector, and 2) an increase in the routine-employment share among Black workers.

I model RBTC as reducing the responsiveness of output to individual skill in routine jobs. Personal computers allowed less skilled workers to do jobs for which they were previously unqualified. Typesetting used to be done by highly skilled typographers. Desktop publishing programs allowed other, less skilled workers to do the same job. While technology also increased the productivity of skilled typographers, it lowered the slope of the output/skill relationship, and by increasing output, lowered the price. Therefore, I model technology as rotating the wage/skill line segment in routine jobs.

Such a technological shock corresponds to a change in period 2 of the value production function for the routine sector, with an increase in α_R (worker-independent productivity) and a decrease in β_R (sensitivity to worker-specific ability).

The new equilibrium is shown in Figure 15. The shift and pivot of $v_{R,t1}$, associated with the changes in α_R and β_R are represented by the dashed line $v_{R,t2}$:

Figure 15: Labor market equilibrium in period 2



The new wage schedule changes the cutoffs that determine employment sorting to $E[\theta|s = s^{**}_{rR}]$, $E[\theta|s = s^{**}_{rA}]$, shifting both to the left. In the example, the parameter changes lead to a shrinkage of the routine sector. This ultimately depends on the densities of the signal distributions and, hence, on whether the density change caused by the shift for the cutoff between the manual and routine sectors is smaller than the one brought about by the cutoff between the routine and abstract sectors.

These parameter assumptions imply that the employment share of the manual sector falls. This appears to contradict evidence that low-skill service employment increased (Autor and Dorn [2013]). However, this growth occurred primarily after 2000[8] and,

[8]See Figure 10 in Acemoglu and Autor [2011].

therefore, does not apply to the period I study. In addition, I abstract from the distinction between service occupations and occupations in transportation and blue collar trades; during the 1980s and 1990s the decline in the latter outweighed the increase in the former occupation.

These changes in the threshold values for signals are not sufficient to generate the changes in racial differences in employment-share changes observed in the data. The following conditions are necessary and sufficient for an increase in the routine employment share for Black workers and a decrease for white workers:

$$|\Phi(s^{**}_{WA}) - \Phi(s^{*}_{WA})| > |\Phi(s^{**}_{WR}) - \Phi(s^{*}_{WR})| \tag{12}$$

$$|\Phi(s^{**}_{BA}) - \Phi(s^{*}_{BA})| < |\Phi(s^{**}_{BR}) - \Phi(s^{*}_{BR})| \tag{13}$$

The first condition states that the changes in $E[\theta|s = s^{*}_{rR}]$ and $E[\theta|s = s^{*}_{rA}]$ have to be such that for white workers the shift out of the routine sector (LHS) is larger than the shift into the routine sector (RHS), while the second condition requires the opposite for Black workers.

In Figure 16 and 17, I illustrate how these conditions are portrayed in terms of signal distributions.

Figure 16: Equilibrium in period 2 - Black workers

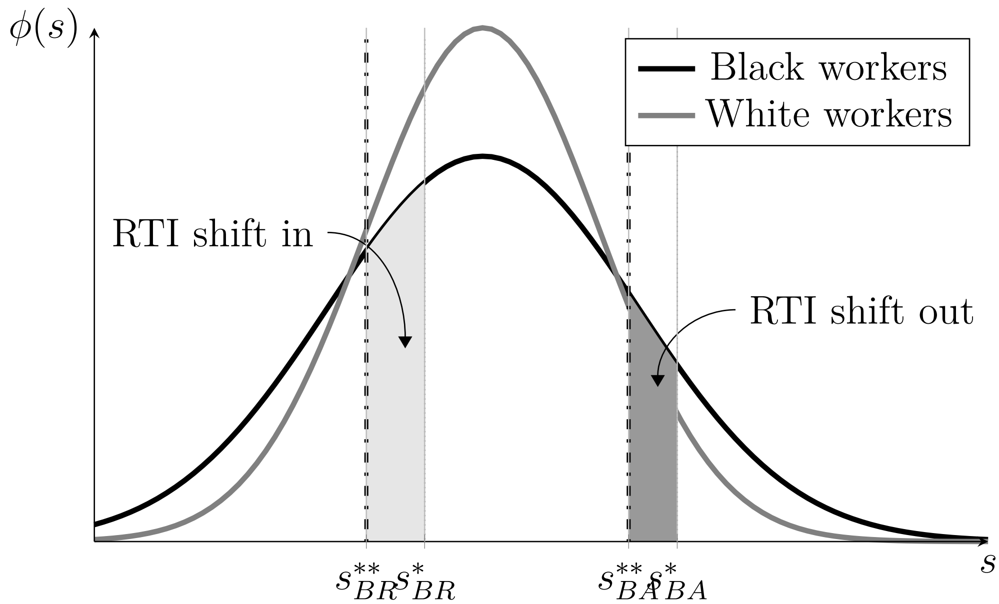
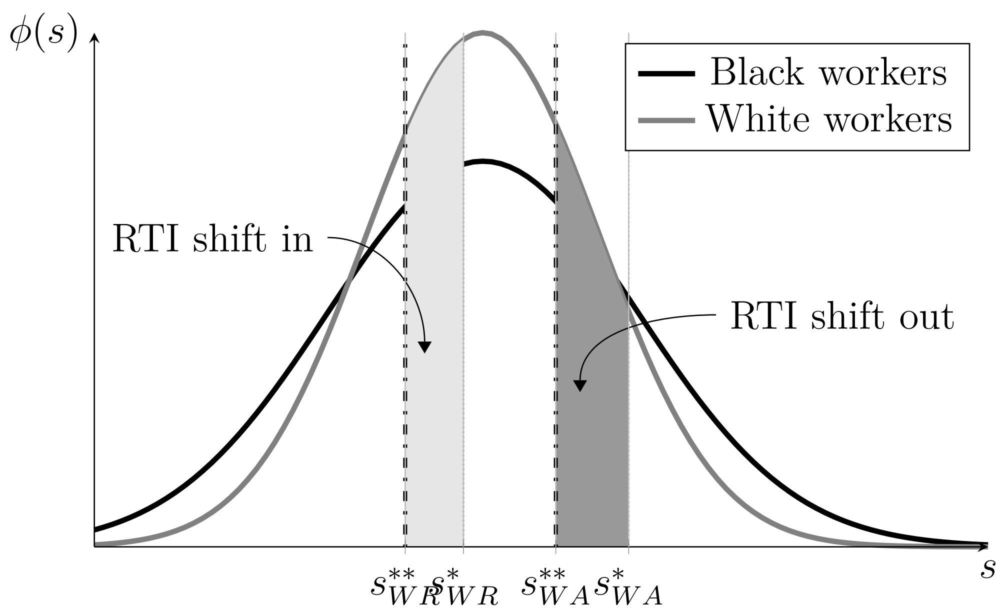


Figure 17: Equilibrium in period 2 - White workers



In both Figures 16 and 17, dashed lines denote cutoffs in period 2 (labelled with **), while lighter dotted lines represent cutoffs from period 1. As previously stated, a labor market shift in wage cutoffs corresponds to different changes in signals of Black and white workers. In Figure 16, it is possible to observe workforce shifts for Black workers, with the darker shaded area representing movement out of the routine sector, and the lighter shaded area movement into it. Similarly, Figure 17 represents employment shifts for white workers. Overall, the two pictures show a case in which a change in the wage cutoffs of the routine and abstract sectors can cause a net shift into the routine sector for Black workers, and out of it for white workers.

5.5 Discussion

The model is designed to rationalize the racially different patterns with respect to routine-intensive occupations by enriching a framework of routine-biased technological change with statistical discrimination.

I have modeled RBTC differently from the approach in the task literature. This literature (Autor et al. [2003]; Acemoglu and Autor [2011]; Autor and Dorn [2013]) models RBTC as a fall in computer prices that leads to the substitution of workers by machines in the routine sector. Consequently, this sector contracts and wages fall. The standard model predicts that employment shifts from low-wage routine jobs to manual jobs, which does not allow for different racial patterns.

The narrative I introduce is more closely related to Cavounidis et al. [2021]. There, the authors show how increases in productivity of a given skill can lead to a decrease in employment in occupations that use it intensively.

The model is highly stylized, but provides a simple framework that explains the otherwise counter-intuitive empirical findings I presented earlier. At the same time, without modification, it is inconsistent with some other regularities. In what follows, I acknowledge and briefly address these concerns.

1. *Increase in returns to abstract occupations*

I have not addressed the increased return to abstract skills, which exacerbated racial wage disparity (Hurst et al. [2024]). My model can easily be extended to allow for an increase in β_A, which would further reduce routine employment, especially among white workers. Provided the density of Black workers around the cutoff is sufficiently small, nothing else would change.

2. *Race-specific share of employment in manual occupations*

The model predicts counterfactually that a higher share of white than of Black workers will be employed in manual jobs. This reflects the assumption that the two ability distributions have the same mean. The model could easily be extended to allow $\mu_B < \mu_W$. This would make it easier to have a much higher density of Black workers around the manual-routine cutoff and a lower density around the routine-abstract cutoff, reinforcing the main result. It would not, however, alter the fundamental features of the model. Note that $\mu_B < \mu_W$ can be endogenous to statistical discrimination as in Lundberg and Startz [1983], where statistical discrimination leads to less unobserved investment among Black workers.

3. *Static model*

Finally, the model is static and thus abstracts from changes over time in the composition of the labor force.[9] The focus on male workers in the empirical work makes this issue less problematic, since, over time, they did not change their labor force participation as much as women did.

6 Conclusion

This paper studies the role of routine-biased technological change (RBTC) in hindering the Black-white male wage gap convergence over 1980-2000. I show that this economic shock has a differential impact across demographic groups and along the wage distribution. This results in increased racial wage gaps despite the advancements achieved through increased levels of education for Black workers observed over the same period.

[9] This implies that the framework doesn't contemplate training on the job or updating beliefs for observed ability by either the employer or the worker after job-matching.

I present three new major empirical facts. First, I observe an increase in the share of employment in routine-intensive occupations for Black workers, while there is a significant decrease for white workers. This is a surprising pattern in light of the current literature, which predicts instead that employment in these jobs should decline for all workers. Second, I show that this different trend holds when conditioning for levels of education and age brackets, with the increase in Black routine-intensive employment being driven by workers with a high school diploma or less, and that the trend is stronger for younger cohorts. Lastly, using the Oaxaca-RIF decomposition methodology, I show that changes in the composition of the workforce increase wage gaps, in contrast to the observed wage convergence between groups at the bottom of the wage distribution. This finding is mainly explained by the occupational sorting differences among the two groups, and counters the concurrent decrease in differential returns.

I rationalize these empirical findings with a novel RBTC framework that incorporates statistical discrimination. The model is characterized by three sectors (manual, routine, and abstract) with different productivity sensitivity to individual skills, and workers of two groups whose ability is noisily observed. I demonstrate that a technological shock decreasing skill responsiveness for the middle sector has predictions in line with empirical patterns: it shrinks the overall share of employment in routine occupations, while causing a net shift into (out of) routine jobs for workers with higher (lower) ability noise.

Taken together, these results underscore the role of technological change as a key contributor to the evolution of the wage gap across demographic groups. Future work could extend this analysis by examining longer time horizons and by studying the interaction of RBTC with other major structural forces, such as declining unionization and increased trade exposure, as well as by exploring whether similar mechanisms shape wage dynamics among different demographic groups.

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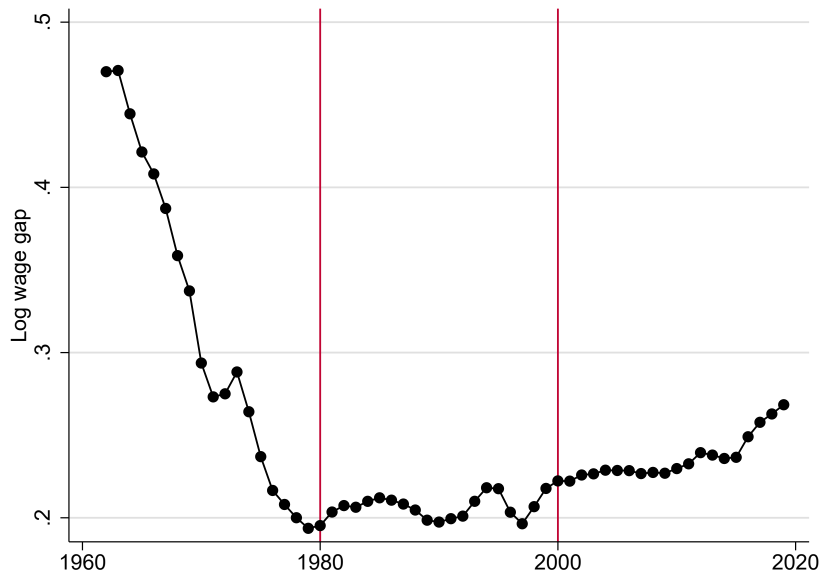
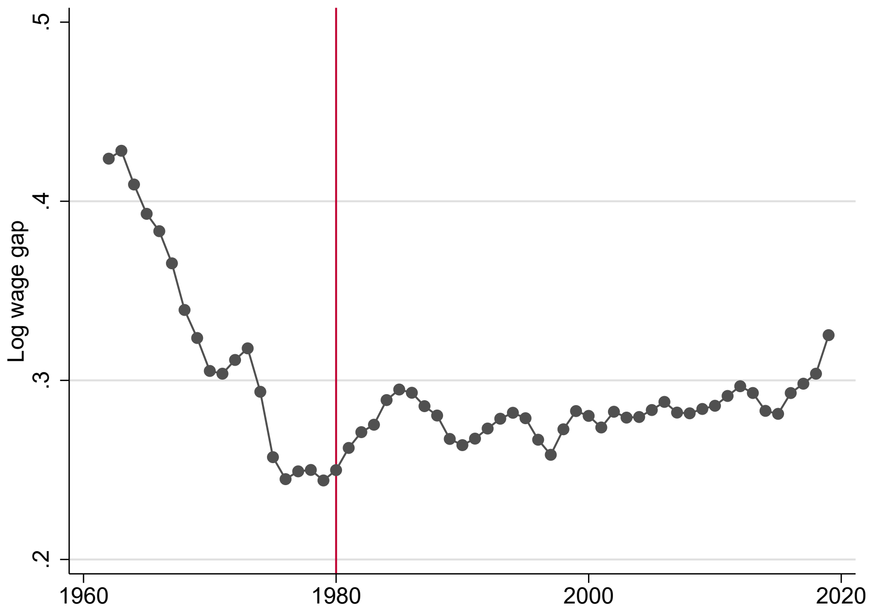
Appendix

Figure 18: Raw white-Black annual wage gap



Source: CPS ASEC. Sample: All civilian 20-64 Black and white workers with non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

Figure 19: Raw white-Black hourly wage gap – Males

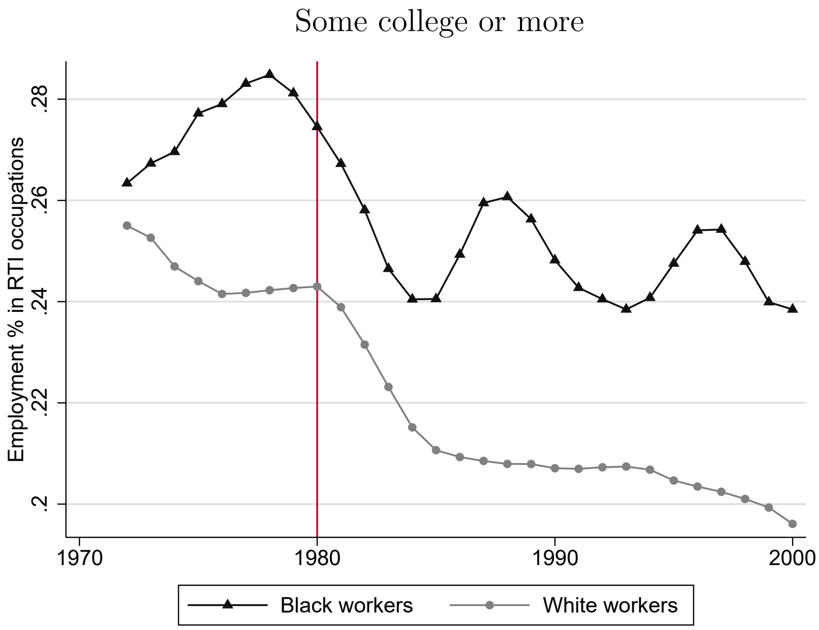


Source: CPS ASEC. Sample: Male 20-64 Black and white workers with non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

Figure 20: Race-specific employment share in top RTI occupations

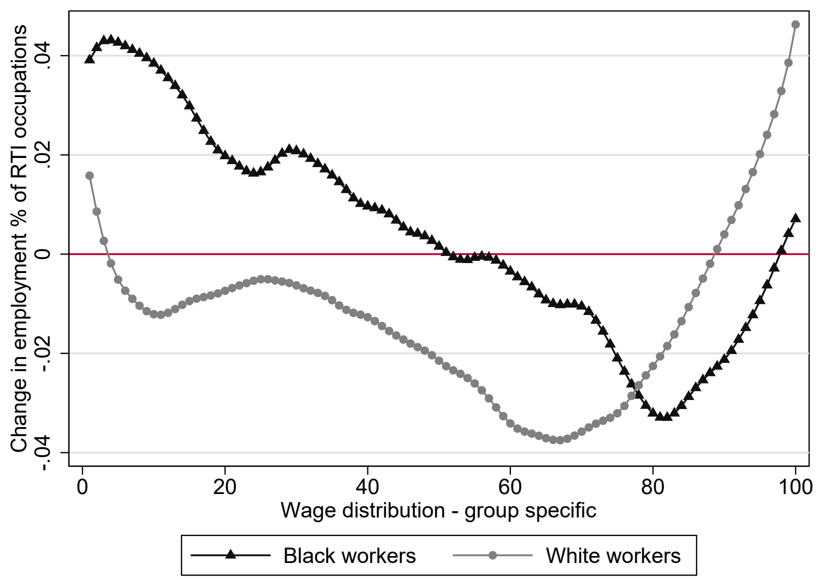
Source: CPS. Sample: All civilian 20-64 Black and white workers working at least 30 hours per week, for at least 40 weeks with non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

Figure 21: Race-education employment share in top RTI occupations



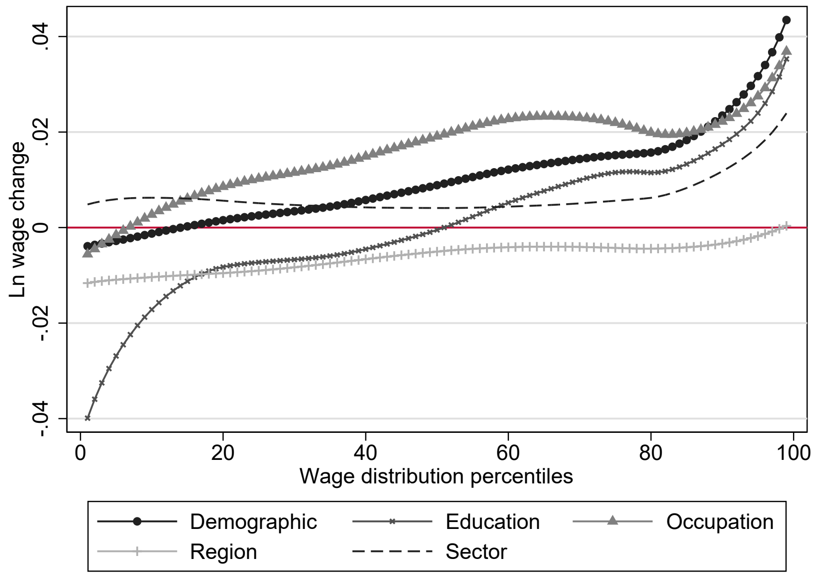
Source: CPS. Sample: All civilian 20-64 Black and white workers with some college or more, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

Figure 22: 1980-2000 top RTI change along wage distribution



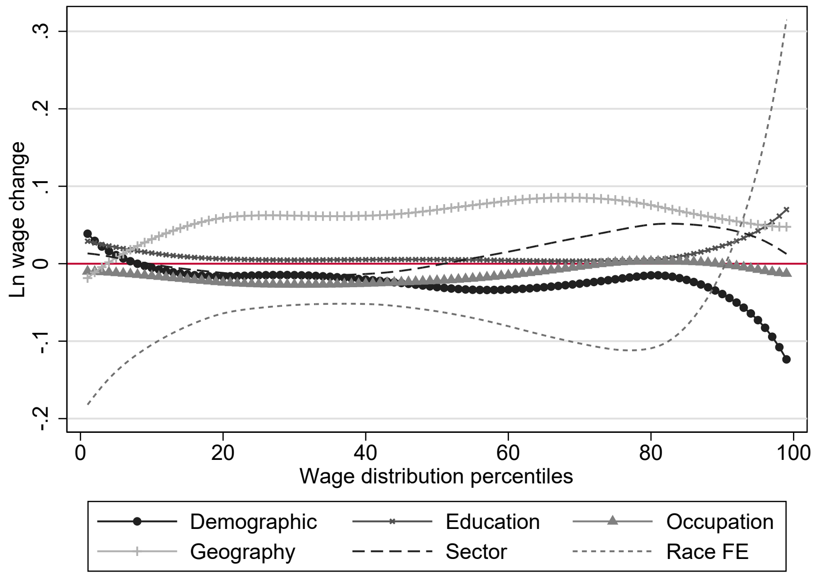
Source: IPUMS. Sample: All civilian 20-64 Black and white workers, with hourly wage ≥ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Wage distribution defined separately by race-gender groups. Smoothing bandwidth: 0.2.

Figure 23: 1980-2000 white-Black detailed *composition* change



Source: IPUMS. Sample: All civilian 20-64 Black and white workers, with hourly wage ≥ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Wage distribution defined separately by race-gender groups. Smoothing bandwidth: 0.2.

Figure 24: 1980-2000 white-Black detailed *diff returns* change



Source: IPUMS. Sample: All civilian 20-64 Black and white workers, with hourly wage ≥ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Wage distribution defined separately by race-gender groups. Smoothing bandwidth: 0.2.