Technological Change and Racial Disparities

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Abstract

The wage gap between black and white Americans has narrowed between the 1960s and the 1970s, but its progress has stalled since 1980. This study argues that routine biased technological change (RBTC) contributed to dampening wage gap convergence in 1980-2000, having a differential impact across races and along the wage distribution. Thus, I present new empirical evidence on occupational patterns by race and on determinants of wage disparities along the wage distribution, and rationalize them with an RBTC model in which firms engage in statistical discrimination. I show that, surprisingly, the share of employment in routine intensive occupations has increased for black workers, in contrast with a significant decrease observed for white workers. I decompose the wage gap changes using the Oaxaca-RIF methodology and show that differences in occupational sorting of the workforce increase wage disparities, thwarting wage convergence between races at the bottom of the wage distribution. Together, these new empirical findings and model provide insights to better understand the mechanisms behind racial disparities at the end of the 20th century.

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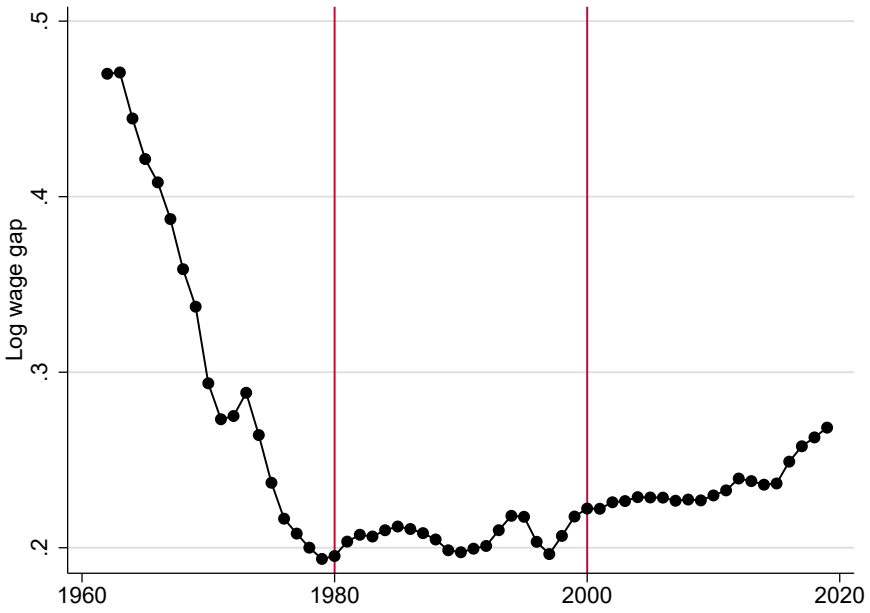
1 Introduction

After striking progress in the 1960s and 1970s, the hourly wage gap between black and white workers stalled at about 20% starting in the 1980s (see Figure 1), but there is no consensus in the literature as to why.[1]

Figure 1: Raw white-black hourly wage gap



Source: CPS ASEC. Sample: All 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.

I argue that routine-biased technological change (RBTC) contributed significantly to the failure of the wage gap to decline because it affected black and white workers differently. After 1980, technological progress, particularly computerization, reduced employment and wages in occupations such as clerical jobs and jobs in operations and production, that used routine skills intensively (Autor et al., 2003, Autor and Dorn,

[1]For trends in the gap of mean annual wage, see Figure 1A. Patterns are invariant in essence, but the gap from 1980 onward is slightly larger.

2013). The standard view is that routine-intensive jobs were mostly concentrated in the lower middle of the wage distribution and that RBTC polarized the US labor market by shifting employment to both lower and high-skill jobs (See Figure 2).

Figure 2: Change in employment 1980-2000

Source: IPUMS. Sample: All 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.

I focus on male black and white workers between 1980 and 2000 and first show that, surprisingly, black workers increased their employment share in routine-intensive occupations. This shift is prevalent among those with a high school diploma or less, and younger cohorts. However, the diverging patterns between black and white workers is not explained by difference in their demographics. These findings are robust to various sample choices.

I then show how the wage gap changed at different points of the wage distribution. While the mean gap in hourly wage was stagnant, disparities decreased in the bottom half of the distribution and increased in the top half. Using a Oaxaca-RIF

decomposition (Firpo et al., 2009), I show that changes in occupational sorting associated with RBTC increased the wage gap across the entire wage distribution. In the bottom half of the wage distribution, it only partially counteracted the decreases in disparities due to increased educational achievement among black workers and reduced gaps in racially-specific returns to worker characteristics. Consistent with this pattern, the wage gap narrowed throughout the distribution in commuting zones with low proportions of routine-intensive workers.

Lastly, I show that when firms engage in statistical discrimination, RBTC can generate the racial resorting of workers that we observe. I consider a labor market with two types of workers, black and white, and three sectors: manual (lowest paying sector), routine (middle paying sector), and abstract (highest paying sector). I model technological change as a shock that reduces wage responsiveness to individual ability in occupations in the routine sector. When firms observe a signal of ability that is less precise for black than for white workers, this form of technological change can generate racial differences in net movements in and out of the routine sector. Thus, I rationalize my empirical finds. as possible in this setting, something that is not possible in the model of RBTC developed in Acemoglu and Autor (2011).

This study is related to two main strands of literature in labor economics: racial disparities and routine biased technological change.

Racial disparities. This paper contributes to deepen our understanding of the evolution of the racial wage gap in the second half of the 20th century. It is therefore linked to an extensive body of literature studying the mechanisms behind racial disparities and discrimination (Coate and Loury, 1993, Fang and Moro, 2011, Lundberg and Startz, 1983). Another consistent set of studies focuses on the evolution of wage inequality over time (Bound and Freeman, 1992, Juhn et al., 1993, Altonji and Blank, 1999), documenting a reduction in the gap between 1940s and 1980s, but a slow-down in the following period. Some studies instead assess the role of specific anti-discrimination policies, such as school desegregation or the Voting Rights Act (Wright, 2015, Aneja and Avenancio-Leon, 2019). Others, examine the effects of broad economic changes, such as the increase in education level of African-Americans (Smith and Welch. 1986). Derenoncourt and Montialoux (2021) provide evidence

that the extension of the federal minimum wage (Fair Labor Standards Act of 1966) contributed to earning-gaps reductions in the 1960s and 1970s. Thus, like this paper, they use a racially-neutral economic shock to explain changes in racial disparities. Batistich and Bond (2019), instead, focus on the effects of the Japanese manufacturing trade shock of the mid-1970s, and show that black employment was negatively affected. As in this paper, they implement a spatial strategy for their analysis, by using differences across labor markets in initial exposure to identify the effects of the shock. Lastly, this paper is also related to Bayer and Charles (2018), in which they show how racial gap patterns differ along the wage distribution.

Routine biased technological change. In the last twenty years there has been a significant increase in contributions to the technological change literature, especially regarding the role played by technology in explaining the polarization of the US labor market, as well as of other markets in the developed world (Goos et al., 2014). One strand has focused on understanding and correctly interpreting the mechanisms through which this technological change has affected the labor market (Autor et al. 2003, Autor and Dorn 2013, Cavounidis and Lang 2019, Cavounidis et al. 2021). Other papers have explored how this shock has affected men and women differently (Autor and Price 2013, Black and Spitz-Oener 2010, Cavounidis et al. 2021).

However, research on technological change in relation to racial disparities has been scant. The recent paper by Hurst et al. (2021) is a notable exception. Their work develops a task-based framework that shows how the effects of decreases in the racial-skill gap and taste-based discrimination were counteracted by the increase in returns to abstract skills, which favors white workers. My work can be viewed as complementary to theirs, in that it addresses other aspects of the impact of RBTC on racial disparities. It provides a more comprehensive picture of the changes that occurred along the entire wage distribution and focuses on racially different occupational sorting, rather than economy-wide skill use by race. Importantly, it presents new empirical findings on relevant different occupational patterns between black and white workers, and it rationalizes them by introducing a model of RBTC that, although different, is not incongruous with the existing literature.

The rest of the paper is organized as follows: section 2 describes the data and the

samples used, section 3 presents new empirical facts on racial differences in employment, section 4 analyses the evolution of the wage gap through the Oaxaca-RIF decomposition, section 5 introduces the model of technological change and statistical discrimination, and section 6 concludes.

2 Data and Sample

The focus of this paper is how, between 1980 and 2000, RBTC impacted disparities between male black and white workers. As stagnation of the racial wage gap continued after 2000 (see Figure 2A in the appendix for Figure 1 for male workers only), I focus on the earlier period because it precedes the China trade shock. Such trade shocks are likely to differentially affect different racial groups (e.g., by Batistich and Bond (2020 on the Japan trade shock). The later period is also greatly affected by the Great Recession and, more recently, the pandemic.

Data

I use three data sources for my analysis: the March Current Population Survey (CPS), from 1972 to 2000, the US Census decennial data, from 1980 to 2000, and the third edition of the Dictionary of Occupational Titles, published in 1977. I employ the CPS datasets to show time trends with high (annual) frequency. However, its sample size does not allow for a detailed examination of the evolution of racial disparities, especially changes along the wage distribution and geographical heterogeneity. I therefore use the Census decennial data for such analyses.
Lastly, I use the Dictionary of Occupational Titles to classify occupations in terms of skill-use intensity and whether they are more or less affected by routine-biased technological change.

March CPS

I use the March Annual Social and Economic Supplements (ASEC) of the Integrated Public Use Microdata Series, particularly. These files provide individual-level data

on employment (weeks and hours worked, occupation, and industry) and income, and demographic information such as race, gender, education, age, marital status.
The CPS first used the 1970 Census occupation codes in 1972. Since this study requires observing occupations consistently across time, my sample begins in 1972. I adopt Dorn's (2009) occupational crosswalk, which harmonizes Census decennial classifications into 330 consistent occupations.
Income is given by nominal annual wage and salary in the previous year, and is top coded to prevent identification of high earners. I substitute topcoded values using the dataset created by Larrimore et al. (2008), who built cell mean values by demographics using restricted use CPS data. Before 1976, I do not observe anyone with a top-coded income equal, and, therefore, make no adjustment. Lastly, I use the 2006 Personal Consumption Expenditures Price Index from Federal Reserve Economic Data to transform nominal into real values.
I calculate hourly wages[2] by dividing annual income from wage and salaries and by the reported number of weeks multiplied by hours worked. For earlier years, weeks worked is reported in intervals. Following Dereroncourt and Montialoux (2021), I obtain weekly wages by dividing annual wages by the median number of weeks in the indicated interval, and then smooth it by adding a random number generated from a uniform distribution. I then compute hourly wages by dividing the smoothed weekly wages by the number of hours worked in the previous week, which is consistently reported throughout the period.
The sample used in the main analysis includes all black and white male employees of age 20-64 in the private and public sectors. I exclude self-employed, unpaid family workers, workers in group quarters, workers in agricultural occupations, and workers in the armed forces. I do not limit the sample to full-time full-year workers but show in the appendix that doing so does not change the result. I use ASEC individual weights for all computations.

[2]The Merged Outgoing Rotation Group reports hourly wages starting only in 1983, making it unsuitable for this study.

Census

I use the 5% 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's (2009) 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 is 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 topcoding issues, I make an *ad hoc* adjustment by multiplying top coded annual wages by 1.5.[3]

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).

Dictionary of Occupational Titles

I use the occupation-level measures of routine intensity computed by Autor and Dorn (2013). The data is originally from the Dictionary of Occupational Titles, which is the standard dataset for information on skill use. It provides numerical measures of attitudes, temperaments, and abilities needed to perform a job. The data is at the occupational-title level, but they aggregate it to Census-occupation level. Autor and Dorn (2013) define three measures, for manual, routine, and abstract skills, and use

[3]Lemieux et al. (2006) multiply 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.

the following measure to define routine intensiveness of occupations:

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

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*; manual (M) is defined by the variable measuring *eye, hand, foot coordination.*

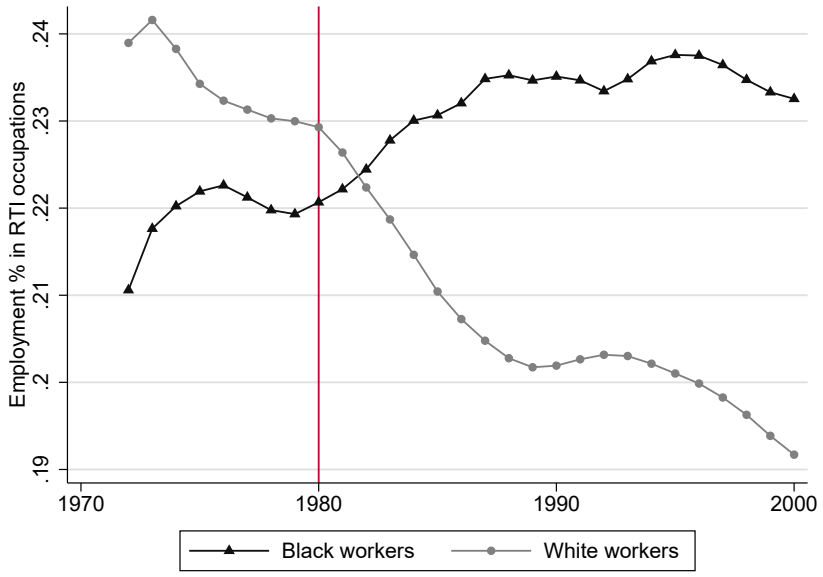
Like them, I use RTI to identify routine-intensive occupations, defined as the top third occupations in terms of RTI.[4] This measure, as well as its individual components, has been used in several studies of Routine-Biased Technological Change. Using it for my analysis allows for consistency with the existing literature. While there may be concerns about the accuracy 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 patters: after 1980, we observe a sharp decrease for white workers, and a significant increase for black workers.

[4]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 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% to 19%. This change, although striking, is expected and consistent with the standard RBTC framework, which predicts that workers will shift out 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.[5] In Figure

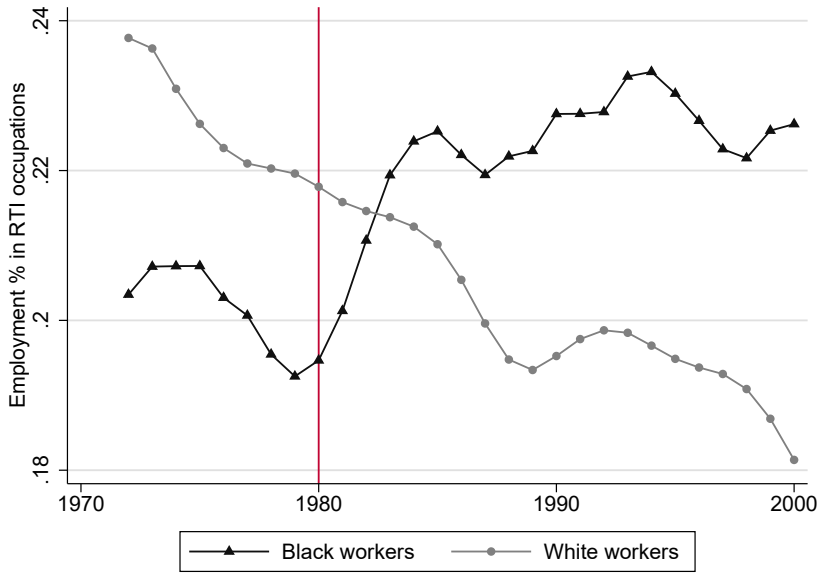
[5]Even if that were the case, it would still be a result incompatible with the current consensus on routine occupations employment patterns.

3A 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 degree 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 concerns 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.

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

High school diploma or less



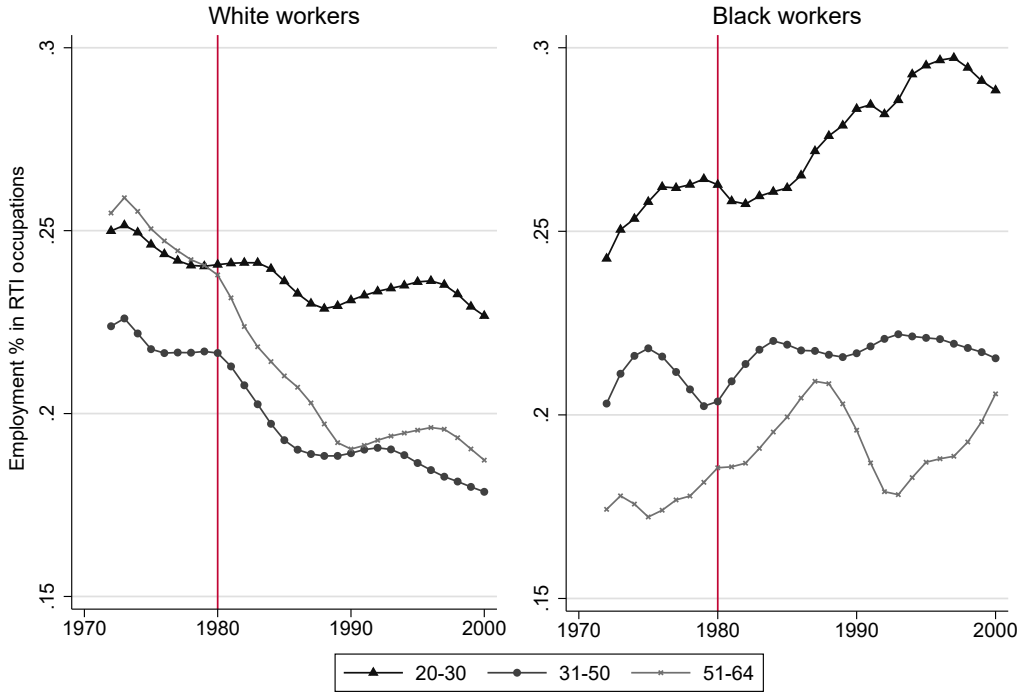
Source: CPS. Sample: All 20-64 black and white workers with high school diploma or less, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

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 4A). 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 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-know 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.[6]. The consequent higher rate of missing men in survey data (Sabety and Spitzer, 2021) among the youngest group could have potentially be a reason for concern, had we observed a higher decrease in routine jobs

[6]From about 1% of the black male population in 1980 to roughly 4% in 2000 (National Research Council,2014)

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 does not allow to determine the types of jobs in which missing men are employed, observing an increase in routine employment for black workers of all age groups provides suggestive evidence that the reliability of these findings is not threatened by sample selection.

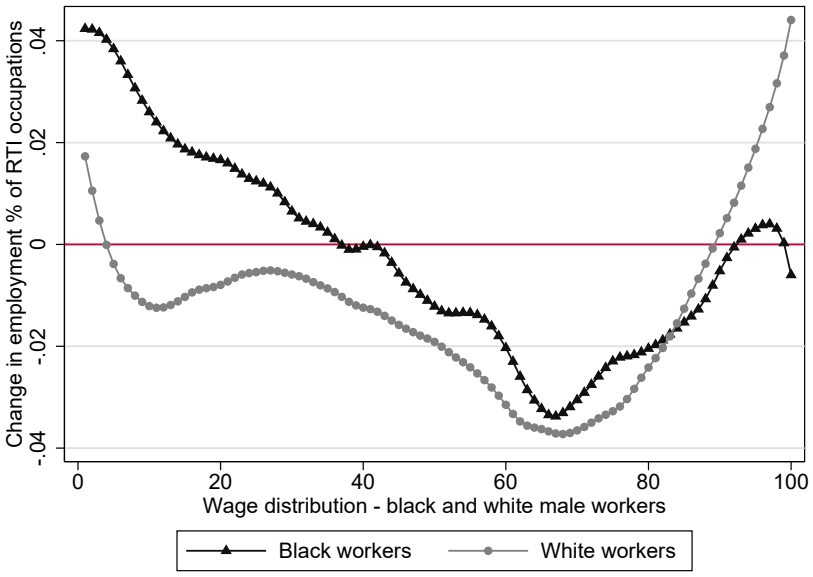
4 Wage disparities

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% and top 10% of the wage distribution[7]. 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.

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

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



Source: IPUMS. Sample: All 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. Wage distribution defined on the entire described sample. Smoothing bandwidth: 0.2.

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:

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

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 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

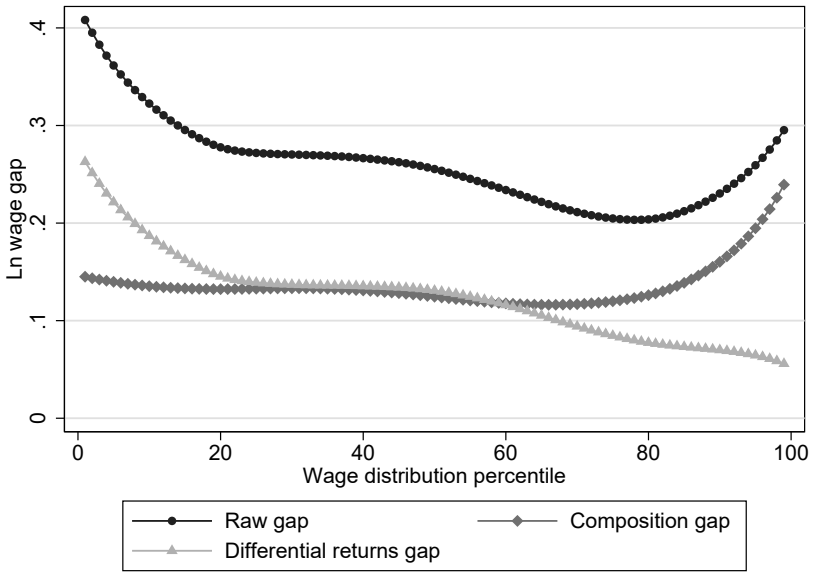
captures the racial disparities in the effects of characteristics on earnings. We can further decompose each of the two elements into specific characteristics, in order to, for instance, show the role played by education and occupations separately.

The Oaxaca-RIF method (Firpo et al., 2009) relies on Recentered Influencial Functions. 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 ones. 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



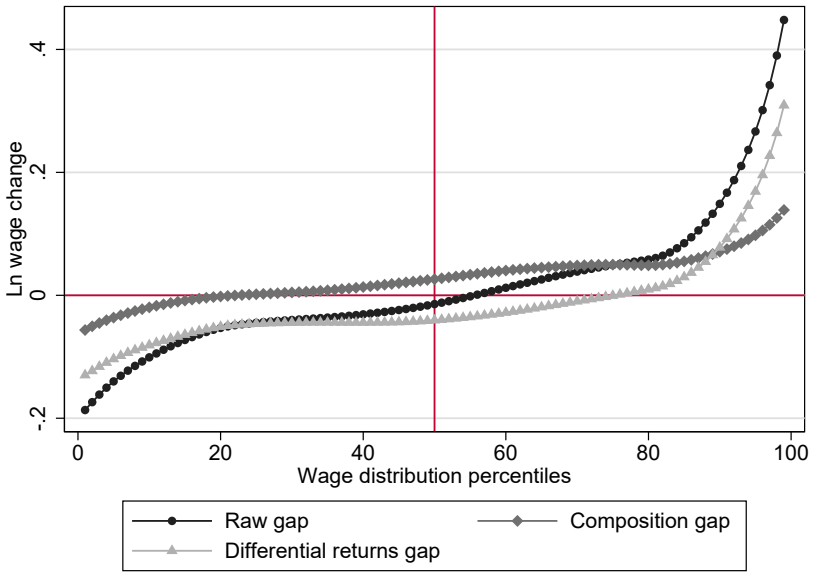
Source: IPUMS. Sample: All 20-64 black and white male workers, with hourly wage ≥ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Race-specific wage distribution. Smoothing bandwidth: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

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:

$$\Delta\text{Hourly wage}^{2000}_{W-B} - \Delta\text{Hourly wage}^{1980}_{W-B} = \underbrace{(X^{2000}_W - X^{2000}_B)\beta^{2000}_W - (X^{1980}_W - X^{1980}_B)\beta^{1980}_W}_{\text{Composition gap}} + \underbrace{X^{2000}_B(\beta^{2000}_W - \beta^{2000}{}_B) - X^{1980}_B(\beta^{1980}_W - \beta^{1980}_B)}_{\text{Differential returns gap}} \quad (3)$$

Figure 8 reports the outcome of this exercise. Recall that because it reports a white-black wage gap change, 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 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.

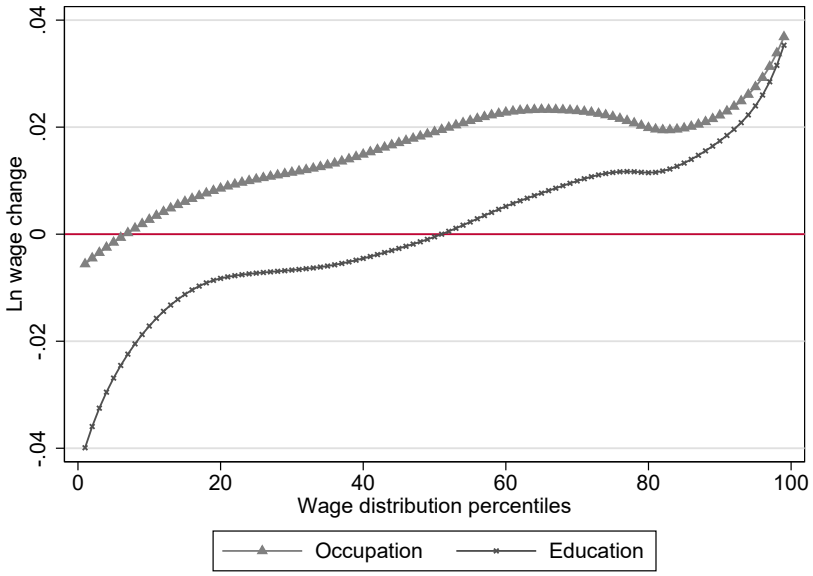
Between 1980 and 2000, the racial wage gap decreased in the bottom half of the distribution and increased in the top half. Consistent with the prior literature, the change in the gap at the median is approximately 0. Strikingly, Figure 8 shows the composition element does reduce the gap. While, throughout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

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

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 6A for all components).

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



Source: IPUMS. Sample: All 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 alone education component increases gap (although less so that the occupational component), consistent with the increase in the college graduation 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 the 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 is the most important skill, those labeled "R" involve the use routine skills mostly, 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 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 this occupations in sufficient numbers to take advantage of the aftermath of RBTC.

Figure 10: 1980-2000 detailed occupation components

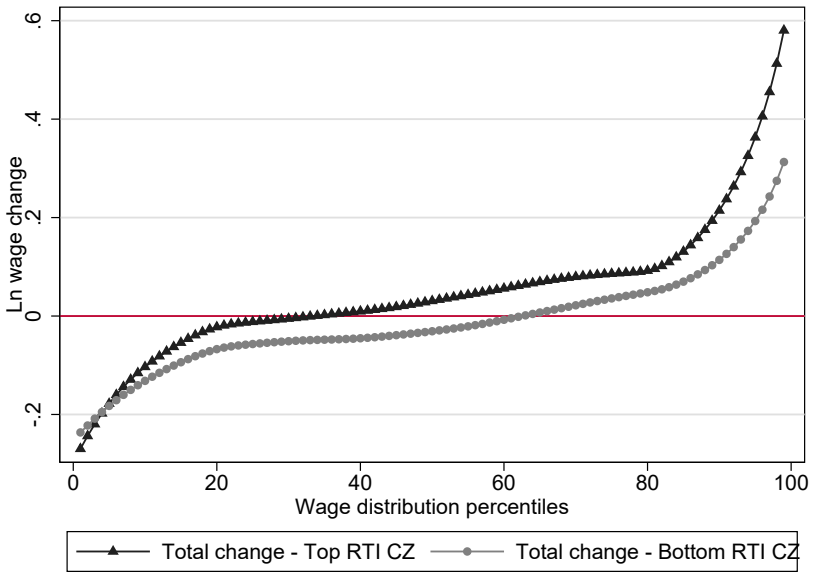
Source: IPUMS. Sample: All 20-64 black and white male workers, with hourly wage ≥ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Race-specific wage distribution. Positive coefficients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

Figure 7A 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) of 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 of the differential returns component of the wage gap.

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 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

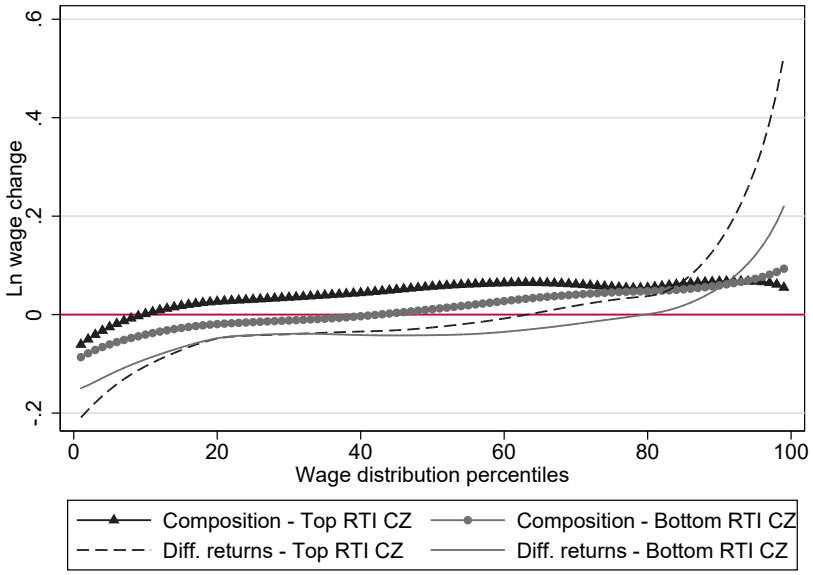


Source: IPUMS. Sample: All 20-64 black and white male workers, with hourly wage ≥ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Race-specific wage distribution

Figure 11 shows that, indeed, the wage gap narrowed only for the bottom 40% of the wage distribution in top routine CZs, while the reduction in bottom routine CZs

affected the bottom 60% of the distribution. Figure 12 below, shows the distribution of the composition and of the differential returns component for the two considered groups of CZs.

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



Source: IPUMS. Sample: All 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 of the wage gap for the bottom 60%. For the composition element, instead, the difference between the two groups are more significant, and in line with our priors: in CZs that were more afftected 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 Model

I now develop a 2-period 3-sector statistical discrimination model to rationalize the empirical findings. The standard model (Acemoglu and Autor, 2011) of routine-biased technological change (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.

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 overall allocation of workers across sectors, ignoring possible firms entry and exit, as well as changes of 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 the routine-sector productivity is less responsive than abstract-sector productivity to workers' ability. For simplicity, I assume that manual-sector productivity is independent of worker's ability.
Condition (3) ensures that for some workers it is optimal to be employed in a sector with lower productivity and wage. 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.

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 the ability signal is less informative is less informative for black than for white workers, i.e. $\sigma_B > \sigma_W$.
The distribution of s_{ir} is therefore:

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

Equilibrium

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

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

and by the standard properties of the bivariate normal distribution:

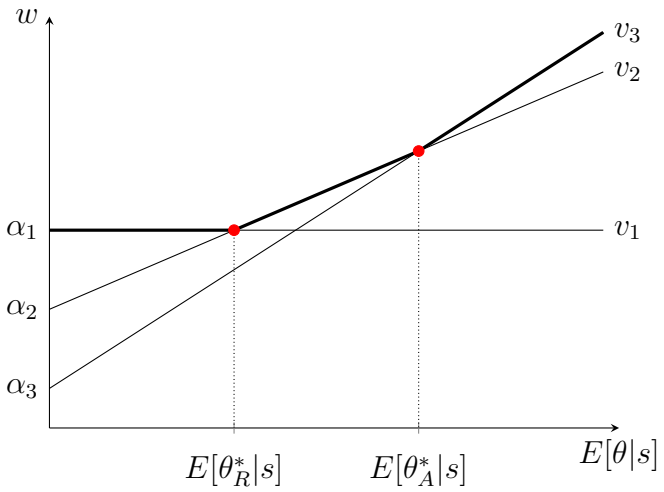
$$w_i(\theta) = \alpha_j + \beta_j \left[\left(1 - \frac{\sigma^2}{\sigma^2 + \sigma_r^2} \right) \mu + \frac{\sigma^2}{\sigma^2 + \sigma_r^2} s \right] \tag{9}$$

The wage is a weighted average of mean of 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 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 sector are:

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

The equilibrium is depicted in the figure below, where the thick line indicates the wage schedule in equilibrium:

Labor market equilibrium in period 1



All workers are employed in equilibrium and they are sorted into sectors on the basis of their signal. $E[\theta_R^*|s]$,$E[\theta_A^*|s]$ 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 then the distribution of $E[\theta|s]$. For any given cutoff wage, the racial difference in signal variance implies that the underlining ability signal is also different. Using (10) the relation between the signals for black and white workers at a given cutoff is:

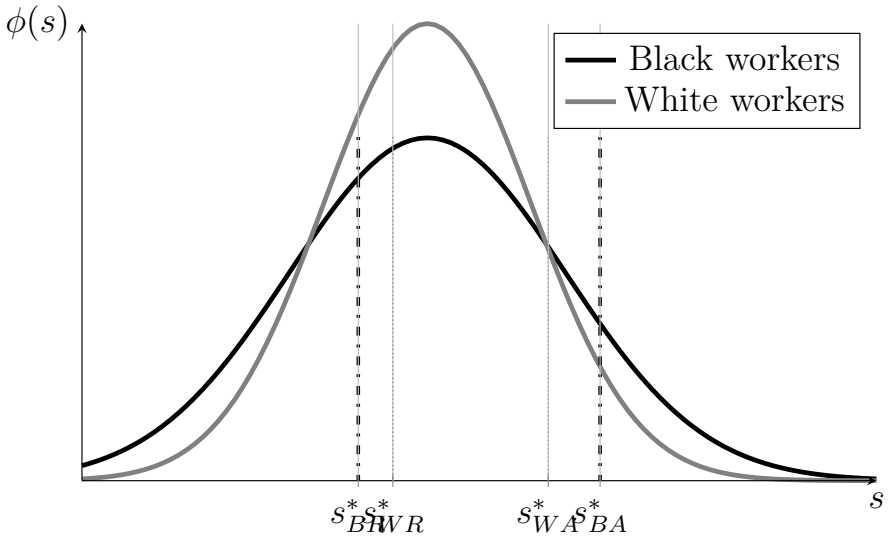
$$s_W = \frac{\sigma_B^2 - \sigma_W^2}{\sigma^2 + \sigma_B^2}\mu + \frac{\sigma^2 + \sigma_W^2}{\sigma^2 + \sigma_B^2}s_B \tag{11}$$

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, $E[\theta_R^*|s] < \mu$ and $E[\theta_A^*|s] > \mu$, and the distance between the two is such that the routine sector share of employment is below 50% .[9] The equilibrium is shown in the figure below.

[9]In this setting, counterfactually, relative to black workers, white workers always have a higher proportion of workers in each of abstract and manual employment. As discussed in the *Discussion* subsection, this concern is easily addressed by allowing μ to be race specific.

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 to the center of the distributions, the narrower the gap between the required racial signals.

Technological Change and New Equilibrium

How does routine-biased technological change 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.

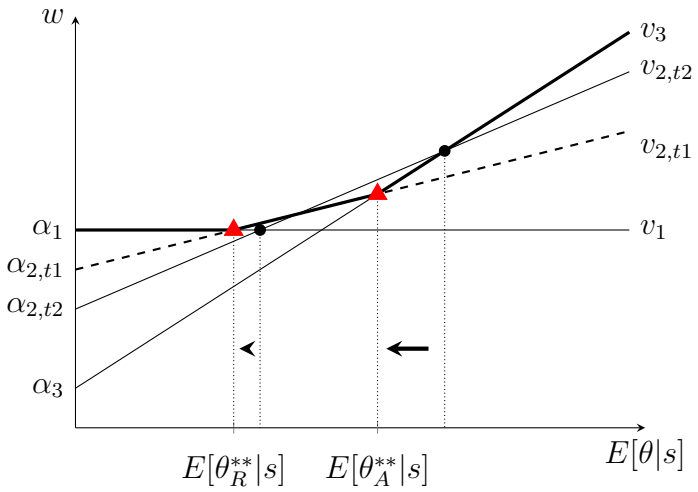
I model RBTC as reducing the responsiveness of output to individual skill in routine jobs. Personal computers allowed less skilled workers to do jobs for which they were previously unqualified. Typesetting use to be done by highly skilled typographers. Desktop publishing programs allowed other, less skilled, workers to do the

same job. While technology also increased the productivity of skilled typographers, it lowered the slope of the output/skill relation, and by increasing output, lower 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 below. 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: Labor market equilibrium in period 2



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

These parameter assumptions imply that employment share of the manual sector falls. This appears to contradict evidence that low-skill service employment in-

creased (Autor and Dorn, 2013). However, this growth is primarily after 2000[10] and, 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 racial differences changes in employment-shares 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:

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

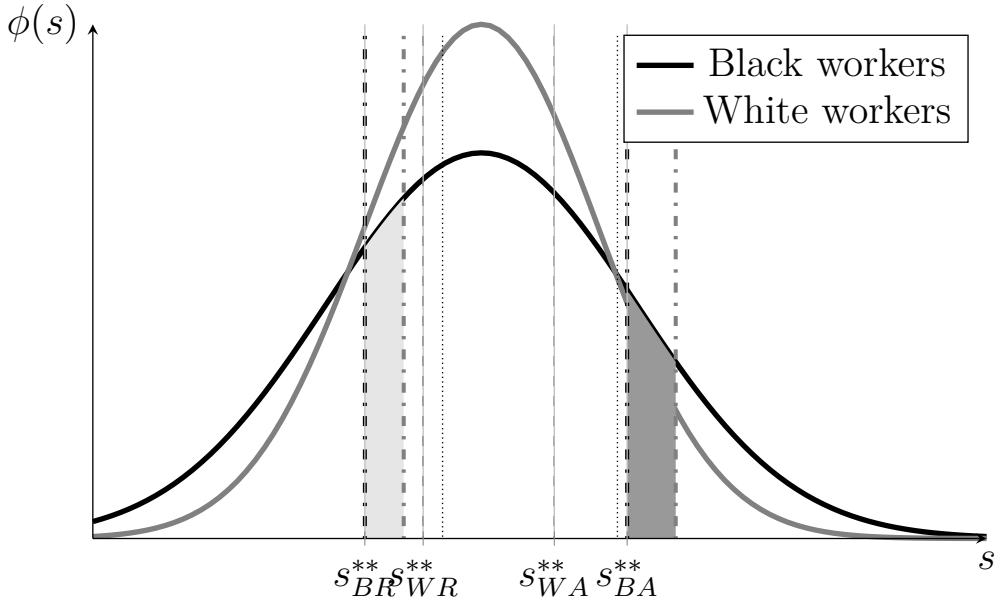
$$\Phi(s^{**}_{WB}) - \Phi(s^{*}_{WB}) < \Phi(s^{**}_{BA}) - \Phi(s^{*}_{BA}) \tag{13}$$

The first condition states that the changes in $E[\theta^*_A|s]$ and $E[\theta^*_R|s]$ 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.

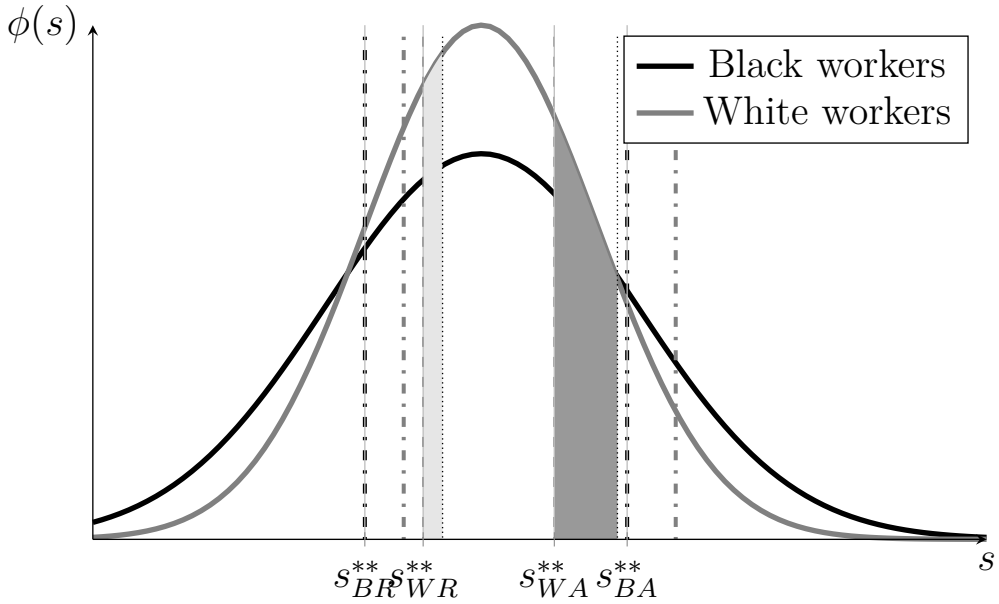
In the example below, I illustrate how these conditions are portrayed in terms of signal distributions.

[10]See Figure 10 in Acemoglu and Autor, 2011

Panel A:Equilibrium in period 2 - Black workers



Panel B: Equilibrium in period 2 - White workers



In both panels A and B, all signal shifts are represented, with the dashed lines indicating cutoff signals for black workers, and dotted lines cutoff signals for white workers. Darker lines denote cutoffs in period 2 (labelled with **), while lighter lines represent cutoffs from period 1. As previously stated, a labor market shift in wage cutoffs corresponds to different changes for signals of black and white workers. In panel A, 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, panel B represents employment shifts for white workers. Overall, the two pictures show a case in which a change in the wage cutoffs of routine and abstract sectors can cause a net shift into the routine sector for black workers, and out of it for white workers.

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 et al. 2011, Autor et al. 2013) models RBTC as a fall in computer prices that leads to 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 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, we 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. 2021). 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. *Racial-specific share of employment in manual occupations*

The model predicts counterfactually that higher share of white than of black workers will be in manual employment. 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 labor force.[11] 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 in 1980-2000. I show that this economic shock has a differential impact across races and along the wage distribution. This results in unfavorable effects on racial disparities despite the advancements

[11]This implies that the framework doesn't contemplate training on the job, nor updating beliefs for observed ability by either the employer or the worker after job-matching.

achieved through increased levels of education for black workers. 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 racially-different trend holds when conditioning for levels of education and age brackets, with the increase in black routine intensive employment being driven workers with a high school diploma or less, and stronger for younger cohorts. Lastly, using the Oaxaca-RIF decomposition methodology, I show that changes in the composition of the workforce increase wage disparities, opposing the observed wage convergence between races 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 racially-differential returns. I rationalize these empirical findings with a statistical discrimination model, characterized by three sectors (manual, routine, and abstract) with different productivity sensitivity to individual skills, and two races of workers 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.

This paper contributes to our understanding of the determinants of trends in racial disparities. In future research, I plan to expand the time horizon of this analysis and study how RTBC has interacted with other major economic events, such as the fall of unionization and the Chinese trade shock, and how their concurrence has influenced the racial wage gap. Another interesting area for future work involves extending the analysis on RTBC impacts to black and white women.

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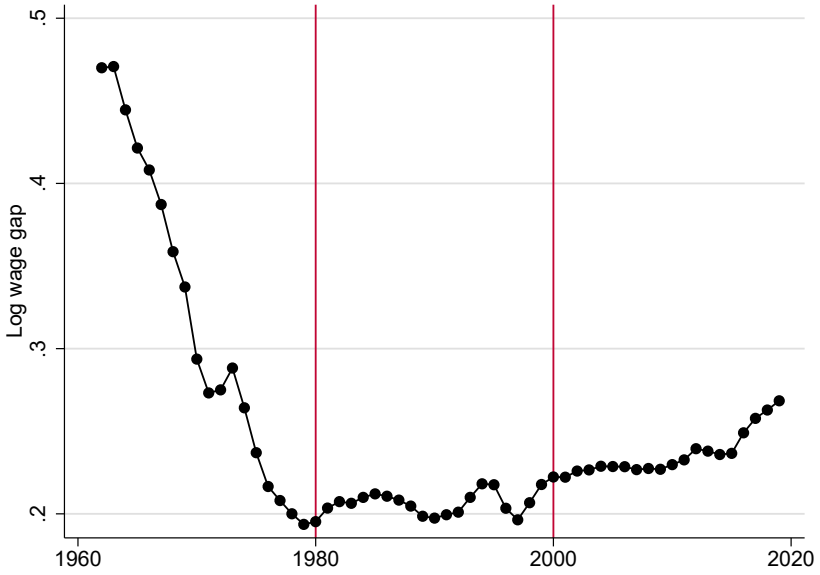
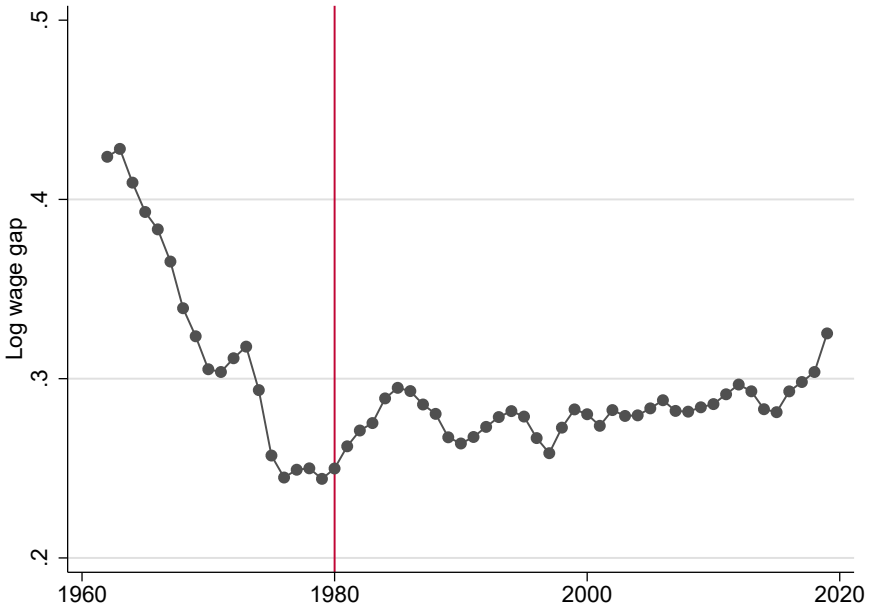
Appendix: Additional figures

Figure 1A: Raw white-black annual wage gap



Source: CPS ASEC. Sample: All 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.

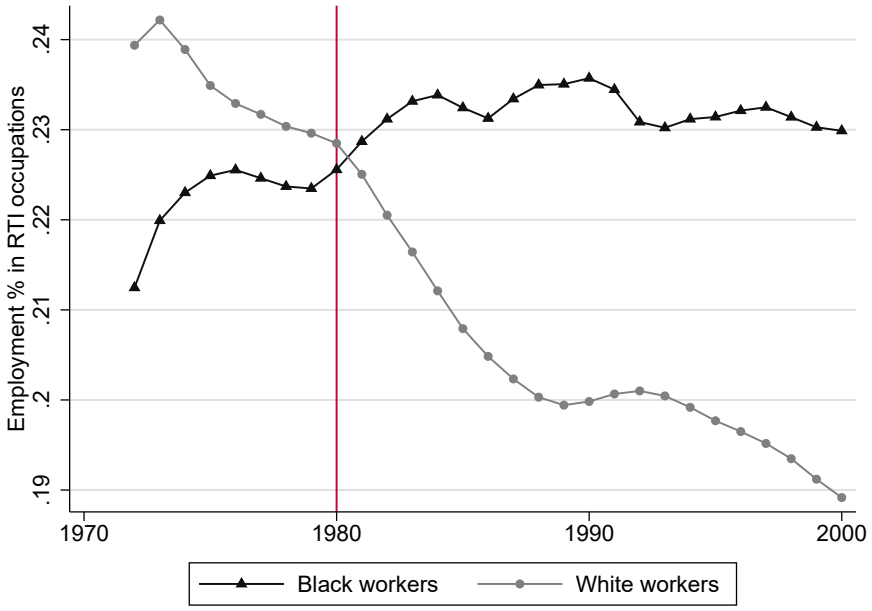
Figure 2A: Raw white-black hourly wage gap – Males



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.

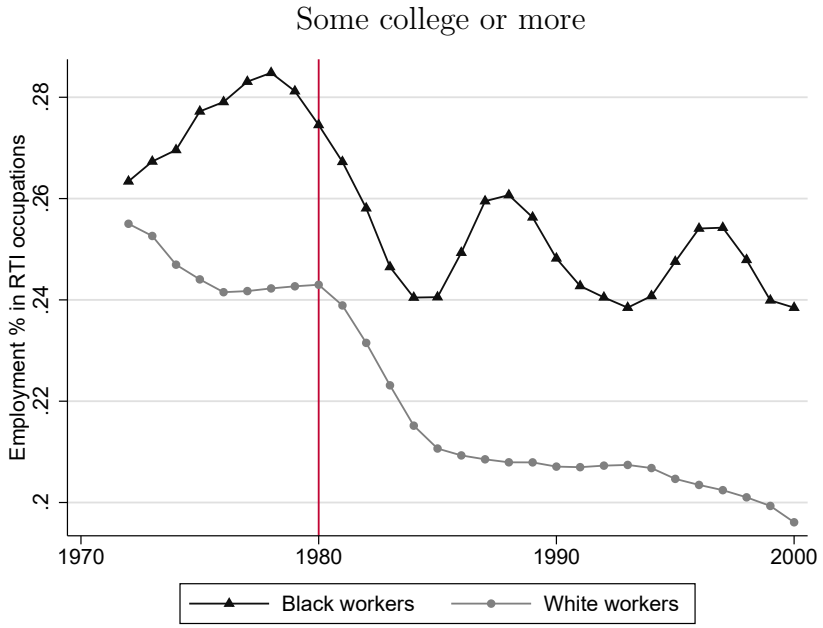
Figure 3A: Race-specific employment share in top RTI occupations

Full-time full-year workers



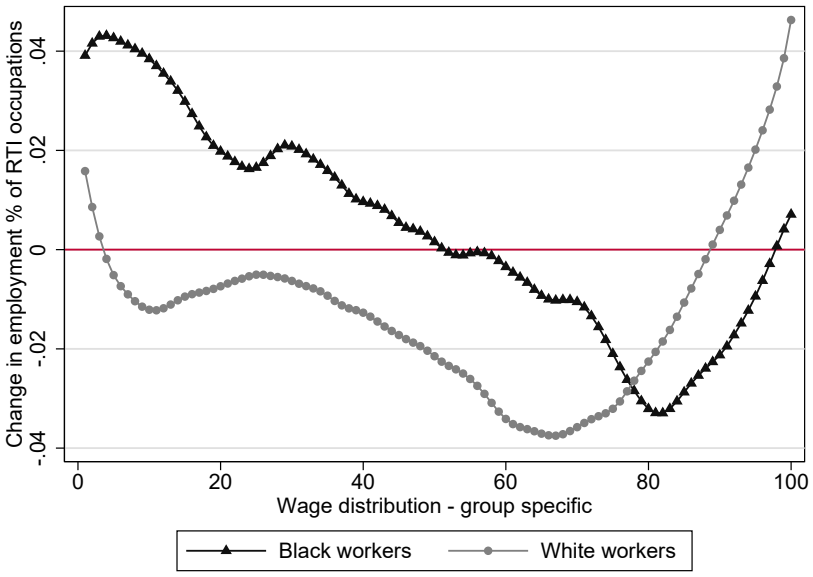
Source: CPS. Sample: All 20-64 black and white workers working at least 30 hours per week, for at least 40 weeks with non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: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

Figure 4A: Race-education employment share in top RTI occupations



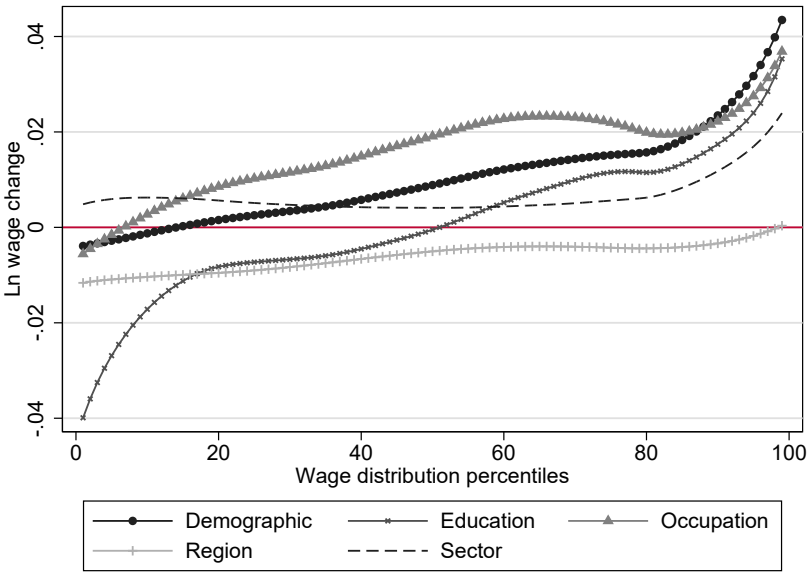
Source: CPS. Sample: All 20-64 black and white workers with some college or more, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Smoothing bandwidth: 0.2.

Figure 5A: 1980-2000 top RTI change along wage distribution



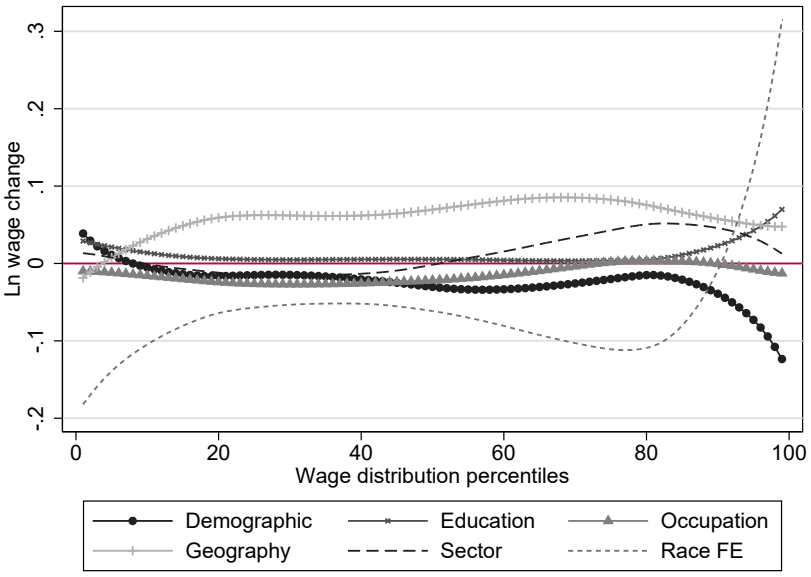
Source: IPUMS. Sample: All 20-64 black and white workers, with hourly wage $\geq$ 1, non-negative personal weights, not in group quarters, not self-employed, not unpaid family workers, not in agricultural occupations, no missing occupation or region. Wage distribution defined separately by race-gender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

Figure 6A: 1980-2000 white-black detailed *composition* change



Source: IPUMS. Sample: All 20-64 black and white 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 separately by race-gender groups. Smoothing bandwidth: 0.2.

Figure 7A: 1980-2000 white-black detailed *diff returns* change



Source: IPUMS. Sample: All 20-64 black and white 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 separately by race-gender groups. Smoothing bandwidth: 0.2.