# The Labor Hub

Job Market Paper Series No. 15

Advisor: Todd Elder

# THE RACIAL WAGE GAP AND TASK SEGREGATION

**Jeongmin Ha**

# The Racial Wage Gap and Task Segregation

Jeongmin Ha*

November 4, 2026

Click here for the most recent version.

**Abstract**

Despite substantial wage convergence between Black and White workers before 1980, the racial wage gap has widened in the past four decades. This paper examines the role of occupational task structure in this widening, distinguishing between changes in task allocation across racial groups (task sorting) and changes in the returns to tasks (task prices). I find that racial disparities in task allocation have narrowed, reducing the wage gap. However, this progress has been more than offset by a sharp rise in the price of Social tasks, which disproportionately benefited White men because Black men remain underrepresented in Social-intensive occupations. To identify the specific Social tasks behind this price effect, I use machine learning to construct a data-driven task classification. I find that the widening gap is not driven by Coordination-Social tasks, such as management and scheduling, but by Analytical-Social tasks, such as analyzing and interpreting information for others. Together, these results suggest that racially neutral changes in task prices are now the central mechanism widening the racial wage gap.

*Michigan State University. Email: jmha@msu.edu. I am grateful to Steven Haider, Stephen Woodbury, and Todd Elder for their detailed comments and valuable advice. I also thank Philip S. DeOrtentiis and participants at several conferences and seminars for helpful comments and suggestions.

# 1 Introduction

The Black–White wage gap among men narrowed substantially between 1960 and 1980. Over the following decades, convergence slowed and then reversed (Juhn et al., 1991; Bayer and Charles, 2018). By 2021, the gap among full-time male workers stood 0.051 log points above its 1980 level.

What accounts for the reversal? Studies of the racial wage gap have traditionally focused on the unequal treatment of observationally similar Black and White workers by employers (i.e., discrimination) (Altonji and Blank, 1999; Lang and Lehmann, 2012; Neumark, 2018). This paper examines a separate but complementary mechanism: differences in the occupations Black and White workers hold and the tasks those occupations entail. Following Acemoglu and Autor (2011), I treat each occupation as a bundle of tasks and ask whether differences in the tasks performed by full-time Black and White male workers have affected the evolution of the racial wage gap over the past four decades.

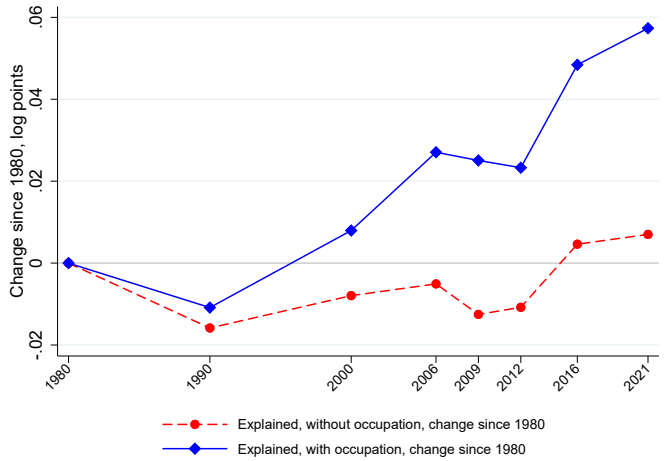
Figure 1 examines the contribution of occupation to the widening racial wage gap since 1980. It plots changes in the part of the gap explained by racial differences in observed characteristics under two specifications. In a conventional Mincerian specification that controls for schooling, age, and state of residence, the explained component rises by only 0.007 log points between 1980 and 2021. Adding occupation raises this increase to 0.057 log points, slightly more than the 0.051 widening of the gap itself.[1]

Occupation indicators, however, do not identify which activities account for these wage differences. Knowing that one worker is a cashier and another a nurse tells us that their pay differs, but not which specific tasks the market rewards. Describing occupations in terms of their tasks reduces several hundred occupation indicators to a small number of task measures, which allows the market returns to different tasks to be estimated and interpreted. Within this framework, the task-related component of the wage gap can widen through two channels. The first is task sorting: changes in racial differences in occupational task content. It can widen the gap when White men shift into occupations with more highly rewarded tasks relative to Black men. The second is task prices: changes in the wage premiums attached to tasks. This channel widens the gap when the market raises the return to tasks that White men disproportionately perform.

In this study, I estimate the contributions of these two channels to the widening racial

[1]The series in Figure 1 are the explained components of Oaxaca–Blinder decompositions (Oaxaca, 1973; Blinder, 1973). Because the explained part rises by more than the overall gap, the unexplained residual falls slightly over the period. However, occupational allocation can itself reflect discrimination, so this decline should not be interpreted as evidence of reduced discrimination (Bergmann, 1974; Darity Jr and Mason, 1998; Altonji and Blank, 1999).

Figure 1: Change in the Explained Black–White Wage Gap, With and Without Occupation




*Notes:* Change since 1980 in the explained component of an Oaxaca–Blinder decomposition of the Black–White log hourly wage gap, using White coefficients. Controls are schooling, age, age squared, and state of residence, plus occupation indicators where indicated. Sample is full-time Black and White men aged 25 to 54 from the IPUMS Censuses and ACS. See Section 2.

wage gap since 1980 and identify which tasks drive each channel. I combine U.S. decennial Census and American Community Survey (ACS) microdata from 1980 to 2021 with task intensity measures drawn from the Occupational Information Network (O*NET) and the Dictionary of Occupational Titles (DOT). I use five composite task categories highlighted in prior work: *Math*, *Routine*, *Manual*, *Social*, and *Contact* (Autor and Dorn, 2013; Deming, 2017; Hurst et al., 2024). I then use an Oaxaca–Blinder-style decomposition to quantify the contributions of task sorting and task prices to the change in the racial wage gap (Oaxaca, 1973; Blinder, 1973; Juhn et al., 1991; Firpo et al., 2018).

I first document that the racial gap in the *Social* intensity of occupations narrowed between 1980 and 2021. However, the equalizing effect of this progress was more than offset by a sharp rise in the labor market returns to *Social* tasks. Because Black men were underrepresented in *Social*-intensive occupations, the rising wage premium for these tasks disproportionately benefited White men. The *Social* task price effect alone contributes 0.062 log points to the gap, exceeding the 0.051 log point increase in the overall racial wage gap. A distributional decomposition using recentered influence functions shows that this widening price effect extends across the wage distribution.

The broad *Social* measure, however, combines distinct interpersonal activities. To identify which activities drive the result, I use an unsupervised machine learning algorithm to group a broader set of O*NET descriptors according to how they vary across occupations. Several of the resulting task clusters are strongly correlated with the *Social* composite but capture different forms of interpersonal work. The largest widening price effect is asso-

ciated with *Analytical-Social* tasks, which combine analyzing information with explaining and interpreting it to others. By contrast, a declining return to *Coordination-Social* tasks, such as management and supervision, narrows the gap. Together, these findings suggest that the market increasingly rewards analysis combined with communication rather than interpersonal work by itself.

This paper contributes to the literature on the evolution of the Black–White wage gap.[2] Prior work shows how changes in the wage structure can offset progress toward racial wage convergence (Juhn et al., 1991; Bayer and Charles, 2018). When returns to a skill rise equally for Black and White workers, the group with greater exposure to that skill benefits more. My analysis applies this insight to occupational task content, separating changes in racial differences in task allocation from changes in task prices.[3]

Recent research also connects occupational tasks to racial wage inequality. The task-based approach has been widely used to study technological change and wage inequality (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Acemoglu and Restrepo, 2022). Hurst et al. (2024) find that rising returns to *Abstract* tasks offset the effects of narrowing racial skill gaps and declining discrimination after 1980.[4] Related work documents racial differences in transitions toward cognitively intensive work (Gray et al., 2024) and examines how routine-biased technological change affects racial occupational sorting and wage gaps (Dicandia, 2021). Research also documents rising returns to combinations of cognitive and social skills (Deming, 2017; Weinberger, 2014), while Borghans et al. (2014) link the growing importance of people skills to slower racial wage convergence. I extend this literature by identifying which specific forms of interpersonal work have widened the racial wage gap through changing task prices and which have exerted an offsetting, equalizing effect.

The rising *Analytical-Social* premium may reflect the spread of information and communication technology and related changes in workplace organization (Autor et al., 2003; Bresnahan et al., 2002). Employers' subjective assessments of interpersonal skills may also limit Black men's access to some jobs intensive in interpersonal work (Moss and Tilly, 1996). Because Black men were initially underrepresented in *Analytical-Social* work, its rising premium contributed to the widening racial wage gap.

The remainder of the paper is organized as follows. Section 2 describes the data and

[2]See, for example, Smith and Welch (1989), Bound and Freeman (1992), Neal and Johnson (1996), Altonji and Blank (1999), and Lang and Lehmann (2012). For a recent review, see Bayer et al. (2025).

[3]Related studies examine the roles of the wage structure and labor demand in racial wage differences (Card and Lemieux, 1994, 1996; Reardon, 1997), as well as the effects of minimum-wage policy (Derenoncourt and Montialoux, 2021) and import competition (Batistich and Bond, 2023).

[4]Their *Abstract* measure averages two Dictionary of Occupational Titles (DOT) measures: General Educational Development in Math (GED-Math) and Direction, Control, and Planning of Activities (DCP).

outlines the construction of the task measures. Section 3 documents forty years of racial differences in occupational task content and trends in task prices. Section 4 presents the mean and distributional Oaxaca–Blinder decompositions and examines how changes in task sorting and task prices contribute to the evolution of the racial wage gap. Section 5 introduces a data-driven classification of O*NET descriptors and reassesses the decomposition. Section 6 concludes.

# 2 Data

## 2.1 Census and ACS Data

The focus of this paper is how occupational task content has shaped the wage gap between Black and White male workers since 1980. I use data from the decennial U.S. Censuses from 1980 through 2000 and the annual American Community Surveys (ACS) from 2005–2023 (Ruggles et al., 2024). To increase sample size and smooth year-to-year variation, I pool adjacent ACS waves: 2005–2007, 2008–2010, 2011–2013, 2014–2018, and 2019–2023, which I refer to as the 2006, 2009, 2012, 2016, and 2021 ACS, respectively. Together with the 1980, 1990, and 2000 Censuses, this yields a consistent set of reference years spanning 1980 to 2021. I restrict the sample to non-Hispanic White and non-Hispanic Black male workers aged 25–54 who do not live in group quarters. I exclude the self-employed and restrict to full-time workers, defined as those currently employed who work at least 30 hours per week and report at least 48 weeks of work in the prior year.

Hourly wages are computed as self-reported annual wage and salary income in the prior year divided by reported annual hours worked. All wages are in 2012 dollars. Unless noted otherwise, regressions control for age, age squared, years of education, and state of residence, and are weighted using the census and the ACS person weights adjusted for weeks and hours worked in the prior year. Table 1 reports descriptive statistics. Across years, roughly 9% of the sample is Black. Black workers have fewer years of education and lower hourly wages than White workers in every period. The education gap narrows substantially between 1980 and 2000 and then changes little through 2021. The wage gap narrows through 2000 and widens again thereafter. One goal of this paper is to understand why racial wage convergence stopped during this period.

Table 1: Descriptive Statistics by Select Years

| | 1980 | | 2000 | | 2021 | |
|---|---|---|---|---|---|---|
| | White | Black | White | Black | White | Black |
| Log hourly wage | 3.09 | 2.78 | 3.18 | 2.90 | 3.22 | 2.85 |
| | (0.60) | (0.71) | (0.62) | (0.57) | (0.70) | (0.66) |
| Years of education | 13.31 | 11.79 | 13.88 | 13.07 | 14.43 | 13.61 |
| | (3.14) | (3.26) | (2.50) | (2.30) | (2.63) | (2.62) |
| Age | 37.78 | 37.43 | 39.33 | 38.58 | 39.45 | 38.81 |
| | (8.67) | (8.55) | (8.09) | (7.95) | (8.62) | (8.56) |
| Math task intensity | 4.28 | 3.43 | 4.41 | 3.70 | 4.56 | 3.87 |
| | (1.67) | (1.38) | (1.72) | (1.53) | (1.76) | (1.63) |
| Routine task intensity | 4.05 | 4.08 | 3.90 | 3.77 | 3.62 | 3.37 |
| | (2.93) | (2.74) | (2.86) | (2.74) | (2.76) | (2.60) |
| Manual task intensity | 1.33 | 1.66 | 1.34 | 1.56 | 1.28 | 1.53 |
| | (1.40) | (1.44) | (1.40) | (1.47) | (1.35) | (1.47) |
| Social task intensity | 3.80 | 2.64 | 3.98 | 3.18 | 4.22 | 3.44 |
| | (2.42) | (2.17) | (2.44) | (2.22) | (2.37) | (2.20) |
| Contact task intensity | 4.93 | 4.13 | 5.16 | 4.81 | 5.38 | 5.19 |
| | (2.66) | (2.66) | (2.61) | (2.63) | (2.48) | (2.52) |
| N | 1,058,639 | 103,380 | 1,357,162 | 135,484 | 1,165,437 | 121,029 |
| Fraction of sample | 0.911 | 0.089 | 0.909 | 0.091 | 0.906 | 0.094 |

*Notes:* This table reports means weighted by labor supply, with standard deviations in parentheses. The sample includes full-time male workers with non-missing wage, education, age, and task measures. Task intensities are assigned at the occupation level and min-max scaled from 0 to 10. The sample is restricted to White and Black workers.

## 2.2 Task Measures

Task measures are constructed from two data sets: the US Department of Labor's Dictionary of Occupational Titles (DOT) and the Occupational Information Network (O*NET).[5] The DOT asks many different questions about the abilities, skills, knowledge, and work activities required in an occupation, and O*NET is the successor of the DOT. In this paper, I use the 1977 DOT and 1998 O*NET to measure the task demands in each occupation.

[5]I download all the task measures used in this paper from David Deming's replication package (Deming, 2017)

I use five composite task measures taken previously from the literature: *Math*, *Routine*, *Manual*, *Social*, and *Contact*. The *Routine* and *Manual* measures are taken from Autor and Dorn (2013) using the DOT data and the *Math* and *Social* measures from Deming (2017) using the O*NET data. The *Contact* measure is created by Hurst et al. (2024) using the O*NET data. Each measure is constructed as the average of the included variables, as follows:

**Math:** The *Math* measure consists of the average of three variables, 1) *mathematical reasoning ability*, 2) *mathematics knowledge*, and 3) *mathematics skill*. This measure evaluates the level of mathematical proficiency required in an occupation.

**Routine:** The *Routine* task measure is an average of two variables, 1) *Finger dexterity*, and 2) *Set limits, tolerances, or standards*. This measure assesses the extent to which a task involves meeting specific standards with precision and/or performing repetitive manual tasks.

**Manual:** The *Manual* task measure corresponds to one variable in the DOT, *Eye-hand-foot coordination*, measuring the degree to which the task demands eye, hand, and foot coordination.

**Social:** The *Social* skills measure consists of the average of four variables, 1) *Social perceptiveness*, 2) *Coordination*, 3) *Negotiation*, and 4) *Persuasion*.

**Contact:** The *Contact* measure consists of the average of two variables, 1) *Job-Required Social Interaction*, and 2) *Deal With External Customers*. This measures the extent to which the workers are required to be in contact and deal with others in order to perform the job.

Because the underlying O*NET and DOT items are reported on ordinal rating scales that differ across variables, I rescale each composite to a 0–10 range, following Deming (2017). An occupation at $\tau_k = 10$ has the highest observed intensity in task $k$; an occupation at $\tau_k = 0$ has the lowest. One point on this scale corresponds to 10 percent of the full observed range in task intensity across occupations.

Table 1 shows that Black workers are employed in occupations with systematically lower *Math*, *Social*, and *Contact* task intensities than White workers in all periods. However, the Black–White gap in these tasks narrows over time, reflecting both an increase in Black workers' exposure to *Math*-, *Social*-, and *Contact*-intensive occupations and a relative con-

vergence in task content across racial groups. In contrast, *Routine* task intensity is similar across groups but declines over time for both Black and White workers, consistent with the long-run decline of routine work (Autor and Dorn, 2013). *Manual* task intensity remains higher for Black workers throughout the sample period.

Autor and Dorn (2013) create a balanced panel of occupation codes and Deming (2017) and Hurst et al. (2024) extend their approach and create a crosswalk between O*NET and Census/ACS at the three-digit occupational code level. I use this crosswalk for my analysis, with over 300 occupations included in the sample each year.

# 3 40 Years of Task Trends

In this section, I document long-run trends in the occupational task structure and examine how these trends differ by race. Using occupation-level task measures, I first describe how Black and White workers have been differentially sorted into tasks over the past four decades. I then examine how the wage returns to these tasks have evolved over time for each group. Together, these patterns provide descriptive evidence on two channels—task sorting and task price——through which changes in task structure may contribute to the persistence of the racial wage gap.

## 3.1 Trends in Racial Task Content Disparities

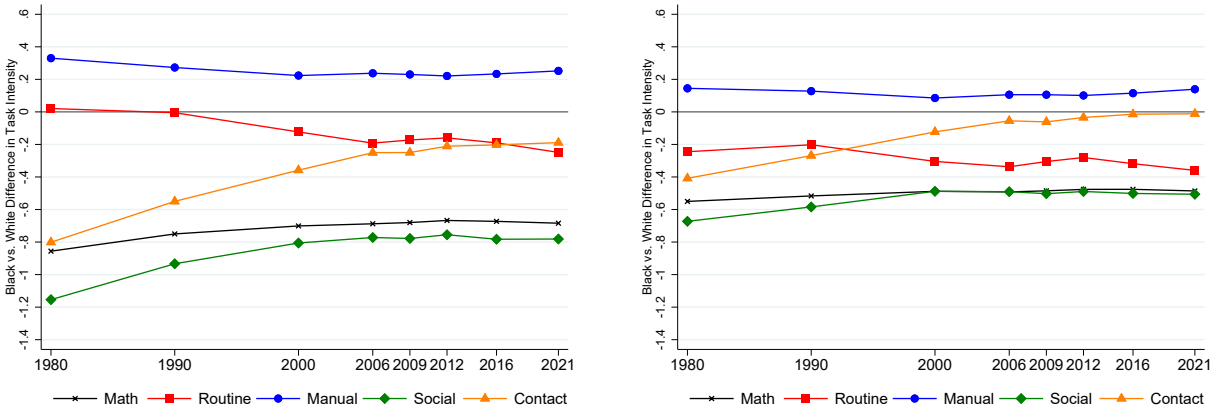
To measure time trends in racial task gaps, I estimate the following regression separately for each task in each year:

$$\tau_{o(it)k} = \alpha_t^k + \lambda_t^k Black_{it} + \Gamma_t^k X_{it} + \epsilon_{ikt}, \tag{1}$$

where $\tau_{o(it)k}$ is the intensity of task $k$ for individual $i$ employed in occupation $o$ in period $t$. The variable $Black_{it}$ is an indicator equal to one if individual $i$ in year $t$ is a Black man. $X_{it}$ includes individual-level covariates such as years of education, age, age squared, and state of residence. The coefficient of interest, $\lambda_t^k$, measures Black–White differences in the task intensity of occupations across individuals in year $t$, reflecting differences in occupational sorting along task $k$.

Figure 2 plots the estimated $\lambda_t^k$ from equation 1, which measures Black–White differences in the task intensity of the occupations. Panel (a) omits the covariates, so $\lambda_t^k$ is the raw difference in mean task intensity. Panel (b) adds the covariates, which are age, schooling, and state. In 1980, Black men worked in occupations with lower *Math*, *Social*, and *Contact* intensity. The largest gap was in *Social*. The 1980 coefficient of $-1.15$ is 0.48 standard

Figure 2: Trends in the Black–White Task Content Gap




(a) Task gap without controls

(b) Task gap with controls

*Notes:* The figure shows the estimated coefficients on a Black indicator from task-intensity regressions ($\lambda_t^k$ in equation 1), so a negative entry means Black men work in occupations that require less of the task. Panel (a) adds no controls and is the mean difference the decomposition in Section 4.1 uses. Controls are age, age squared, years of education and state fixed effects. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year. Task intensities are min-max scaled from 0 to 10. Standard errors clustered by occupation are reported in Table B.1.

deviations of *Social* intensity among male workers. In Panel B, however, adding the covariates leaves 0.67, or 0.28 standard deviations. Table B.1 in the Appendix reports the point estimates plotted in this figure along with their standard errors.

Examining the trends over time, gaps in *Routine* and *Manual* task intensity remain relatively stable, showing little evidence of convergence for these tasks. By contrast, the gap in *Math* task intensity narrows modestly over time from −0.86 to −0.68. The gaps in *Social* and especially *Contact* task intensity exhibit more pronounced convergence in task gap. By the end of the sample period, the difference in *Contact* task intensity has largely closed from −0.80 to −0.19.

A narrowing task gap can mean that Black men entered those occupations or that White men left them. Both races moved in the same direction. The share of all men holding a full-time job in a high-*Contact* occupation rose by 5.9 points among White men and by 12.0 points among Black men, and in a high-*Social* occupation by 7.8 and 11.2 points (Appendix B.2). The convergence also came from cohort replacement rather than from cohorts changing as they aged (Appendix A.1).

Despite this convergence in task content, substantial gaps remain in *Social* and *Math* tasks. Black men are still employed in occupations with lower *Social* and *Math* intensity than White men. Overall, the figure shows substantial heterogeneity in how task content

gaps have evolved, with sharp reductions in some tasks and persistent differences in others.

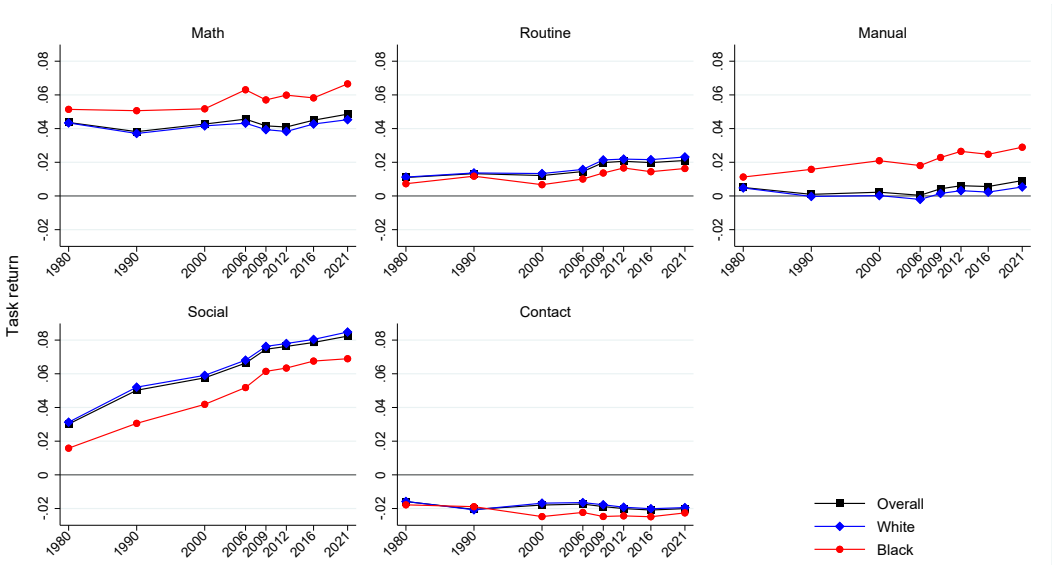
## 3.2 Trends in Task Price

I estimate task prices by regressing the log of hourly wages on the task intensity measure separately for each task in each year and each racial group. Specifically, I run

$$Wage_{iot} = \alpha_t^g + \sum_k \beta_{kt}^g \tau_{o(it)k} + \Gamma_t^g X_{it} + \epsilon_{iot}, \tag{2}$$

where $Wage_{iot}$ is the log hourly wage of individual $i$ working in occupation $o$ in year $t$. $g$ denotes White men ($g = w$), Black men ($g = b$) or overall pooled sample. $\beta_{kt}^g$'s are my coefficients of interest, measuring the Mincerian wage premium of task $k$ in year $t$ for group $g$.

Figure 3: Trends in Task Returns by Race




*Notes:* The figure shows the estimated $\beta_{kt}^g$ in equation 2. The coefficients measure the task return. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year. Task intensities are assigned at the occupation level and min-max scaled from 0 to 10.

Figure 3 plots the estimated task-return coefficients, $\beta_{kt}^g$, separately for the overall sample and by race. In levels, *Social* and *Math* tasks consistently offer the highest reward throughout the period, whereas *Contact* tasks earn the lowest returns. In terms of dynamics, however, most task prices are relatively stable over time. *Math*, *Routine*, *Manual*, and *Contact* show little systematic movement. The clear exception is *Social*, whose return rises sharply over the period. Importantly, the time pattern within *Social* task is similar for Black and White

workers, even though levels differ. This suggests that changes in *Social* task price over time are largely driven by economy-wide forces rather than race-specific shifts in task price. The full set of the estimates and their standard errors can be found in Table B.3 in the Appendix.

Taken together, Figures 2 and 3 point to offsetting forces shaping the racial wage gap. On the one hand, narrowing racial gaps in exposure to certain tasks would tend to reduce wage disparities. On the other hand, rising returns to tasks that remain unevenly allocated across racial groups may instead amplify wage inequality. These opposing forces are particularly pronounced for *Social* tasks, which combine persistent racial differences in task exposure with a sharp increase in task price. Whether changes in task sorting or task price have played the dominant role is ultimately an empirical question. To assess their relative contribution, in the next section, I decompose the task component of the wage gap into task-sorting and task-price effects.[6]

# 4 Decomposing the Racial Wage Gap

In this section, I use a Oaxaca–Blinder decomposition to quantify how occupational task structure contributes to the racial wage gap, then extend the framework of Juhn et al. (1991) to decompose the change in the task component into shifts in racial differences in task content and changes in task returns. All regressions control for age, age squared, years of education, and state fixed effects, and are weighted using labor supply-adjusted person weights provided by the censuses and the ACS.

## 4.1 Oaxaca-Blinder Decomposition

The standard Oaxaca-Blinder decomposition is:

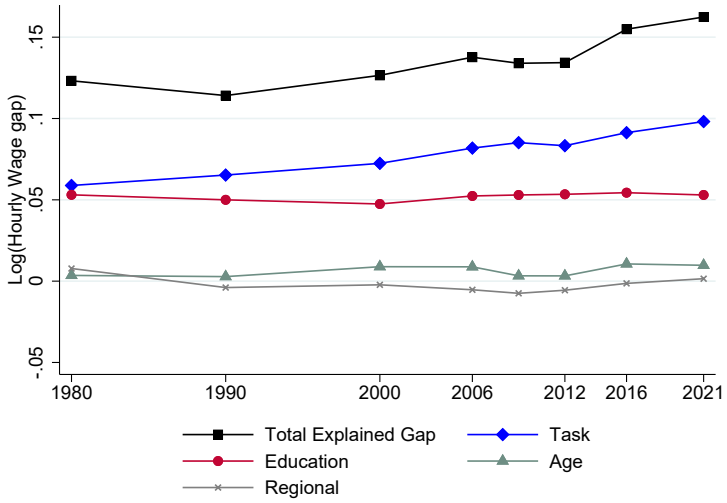
$$\bar{Y}_W - \bar{Y}_B = \bar{X}_W\beta_W - \bar{X}_B\beta_B = \underbrace{(\bar{X}_W - \bar{X}_B)\beta_W}_{\text{Explained gap}} + \underbrace{\bar{X}_B(\beta_W - \beta_B)}_{\text{Unexplained gap}}, \tag{3}$$

where $Y$ is the hourly wage and $X$ is a set of worker's characteristics, including age, years of education, and task intensities required in an occupation. The subscripts $W$ and $B$ indicate

[6]The level difference between $\beta^w_{kt}$ and $\beta^b_{kt}$ apparent in Figure 3 reflects a within-task gap in task return. That is, for a given one-unit increase in task intensity, Black and White men receive different wage premia even conditional on age, education, and state. This within-task return differential is absorbed into the unexplained component of the Oaxaca–Blinder decomposition that follows and is not the object of this paper, which focuses on the between-task sorting and price channels. The relevant observation for this paper is that the time paths of $\beta^w_{kt}$ and $\beta^b_{kt}$ move in parallel, indicating that the trends of task prices are driven by economy-wide forces rather than race-specific shifts.

White and Black workers.[7]

Figure 4: Decomposing the Wage Gap




*Notes:* The figure shows the explained component of the racial wage gap from the Oaxaca-style decomposition specified in equation 3. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year.

The Oaxaca–Blinder decomposition partitions the racial wage gap into an explained and an unexplained component. The explained component, the first term on the right-hand side of equation 3, captures the portion of the wage gap attributable to differences in observed characteristics between Black and White workers. Since the objective of this paper is to quantify the contribution of change in task structure to the racial wage gap, I focus on the task-related explained component in the analysis that follows. [8]

Figure 4 shows the evolution of the explained component of the racial wage gap, which increases from 0.123 log points in 1980 to 0.162 log points by 2021. Racial differences in education contribute about 0.05 log points throughout the period and are essentially flat. One notable pattern is that nearly the entire increase in the total explained gap is accounted for by the task component, whose contribution rose from 0.059 to 0.098 log points. Racial differences in task content did not widen in any category over the period, so the rising task

[7]Equation 3 and all decomposition in the next sections uses White coefficients as the reference wage structure, so the explained component values Black men's characteristics at the return White men receive and racial differences in returns is absorbed in the unexplained component. Appendix Table B.4 repeats the decomposition with Black coefficients and also with a pooled regression that includes a race indicator (Elder et al., 2010). None of the conclusions that follow depends on this choice.

[8]The unexplained component is larger than the explained component in every year, 0.192 log points against 0.123 in 1980 and 0.205 against 0.162 in 2021. But it moves far less over the period, so the rise in the total wage gap comes mostly from the explained side. Appendix Table B.5 reports both components and their parts with standard errors.

contribution must come from a change in how the labor market prices those tasks rather than from a change in who performs them.

## 4.2 Changes in Sorting and Price Effects

To isolate the price channel from the task-sorting channel, I now shift from decomposing the wage gap in a given year to decomposing its change between two periods. I follow the accounting framework used in Juhn et al. (1991); Blau and Kahn (2017), which separates the change in the wage gap into components driven by changes in characteristics, changes in prices, and changes in the residual. Specifically, I consider the change in the wage gap between two periods, year 1 and year 0, which can be written as:

$$\begin{aligned}\left(\bar{Y}_W^{(1)} - \bar{Y}_B^{(1)}\right) - \left(\bar{Y}_W^{(0)} - \bar{Y}_B^{(0)}\right) = &\underbrace{\left[\left(\bar{X}_W^{(1)} - \bar{X}_B^{(1)}\right)\beta_W^{(1)} - \left(\bar{X}_W^{(0)} - \bar{X}_B^{(0)}\right)\beta_W^{(0)}\right]}_{\text{Change in Explained Gap}} \\ &+ \underbrace{\left[\bar{X}_B^{(1)}\left(\beta_W^{(1)} - \beta_B^{(1)}\right) - \bar{X}_B^{(0)}\left(\beta_W^{(0)} - \beta_B^{(0)}\right)\right]}_{\text{Change in Unexplained Gap}}\end{aligned} \tag{4}$$

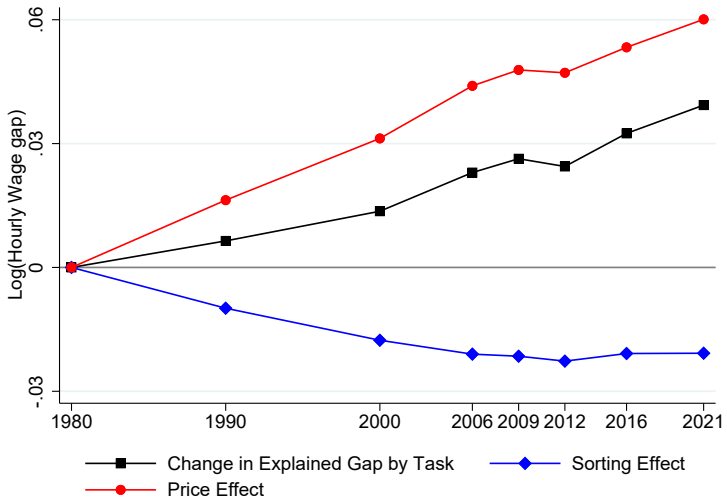
The first term on the right-hand side of equation 4, the change in the explained gap, can be mechanically decomposed further into a component reflecting changes in racial differences in observed characteristics and a component reflecting changes in coefficients:

$$\begin{aligned}\underbrace{\left[(\bar{X}_W^{(1)} - \bar{X}_B^{(1)})\beta_W^{(1)} - (\bar{X}_W^{(0)} - \bar{X}_B^{(0)})\beta_W^{(0)}\right]}_{\text{Change in Explained Gap}} = &\underbrace{\left[(\bar{X}_W^{(1)} - \bar{X}_B^{(1)}) - (\bar{X}_W^{(0)} - \bar{X}_B^{(0)})\right]\beta_W^{(1)}}_{\text{Effect of Changing Means}} \\ &+ \underbrace{\left[(\beta_W^{(1)} - \beta_W^{(0)})(\bar{X}_W^{(0)} - \bar{X}_B^{(0)})\right]}_{\text{Effect of Changing Coefficients}}\end{aligned} \tag{5}$$

In the context of this paper, the former captures changes in the racial wage gap driven by change in task sorting, which I call task sorting effect. The latter captures changes in the gap driven by change in task prices, which I call task price effect. This decomposition has a natural counterfactual interpretation. The task sorting effect captures the portion of the change in the racial wage gap that would have been eliminated if racial differences in task content had remained at their year-0 levels. Conversely, the task price effect measures how much of the change in the racial wage gap would have been removed if task prices had

remained constant over time.[9]

Figure 5: Decomposition: Sorting and Price Effect (Base year = 1980)




*Notes:* The figure shows the estimated results from the detailed Oaxaca-style decomposition specified in equation 5. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year.

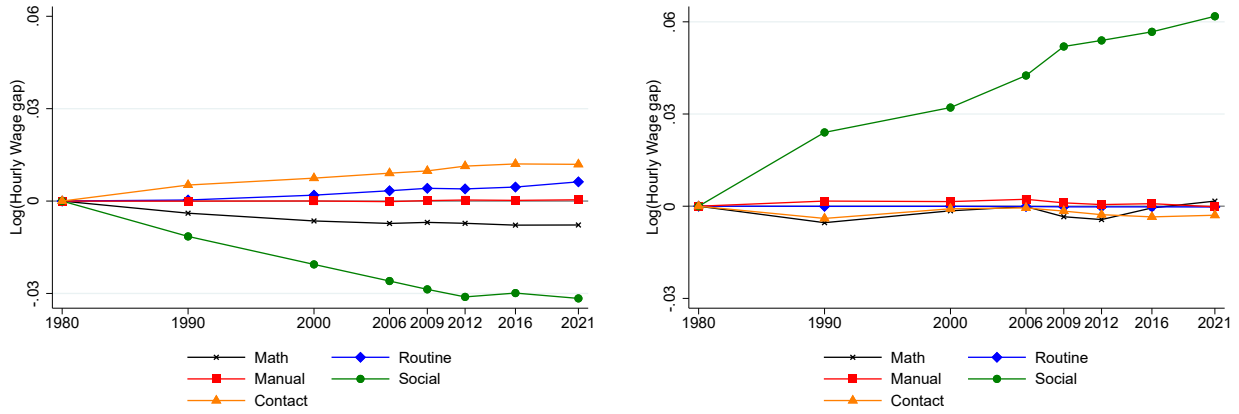
Figure 5 plots the decomposition of the change in the task component of the explained gap into task sorting and task price effects. Task sorting effects are consistently negative, implying that changes in racial differences in task content contribute to a reduction in the wage gap. It reflects convergence in the task content of occupations held by Black and White workers. For instance, holding task prices fixed at their 2021 levels, changes in task sorting reduce the wage gap by 0.009 log points in 1990 and by 0.021 log points by 2021 relative to the base year.

Task price effects dominate the equalizing effect of convergence in task content. In 1990, changes in task prices increase the wage gap by 0.016 log points, while by 2021 the contribution rises to 0.060 log points. As a result, despite the convergence in the task content gap, shifts in task prices play a central role in the expansion of the racial wage gap over time. Appendix table B.6 reports the estimated effects with standard errors from an occupation-cluster bootstrap.

To identify which tasks account for these aggregate sorting and price effects, Figure 6 reports each component separately by task category. Panel (a) shows that convergence in *Social*-task intensity accounts for most of the sorting effect, which narrows the gap. Convergence in *Math* also narrows the wage gap, but its contribution is considerably smaller.

[9]This Oaxaca–Blinder detailed decomposition used here is equivalent, for its explained component, to the identity in Gelbach (2016). An implementation using Gelbach's formulation is reported in the Appendix C and yields the same qualitative pattern.

Figure 6: Sorting and Price Effect by Task




(a) Task sorting effect

(b) Task price effect

*Notes:* The figure reports the contribution of each task category to the task sorting and task price effects in the detailed Oaxaca-style decomposition specified in equation 5. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year.

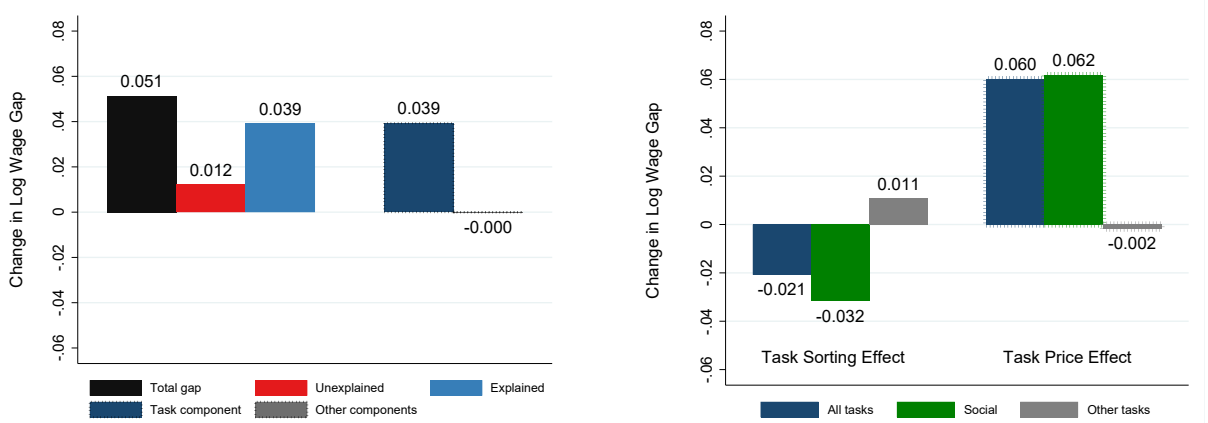
An exception is *Contact*. Because the price of *Contact* tasks is negative, substantial convergence in *Contact* task intensity modestly widens, rather than narrows, the wage gap. The remaining task categories contribute little.

Panel (b) shows that the task price effect is almost entirely a *Social* task effect. The increase in the *Social* task price accounts for nearly all of the widening generated by changes in task prices, whereas price changes for other task categories contribute little. Because Black men remained concentrated in occupations with lower *Social* task intensity, the rising price of these tasks widened the racial wage gap even as the allocation of *Social* tasks became more equal.

Taken together, these results show that while convergence in task intensities, particularly in *Social* tasks, contributes to narrow the racial wage gap, the rising price of *Social* tasks more than offsets it. Changes in task prices therefore became the dominant task-related force widening the racial wage gap after 1980.

Figure 7 summarizes the magnitude of the decomposition results. Panel (a) reports the overall change in the Black–White log wage gap over this period and partitions it into change in explained and unexplained components. The figure indicates that the total wage gap increased by 0.051 log points between 1980 and 2021. Nearly all of this increase is accounted for by changes in the explained component (0.039 log points), while the unexplained component increases only modestly (0.012 log points). Decomposing the explained change further, the task-related component contributes 0.039 log points, nearly the entire explained

Figure 7: Decomposing the Change in the Black–White Wage Gap, 1980–2021




(a) Total change in the wage gap

(b) Sorting vs. Price effect

*Notes:* Panel (a) decomposes the change in the Black–White log hourly wage gap between 1980 and 2021 into explained and unexplained components, and further splits the explained component into task-related and non-task covariates. Panel (b) decomposes the task-related component into task sorting (changes in racial differences in task intensities) and task price effects (changes in returns to tasks), and separately reports the contribution of Social tasks versus all other tasks. All bars are expressed in log points relative to 1980. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year.

increase, whereas other observed covariates contribute little. This pattern highlights changes in occupational task structure as the primary driver of the increase in the wage gap.

Panel (b) further clarifies how task-related changes translate into a wider wage gap. Changes in task sorting reduce the wage gap by 0.021 log points. However, this equalizing force is more than offset by changes in task prices, which increase the wage gap by 0.060 log points. Notably, nearly the entire task price effect is driven by *Social* tasks. Increases in the return to *Social* tasks alone account for 0.062 log points of the total task price effect, while all other tasks together contribute only -0.002 log points. Moreover, the *Social* task price effect is larger than the increase in the total wage gap (0.051 log points), implying that absent the rise in *Social* task prices, the Black–White wage gap would have declined rather than increased between 1980 and 2021.

Four robustness checks on this decomposition are reported in the appendix. First, Appendix C reports a decomposition in the style of Gelbach (2016). Second, the two-way split in equation 5 is not unique: the underlying identity contains an interaction term between changes in sorting and changes in price, and Appendix D shows the paper's conclusions are unchanged under two alternative ways of assigning the interaction term, with the price effect exceeding the sorting effect in absolute value under every assignment (Appendix Table D.1). Third, instead of using White coefficient ($\beta_W^{(t)}$) in equation 5, Table B.4 repeats

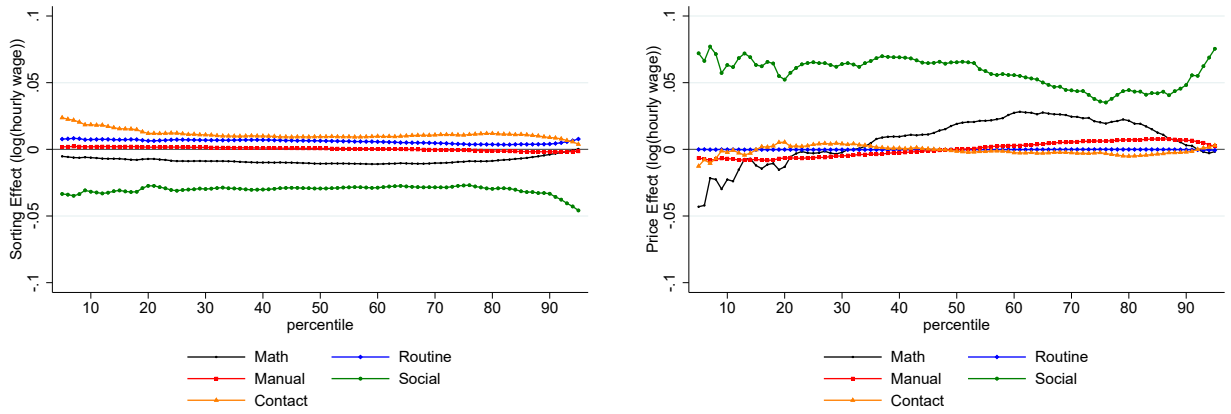
the decomposition with Black coefficients and also with a pooled regression that includes a race indicator. Fourth, task content is held at the 1998 O*NET throughout the paper. Table B.8 re-estimates the decomposition with *Math*, *Social* and *Contact* measured on the 2023 O*NET. The main conclusions remain unchanged. The price effect continues to exceed the sorting effect and most of the effects are from *Social*.

## 4.3 Beyond the Mean: OB–RIF Decomposition

The previous subsection shows that the mean Black–White wage gap increased by 0.051 log points between 1980 and 2021. However, this change was not uniform across the wage distribution. The gap narrowed at lower percentiles but widened from approximately the 40th percentile onward, as shown in the Appendix Figure A.2. This pattern suggests that the mean decomposition may mask differences in how task sorting and task prices affect workers at different points of the wage distribution.

I therefore extend the decomposition across the wage distribution using the recentered influence function (RIF) approach of Firpo et al. (2009, 2018). The OB–RIF framework replaces the wage outcome with its recentered influence function and applies the same decomposition used in the previous subsection at each unconditional wage percentile. I report estimates from the 5th through the 95th percentile because estimates at the extremes are often unstable. Appendix Section E provides the detailed method and equations.

Figure 8: OB–RIF Decomposition of Task Sorting and Price Effects by Task




(a) Sorting effect

(b) Price effect

*Notes:* The figure reports task-by-task OB–RIF decompositions of the 1980–2021 change in the explained Black–White wage gap across the wage distribution. Panel (a) reports the task sorting effect for each task, evaluated at 2021 task prices. Panel (b) reports the task price effect for each task, evaluated using racial differences in task intensities in 1980. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year. Estimates are reported from the 5th through the 95th percentile.

Figure 8 reports the sorting and price effects from the five task categories. *Social* tasks account for most of both effects throughout the distribution. Convergence in *Social* task intensity narrows the wage gap across most percentiles, whereas the rising price of *Social* tasks widens it throughout the distribution, with the largest effects at the lower and middle percentiles. The *Social* task price effect is therefore not confined to a particular part of the wage distribution and more than offsets the equalizing sorting effect. The remaining task effects are generally small, although the *Math* task price effect varies notably across percentiles: it narrows the wage gap at the lower end of the distribution but reverses direction toward the top. Taken together, these distributional results confirm the central conclusion of the mean OB-decomposition and show that it is not driven by a particular segment of the wage distribution.

# 5 Alternative Task Classification: Unbundling Social Tasks

The dominance of the *Social* task price effect raises a question the baseline cannot answer: what, empirically, is the *Social* task whose price has risen so sharply? To answer that, one has to look inside the *Social* measure. The five task measures are composites, formed by averaging O*NET and DOT descriptors chosen in advance, and chosen by a literature comparing broad kinds of work rather than pricing dimensions within them. Fixing the task categories before the analysis begins also fixes the set of tasks to which the analysis can attribute a price effect. Specifically, this construction imposes three assumptions that the data itself does not. First, it assumes that the descriptors grouped within each composite belong together as a single task, even though the market may price those components differently. Second, it assumes that descriptors outside a composite do not belong to it, even though they may capture similar underlying tasks. Third, it assumes that descriptors omitted from all five composites contribute little or nothing to wages, even though they plausibly carry independent labor-market value.

This section therefore rebuilds the task classification from the data, with no categories imposed in advance, and revisits the decomposition analysis. Throughout this section, I refer to the resulting task clusters as *ML task clusters*.

## 5.1 K-means Clustering

I build the ML task clusters using $K$-means clustering. This clustering method is an unsupervised classification algorithm that minimizes within-cluster variances. Specifically,

it partitions a set of objects into $K$ non-overlapping groups by assigning each object to the group whose centroid is nearest in the feature space. [10] The algorithm, therefore, groups together task descriptors that tend to have similar intensities across the same occupations.

The construction proceeds in three steps.

*Step 1. Preprocessing.* The input is 187 O*NET task descriptors drawn from four content domains, including skills, abilities, work activities, and work contexts.[11] Before clustering, I standardize the O*NET ratings in two steps. First, I subtract the mean rating within each occupation and divide by its within-occupation standard deviation. This removes the common tendency for some occupations to receive high ratings across many O*NET dimensions, so that the clustering reflects the relative profile of task requirements within each occupation. Without this step, descriptors could be grouped together because they all receive high ratings in generally complex occupations rather than because they show similar relative patterns across occupations. Second, I standardize each descriptor across occupations so that descriptors with greater dispersion do not receive greater weight in the distance measure used by $K$-means.

*Step 2. Clustering.* In the raw O*NET data, the unit of observation is an occupation. Since I cluster task descriptors rather than occupations, I transpose the data so that each descriptor is represented by its vector of standardized scores across occupations. Two descriptors are close in this space when they display similar profiles across occupations. I set $K = 10$, which retains enough detail to distinguish different task dimensions without producing an unnecessarily large number of clusters.[12] Each resulting cluster therefore consists of descriptors that tend to be required together across occupations. Because $K$-means is sensitive to the initial placement of cluster centroids, I run the algorithm using 10,000 random initializations and retain the solution with the lowest WCSS.

*Step 3. Aggregation.* The standardization in Step 1 is used only to determine which descriptors are assigned to the same cluster. For each occupation, I then construct an intensity score for each of the ten clusters by averaging the original O*NET ratings of the descriptors assigned to that cluster. I rescale each score to a 0–10 range. The output is a vector of ten continuous cluster-level task intensities for each occupation, directly analogous to the five pre-labeled task measures used in Section 2. [13]

[10] See Hastie et al. (2009) for a general overview.

[11] I exclude the knowledge domain because those items capture what workers need to *know* rather than what they *do*, which would conflate task content with educational prerequisites already controlled for in the wage regressions.

[12] The corresponding classification results for $K = 7$ and $K = 13$ are reported in the Appendix B.11.

[13] Principal components analysis provides a natural benchmark. At the same dimensionality, neither method consistently explains more wage variation across years. I use $K$-means because it assigns each descriptor to one cluster, making it easier to trace an estimated price effect to a specific set of tasks.

Appendix F provides the full descriptor list, the standardization formulas, the optimization procedure, and results for alternative values of $K$.

## 5.2 Cluster Characterization

Table 2 reports the ten resulting clusters, listing for each the five tasks closest to the cluster centroid and correlations with the five pre-labeled task measures.[14] Although the clustering itself is fully data-driven, I assign descriptive labels to the resulting clusters for interpretive convenience. These labels are the author's summaries of the cluster, not inputs into the algorithm. Also, for convenience, cluster numbering is based on the correlation with the pre-labeled *Social* composite: C1 has the lowest correlation, and C10 has the highest.

Table 2: Representative Tasks by Cluster (K=10)

| **Cluster** | **Representative Tasks** | **Pre-labeled Corrs** |
|---|---|---|
| C1<br>Heavy<br>Manual | Dynamic Strength<br>Bending or Twisting the Body<br>Performing General Physical Activities<br>Explosive Strength<br>Static Strength<br>Multilimb Coordination | Math: -0.40<br>Routine: 0.27<br>Social: -0.47<br>Contact: -0.45<br>Manual: 0.59 |
| C2<br>Routine -<br>Fine Motor | Using Hands on Objects, Tools, Controls<br>Finger Dexterity<br>Arm-Hand Steadiness<br>Making Repetitive Motions<br>Manual Dexterity<br>Wrist-Finger Speed | Math: 0.04<br>Routine: 0.60<br>Social: -0.39<br>Contact: -0.46<br>Manual: 0.04 |

Continued on next page

Appendix Table B.9 reports the comparison.

[14]The full lists of tasks in each cluster are shown in Table B.10 in the Appendix.

Table 2 – continued from previous page

| Cluster | Representative Tasks | Pre-labeled Corrs |
|---|---|---|
| C3<br>Repair<br>& Maint | Troubleshooting<br>Equipment Maintenance<br>Repairing<br>Operation Monitoring<br>Repairing & Maintaining Mech Equip<br>Inspecting Equipment,Structures,Material | Math: 0.19<br>Routine: 0.48<br>Social: -0.21<br>Contact: -0.46<br>Manual: 0.21 |
| C4<br>Sensory -<br>Reaction | Response Orientation<br>Peripheral Vision<br>Reaction Time<br>Far Vision<br>Sound Localization<br>Depth Perception | Math: -0.03<br>Routine: -0.13<br>Social: 0.10<br>Contact: 0.11<br>Manual: 0.49 |
| C5<br>Hazard<br>Exposure | Deal With Physically Aggressive People<br>Diseases/Infections<br>Radiation<br>Special Uniform<br>Sitting<br>Importance of Being Aware of New Events | Math: 0.19<br>Routine: -0.32<br>Social: 0.49<br>Contact: 0.56<br>Manual: 0.09 |
| C6<br>Pure<br>Analytical | Deductive Reasoning<br>Inductive Reasoning<br>Mathematical Reasoning<br>Speed of Closure<br>Number Facility<br>Category Flexibility | Math: 0.89<br>Routine: -0.01<br>Social: 0.62<br>Contact: 0.23<br>Manual: -0.17 |
| C7<br>Analytical<br>Communication | Analyzing Data or Information<br>Processing Information<br>Interpreting Meaning of Info to Others<br>Getting Information Needed to Do the Job<br>Making Decisions and Solving Problems<br>Provide Consultation & Advice to Others | Math: 0.84<br>Routine: -0.21<br>Social: 0.80<br>Contact: 0.44<br>Manual: -0.28 |

Continued on next page

Table 2 – continued from previous page

| Cluster | Representative Tasks | Pre-labeled Corrs |
|---|---|---|
| C8 Strategic Thinking | Idea Evaluation<br>Idea Generation<br>Solution Appraisal<br>Active Learning<br>Visioning<br>Implementation Planning | Math: 0.79<br>Routine: -0.19<br>Social: 0.84<br>Contact: 0.39<br>Manual: -0.18 |
| C9 Contact - Social | Social Perceptiveness<br>Job-Required Social Interaction<br>Deal With External Customers<br>Communicating With Persons Outside Org<br>Active Listening<br>Establishing & Maintaining Relationships | Math: 0.44<br>Routine: -0.56<br>Social: 0.89<br>Contact: 0.92<br>Manual: -0.20 |
| C10 Managerial Coordination | Guiding, Directing & Motivating Subord<br>Management of Personnel Resources<br>Scheduling Work and Activities<br>Coordinating Work & Activities of Others<br>Developing and Building Teams<br>Supervise, Coach, Train Others | Math: 0.63<br>Routine: -0.35<br>Social: 0.90<br>Contact: 0.55<br>Manual: -0.10 |

*Notes:* Clusters are obtained from the $K$-means classification of 1998 O*NET descriptors in Section 5.1. Representative tasks are the six descriptors closest to each cluster centroid. Pre-labeled Corrs report unweighted correlations across occupations between each cluster intensity and each of the five pre-labeled task measures in Section 2. Math, Social, and Contact are constructed from the 1998 O*NET, and Routine and Manual from the 1977 DOT. Clusters are numbered in ascending order of the correlation with Social.

Several clusters map cleanly onto familiar task categories: C1 (*Heavy Manual*) captures physically demanding work; C2 (*Routine–Fine Motor*) captures repetitive precision tasks; C3 (*Repair & Maintenance*) captures equipment-oriented troubleshooting; C4 (*Sensory–Reaction*) captures perceptual alertness and real-time responsiveness; C5 (*Hazard Exposure*) captures work in adverse physical conditions. The first four clusters align closely with the manual and routine-manual categories familiar from the task-based literature (Autor et al., 2003; Acemoglu and Autor, 2011). Cluster 5 (*Hazard Exposure*) is a partial exception. Its representative descriptors come primarily from the O*NET Work Context module and describe the environment in which work is performed rather than the activities themselves.

C6 (*Pure Analytical*) isolates analytical content that is less tied to social interaction

compared to C7–C10. This cluster captures mathematical and logical reasoning, which is the closest data-driven analogue to the *Math* composite in Section 2.

The *Social* composite does not survive as a single dimension. Four clusters are strongly correlated with the *Social* composite but capture different forms of interpersonal work. Clusters 9 and 10 capture relatively accessible forms of social interaction: customer contact and hierarchical management. Clusters 7 and 8 capture cognitively demanding interpersonal tasks that require analytical depth before the social element becomes operative. These two groups of task clusters may face different market dynamics and different patterns of racial sorting.

- **C7: Analytical Communication.** Unlike C6 (*Pure Analytical*), the analytical content in C7 is applied to communicate with or advise someone else. Representative tasks include analyzing and processing information, interpreting meaning of information to others, and providing consultation and advice to others. That is, this cluster captures a cognitive–interpersonal hybrid: the ability to synthesize complex or technical information and translate it into actionable judgments for others. This cluster is the clearest candidate for the type of work Deming (2017) describes as combining cognitive and social tasks.

- **C8: Strategic Thinking.** This cluster captures high-level creative problem-solving and ideation tasks. Representative tasks include idea evaluation, idea generation, solution appraisal, active learning, and visioning. Rather than processing existing data, C8 groups cognitive tasks that are forward-looking and decision-oriented. C8 describes the cognitive component of leadership and strategic decision-making. It is conceptually close to C7 but differs in orientation. C7 is about communicating analysis, C8 is about forming it.

- **C9: Contact–Social.** C9 captures the face-to-face, client-facing dimension of interpersonal work. Representative tasks include social perceptiveness, job-required social interaction, dealing with external customers, and communicating with persons outside the organization. This cluster most closely mirrors the pre-labeled *Contact* task.

- **C10: Managerial Coordination.** C10 groups descriptors that describe directing others within an organizational hierarchy: guiding and directing subordinates, managing personnel resources, staffing organizational units, and supervising and coordinating the work of others. It captures internally directed, vertical management, in contrast to the externally directed client work of C9.

The split between C6 and C7 is worth pausing on. Analyzing information and interpreting its meaning for others were placed in the same cluster, while analytical work performed without an audience was placed in a different one. While Deming (2017) and Weinberger (2014) identify the complementarity between cognitive and interpersonal skills by interacting two separately constructed measures, it appears in these data not as an interaction between two tasks but as a single task: a set of activities that occupations require together.

The four *Social*-related clusters separate along their cognitive content. I use *Coordination-Social* for interpersonal work directed at internal coordination, which is supervising, scheduling, staffing, and related management activity, corresponding to C10. I use *Analytical-Social* for interpersonal work that carries cognitive depth, which is analyzing information, interpreting what it means, advising others, and exercising strategic judgment, corresponding to C7 and C8.[15]

Overall, the ML clusters show that the pre-labeled *Social* composite is not a single task but a bundle of distinct interpersonal task dimensions. The next subsections revisit the long-run trends in sorting and premia across the clusters and the decomposition of the racial wage gap using this alternative classification.

## 5.3 Task Sorting and Prices Across Clusters

Figure 9 plots the 1980–2021 change in racial task gaps and in task premia for the ten clusters. The discussion focuses on the four interpersonal clusters, C7 through C10, with C6 (*Pure Analytical*) as a benchmark.

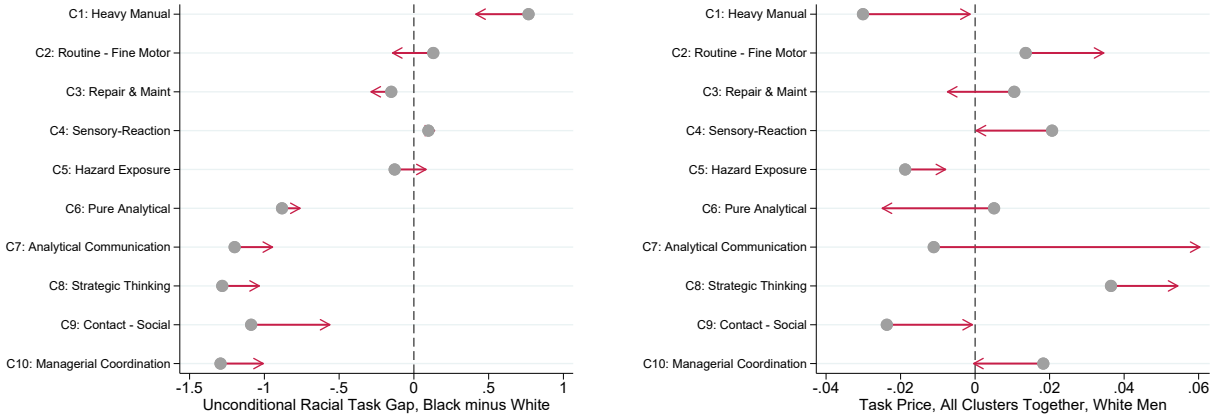
Panel A reports racial gaps in cluster intensity. In 1980, Black men were underrepresented in all four interpersonal clusters. However, the convergence in those tasks since then has been uneven. Black men made substantial progress in sorting into C9, the cluster that captures direct client contact. Progress was more limited in C7 and C8, where Black men remain markedly underrepresented in 2021. Convergence in the *Social* composite is therefore not uniform. It is clearest in people-facing interaction and weakest in the analytically demanding clusters.

Panel B shows that prices moved differently across the task clusters. The price of C7 rises strongly over the period and C8 also becomes more highly rewarded, while the price of C6 and C10 decline and the price of C9 increases. Neither analytical work without communication nor coordination without analytical depth carries rising returns, while the clusters that combine the two types of tasks do. Taken together, the figure shows that the

[15]The fourth interpersonal cluster, C9, captures external-facing customer contact. It correlates the most strongly with the pre-labeled *Contact* composite ($\rho = 0.93$), so I group it with *Contact* rather than with either social type.

baseline *Social* result is not driven by a broad increase in the return to interpersonal work. It is driven by a narrower set of analytically demanding social tasks, where Black workers remain relatively underrepresented.

Figure 9: Long-Run Trends in Task Gaps and Task Prices by ML Cluster




(a) Change in Task Content Gap

(b) Change in Task Premia

*Notes:* The ten clusters are the machine-learning task classification described in Section 5. Each row is one cluster: the grey dot marks the 1980 value and the arrow head the 2021 value. Panel (a) is the coefficient on a Black indicator from cluster-intensity regressions with no controls, so a negative value means Black men work in occupations that require less of the cluster's tasks. Panel (b) is the coefficient on cluster intensity in a log hourly wage regression estimated on White men that enters all ten clusters together, which is the price the decomposition values the racial gap at. Point estimates and standard errors are in Table B.13 and Table B.14. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year. Task intensities are min-max scaled from 0 to 10.

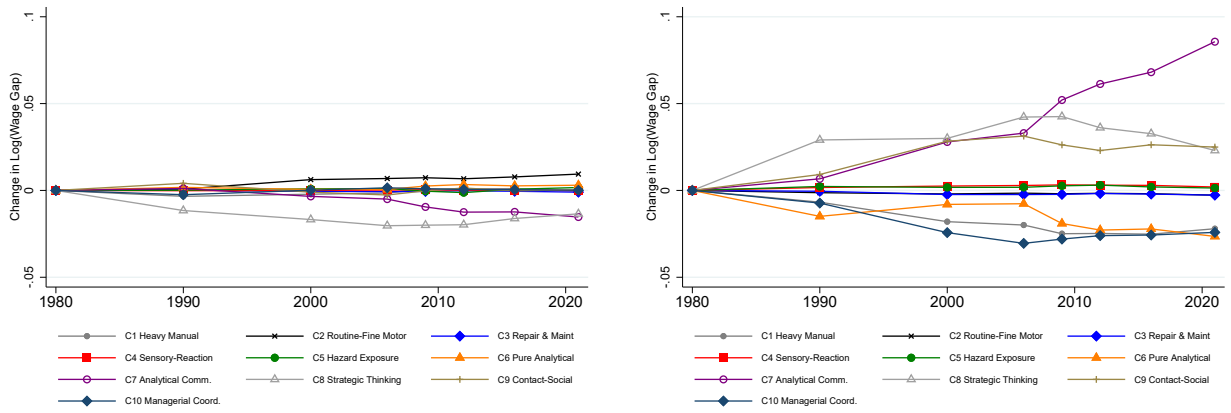
## 5.4 Mean and Distributional Decomposition with ML Clusters

I now repeat the Oaxaca–Blinder and OB–RIF decompositions of Sections 4.2 and 4.3, replacing the five pre-labeled task measures with the ten cluster intensities. The decomposition follows Equation (5), separating the change in the task-cluster component of the explained gap into a sorting effect and a price effect for each cluster.

Figure 10 reports the mean decomposition. Panel (a) shows that sorting effects remain small across all ten clusters, consistent with the baseline result that change in task allocation contributes only modestly to the change in the gap. Panel (b) reports the price effect. From 1980 to 2021, the rising price of C7 (*Analytical Communication*) widens the gap by 0.086 log points on its own, more than the 0.062 log points that all ten clusters contribute together. C8 (*Strategic Thinking*) widens it by 0.023 and C9 (*Contact–Social*) by 0.025. C10 (*Managerial Coordination*) runs in the opposite direction. Black men remain underrepresented in the

cluster, but its premium falls over the period, so the price channel narrows the gap by 0.024 log points. Appendix Table B.15 shows the detailed results for all ten clusters with standard errors.

Figure 10: Task Sorting and Price Effect: ML Clusters




(a) Sorting Effect

(b) Price Effect

*Notes:* The ten clusters are the machine-learning task classification described in Section 5. Both panels report each cluster's contribution to the change in the explained Black–White wage gap since 1980, in log points. Panel (a) is the sorting effect, the change since 1980 in the racial difference in cluster intensity valued at that year's White price. Panel (b) is the price effect, the 1980 racial difference in cluster intensity valued at the change since 1980 in the White price. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year.

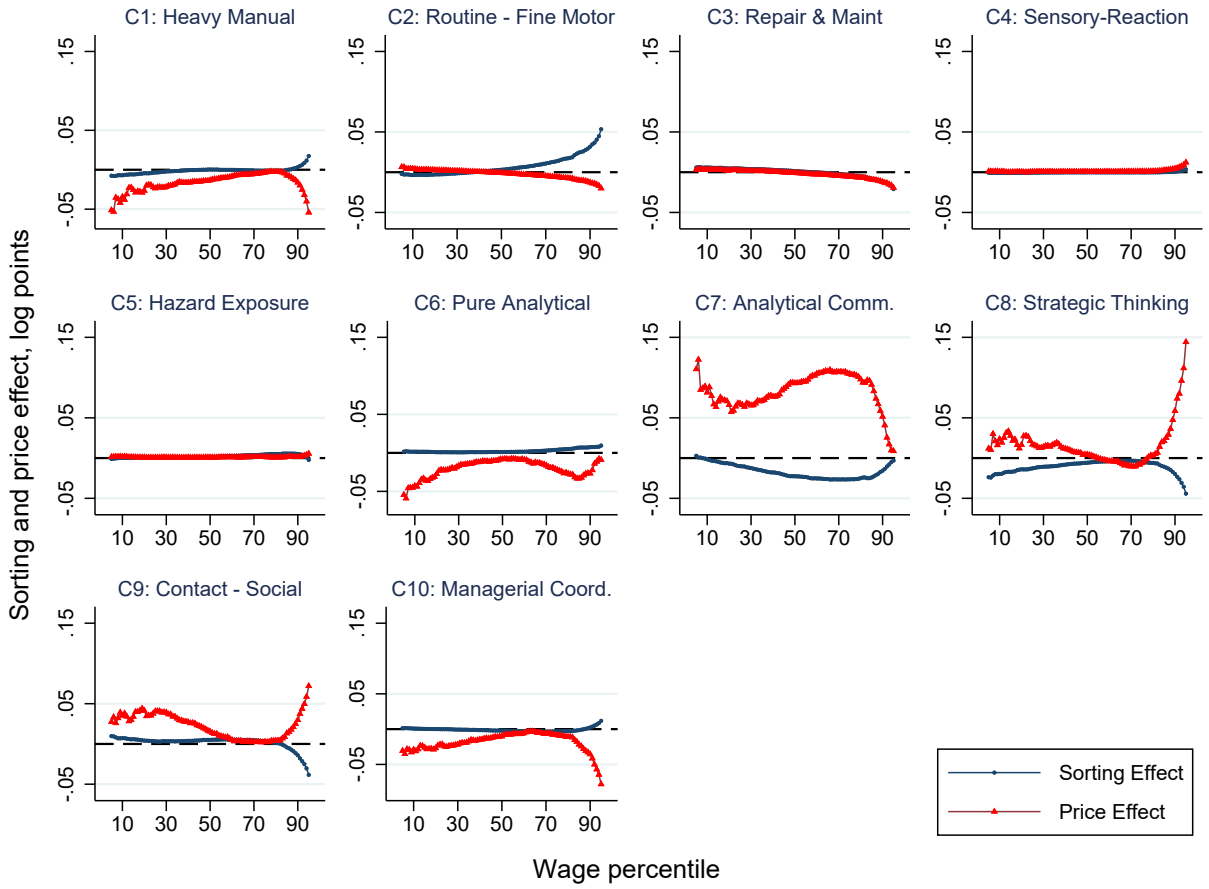
Figure 11 reports the same decomposition across the wage distribution. Three patterns stand out in the price effects. First, the C7 effect is large and positive across the distribution and largest between the 30th and 70th percentiles, so the mechanism operates broadly among middle earners rather than only at the top or bottom. Second, the C8 effect is concentrated above the 80th percentile, implying that high-earning White men benefit disproportionately from the rising price of strategic content.[16] Third, the C10 effect is modestly negative in the lower and upper percentiles.

## 5.5 Interpretation

The ML cluster decomposition confirms the baseline result. Changes in task prices account for most of the widening, while changes in task sorting partly offset it. It also shows that the price effect is concentrated in a specific type of social task. The price of *Analytical-Social* content rose, while the price of *Coordination-Social* content fell. Since Black men

[16]RIF decompositions approximate a distributional statistic linearly around each percentile and are less stable at the tails. I trim the top and bottom 5 percent of the wage distribution, and estimates above the 90th and below the 10th percentile should be read with caution.

Figure 11: OB–RIF Decomposition: ML Clusters




*Notes:* The ten clusters are the machine-learning task classification described in Section 5. Each panel is one cluster and reports its contribution to the 1980–2021 change in the explained Black–White wage gap at each percentile of the wage distribution, from the 5th to the 95th. Circles are the sorting effect and triangles the price effect, each defined as in Figure 10. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year.

were underrepresented in both in 1980, the two price changes pushed the racial wage gap in opposite directions. The increase in the C7 price widened the gap and the decline in the C10 price narrowed it. The effect from C7 was larger.

Deming (2017) and Weinberger (2014) document a growing return to jobs and workers that combine cognitive and social tasks. Their measures identify jobs and workers that score highly on separate cognitive and social indices. These measures do not show whether the two skills are used in unrelated tasks or within the same type of work. The clustering results identify a distinct task cluster in which the two are integrated. C7 (*Analytical Communication*) includes analyzing information, interpreting its meaning for others, and providing consultation and advice, while C6 (*Pure Analytical*) contains analytical work without the interpersonal component. The largest price increase is concentrated in the cluster that combines analysis and communication.

A possible explanation for the rising price of this cluster is the spread of information and communication technology and related changes in workplace organization. Computerization substitutes for tasks that can be described by explicit rules and complements nonroutine problem solving and complex communication (Autor et al., 2003). At the firm level, IT use is complementary with decentralized workplace organization and greater demand for skilled labor (Bresnahan et al., 2002). These changes may increase the value of work that combines analysis and communication, although the decomposition does not identify the source of the price change.

Prices alone do not produce a racial wage gap. A rising price widens the gap only where Black and White men hold different amounts of the task being repriced. Interpersonal skills are evaluated more subjectively than technical ones in hiring, which historically created scope for racial barriers in occupations intensive in interpersonal interaction (Moss and Tilly, 1996). Borghans et al. (2014) identify a second barrier that operates on the job rather than at hiring. They argue that racial and cultural differences interfere with the performance of people tasks, not through any difference in the ability to perform them, but because interactions across groups are harder and because customers and coworkers may be prejudiced. Both barriers leave Black men underrepresented in interpersonal work, so a rising price for that work widens the gap.

The cluster results add a distinction within interpersonal tasks. Black men were underrepresented in both types of social content in 1980, and sorting into *Contact-Social* (C9) converged substantially while progress in *Analytical-Social* (C7) was more limited. The price of C9 rose as well but contributed less to the widening than C7. For the racial wage gap, the main task price channel therefore does not come from interpersonal work as a whole. It comes primarily from Black men's continued underrepresentation in occupations intensive in

*Analytical-Social* tasks, where the price rose most. Sorting moved toward convergence, but the remaining difference in task exposure was large enough for the price increase to widen the wage gap.

# 6 Conclusion

This paper examines how changes in occupational task structure shaped the Black–White wage gap among men between 1980 and 2021. I separate changes in task sorting, which capture racial differences in the tasks workers perform, from changes in task prices, which capture changes in the wage returns attached to those tasks. I use U.S. Census and ACS data linked to occupation-level task measures from the DOT and O*NET.

Over this period, the mean wage gap increased by 0.051 log points. Racial differences in occupational task content generally narrowed. Holding task prices at their 2021 levels, changes in task sorting reduced the gap by 0.021 log points. Changes in task prices instead increased it by 0.060 log points. Nearly all of this widening price effect comes from the *Social* task measure. The increase in its price widened the gap by 0.062 log points, more than the total increase in the mean wage gap. The OB–RIF decomposition shows that this price effect operates across the wage distribution, with especially large effects in the lower and middle percentiles.

The pre-labeled *Social* measure cannot show which interpersonal activities account for this result. The data-driven classification separates *Social*-related tasks into four clusters with different price movements. The largest widening effect comes from C7 (*Analytical Communication*). The increase in its price widened the mean wage gap by 0.086 log points. C8 (*Strategic Thinking*) and C9 (*Contact–Social*) also make positive but smaller contributions, while C10 (*Managerial Coordination*) moves in the opposite direction. The price increase is therefore not shared evenly across interpersonal work. It is concentrated in *Analytical-Social* tasks.

The decomposition does not identify why the price of *Analytical-Social* tasks rose. Occupation-level task measures also cannot capture differences in task assignments between Black and White men within the same occupation. The results do show that task sorting and task prices moved the racial wage gap in opposite directions after 1980. Narrowing racial differences in occupational task content reduced the gap, but the rising price of work that combines analysis and communication more than offset that progress.

Two implications follow. First, understanding the post-1980 evolution of the racial wage gap requires tracking both the tasks workers perform and the prices attached to those tasks. Second, treating interpersonal work as a single *Social* category obscures which tasks were

repriced. The rising premium is concentrated in *Analytical-Social* work rather than interpersonal interaction in general. The findings identify *Analytical communication* as an important area for studying barriers to Black men's access to highly rewarded work.

# References


**Acemoglu, Daron and David Autor**, "Skills, tasks and technologies: Implications for employment and earnings," in "Handbook of labor economics," Vol. 4, Elsevier, 2011, pp. 1043–1171.

_ **and Pascual Restrepo**, "Tasks, Automation, and the Rise in U.S. Wage Inequality," *Econometrica*, 2022, *90* (5), 1973–2016.

**Altonji, Joseph G and Rebecca M Blank**, "Race and gender in the labor market," *Handbook of labor economics*, 1999, *3*, 3143–3259.

**Autor, David H and David Dorn**, "The growth of low-skill service jobs and the polarization of the US labor market," *American economic review*, 2013, *103* (5), 1553–1597.

**Autor, David H., Frank Levy, and Richard J. Murnane**, "The Skill Content of Recent Technological Change," *Quarterly Journal of Economics*, 2003, *118* (4), 1279–1333.

**Batistich, Mary Kate and Timothy N Bond**, "Stalled racial progress and Japanese trade in the 1970s and 1980s," *Review of Economic Studies*, 2023, *90* (6), 2792–2821.

**Bayer, Patrick and Kerwin Kofi Charles**, "Divergent paths: A new perspective on earnings differences between black and white men since 1940," *The Quarterly Journal of Economics*, 2018, *133* (3), 1459–1501.

_ , _ , **and Ellora Derenoncourt**, "Racial inequality in the labor market," in "Handbook of Labor Economics," Vol. 6, Elsevier, 2025, pp. 159–228.

**Bergmann, Barbara R**, "Occupational segregation, wages and profits when employers discriminate by race or sex," *Eastern economic journal*, 1974, *1* (2), 103–110.

**Blau, Francine D and Lawrence M Kahn**, "The gender wage gap: Extent, trends, and explanations," *Journal of economic literature*, 2017, *55* (3), 789–865.

**Blinder, Alan S**, "Wage discrimination: reduced form and structural estimates," *Journal of Human resources*, 1973, pp. 436–455.

**Borghans, Lex, Bas Ter Weel, and Bruce A Weinberg**, "People skills and the labor-market outcomes of underrepresented groups," *ILR Review*, 2014, *67* (2), 287–334.

**Bound, John and Richard B Freeman**, "What went wrong? The erosion of relative earnings and employment among young black men in the 1980s," *The Quarterly Journal of Economics*, 1992, *107* (1), 201–232.

**Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt**, "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence," *Quarterly Journal of Economics*, 2002, *117* (1), 339–376.

**Card, David and Thomas Lemieux**, "Changing wage structure and black-white wage differentials," *The American Economic Review*, 1994, *84* (2), 29–33.

**_ and _** , "Wage dispersion, returns to skill, and black-white wage differentials," *Journal of Econometrics*, 1996, *74* (2), 319–361.

**Deming, David J**, "The growing importance of social skills in the labor market," *The quarterly journal of economics*, 2017, *132* (4), 1593–1640.

**Derenoncourt, Ellora and Claire Montialoux**, "Minimum wages and racial inequality," *The Quarterly Journal of Economics*, 2021, *136* (1), 169–228.

**Dicandia, Vittoria**, "Technological change and racial disparities," 2021.

**Elder, Todd E, John H Goddeeris, and Steven J Haider**, "Unexplained gaps and Oaxaca–Blinder decompositions," *Labour Economics*, 2010, *17* (1), 284–290.

**Firpo, Sergio, Nicole M Fortin, and Thomas Lemieux**, "Unconditional quantile regressions," *Econometrica*, 2009, *77* (3), 953–973.

**Firpo, Sergio P, Nicole M Fortin, and Thomas Lemieux**, "Decomposing wage distributions using recentered influence function regressions," *Econometrics*, 2018, *6* (2), 28.

**Gelbach, Jonah B**, "When do covariates matter? And which ones, and how much?," *Journal of labor economics*, 2016, *34* (2), 509–543.

**Gray, Rowena, Siobhan M O'Keefe, Sarah Quincy, and Zachary Ward**, "Tasks and Black-white Inequality over the Long Twentieth Century," Technical Report, National Bureau of Economic Research 2024.

**Hastie, Trevor, Robert Tibshirani, Jerome Friedman et al.**, "The elements of statistical learning," 2009.

**Hurst, Erik, Yona Rubinstein, and Kazuatsu Shimizu**, "Task-based discrimination," *American Economic Review*, 2024, *114* (6), 1723–1768.

**Jr, William A Darity and Patrick L Mason**, "Evidence on discrimination in employment: Codes of color, codes of gender," *Journal of Economic Perspectives*, 1998, *12* (2), 63–90.

**Juhn, Chinhui, Kevin M Murphy, and Brooks Pierce**, "Accounting for the slowdown in black-white wage convergence," *Workers and their wages*, 1991, pp. 107–43.

**Lang, Kevin and Jee-Yeon K Lehmann**, "Racial discrimination in the labor market: Theory and empirics," *Journal of Economic Literature*, 2012, *50* (4), 959–1006.

**Moss, Philip and Chris Tilly**, ""Soft" Skills and Race: An Investigation of Black Men's Employment Problems," *Work and Occupations*, 1996, *23* (3), 252–276.

**Neal, Derek A and William R Johnson**, "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, 1996, *104* (5), 869–895.

**Neumark, David**, "Experimental research on labor market discrimination," *Journal of Economic Literature*, 2018, *56* (3), 799–866.

**Oaxaca, Ronald**, "Male-female wage differentials in urban labor markets," *International economic review*, 1973, *14* (3), 693–709.

**Reardon, Elaine**, "Demand-side changes and the relative economic progress of black men: 1940-90," *Journal of Human Resources*, 1997, pp. 69–97.

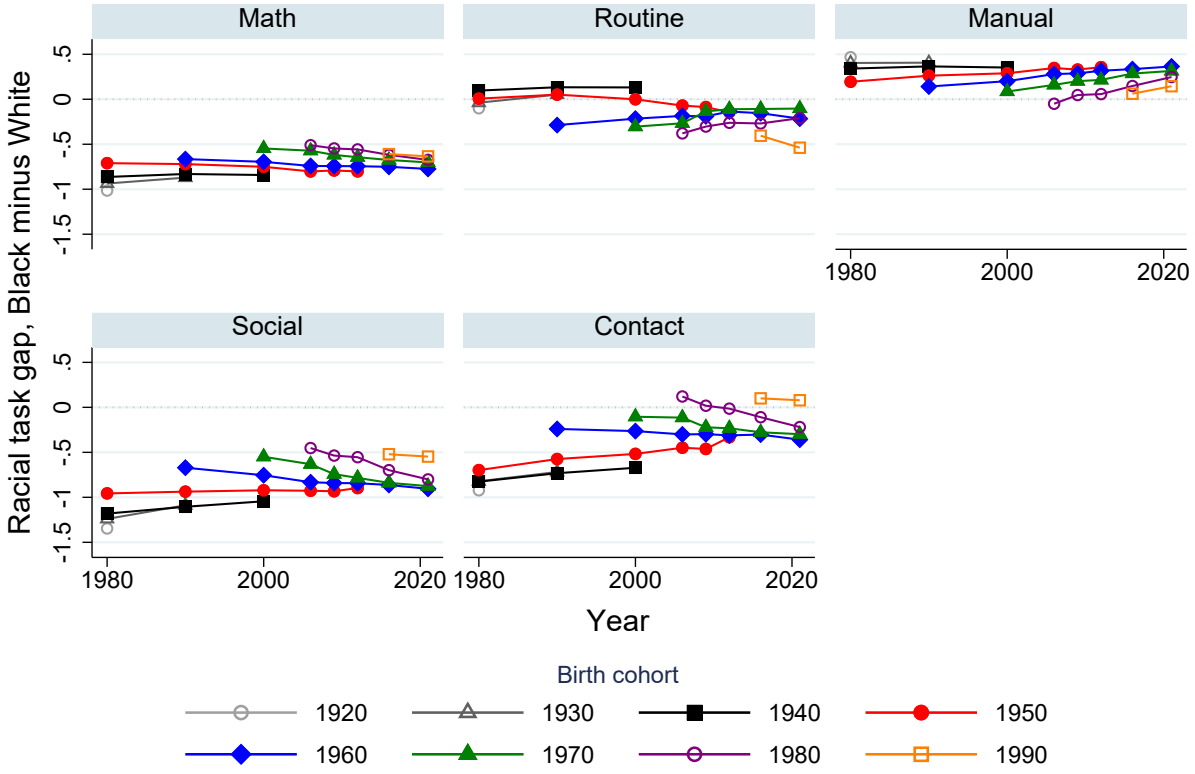
**Ruggles, Steven, Sarah Flood, Matthew Sobek, Daniel Backman, Annie Chen, Grace Cooper, Stephanie Richards, Renae Rodgers, and Megan Schouweiler**, "IPUMS USA: Version 15.0 [dataset]," *Minneapolis, MN: IPUMS*, 2024.

**Smith, James P and Finis R Welch**, "Black economic progress after Myrdal," *Journal of economic literature*, 1989, *27* (2), 519–564.

**Weinberger, Catherine J**, "The increasing complementarity between cognitive and social skills," *Review of Economics and Statistics*, 2014, *96* (5), 849–861.

# Appendix A. Appendix Figures

Figure A.1: Racial Differences in Task Content, by Birth Cohort




*Notes:* Each line follows one birth decade across the survey years in which its members are aged 25 to 54. The gap is Black minus White, matching Figure 2, so a line rising toward zero is convergence. Successive lines starting higher is between-cohort convergence; a line falling as it runs to the right is within-cohort divergence.

Figure A.2: Change in the Racial Wage Gap Across the Distribution (1980–2021)




*Notes:* The figure shows the change in the unconditional Black–White wage gap at each percentile of the wage distribution between 1980 and 2021, calculated as the difference in percentile gaps across the two years. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year. Percentile-based results are reported for the 5th to 95th percentiles.

# Appendix B. Appendix Tables

Table B.1: Black–White Differences in Task Intensity

| | Math | Routine | Manual | Social | Contact |
|---|---|---|---|---|---|
| *Panel A. Unconditional* | | | | | |
| 1980 | -0.856*** | 0.021 | 0.330*** | -1.154*** | -0.801*** |
| | ( 0.092) | ( 0.270) | ( 0.116) | ( 0.195) | ( 0.260) |
| 1990 | -0.750*** | -0.005 | 0.273*** | -0.933*** | -0.550** |
| | ( 0.078) | ( 0.238) | ( 0.102) | ( 0.166) | ( 0.226) |
| 2000 | -0.701*** | -0.123 | 0.223** | -0.806*** | -0.358* |
| | ( 0.081) | ( 0.206) | ( 0.108) | ( 0.163) | ( 0.187) |
| 2006 | -0.688*** | -0.192 | 0.237* | -0.772*** | -0.251 |
| | ( 0.076) | ( 0.220) | ( 0.125) | ( 0.161) | ( 0.191) |
| 2009 | -0.680*** | -0.173 | 0.230* | -0.778*** | -0.250 |
| | ( 0.078) | ( 0.210) | ( 0.121) | ( 0.156) | ( 0.185) |
| 2012 | -0.667*** | -0.160 | 0.221* | -0.755*** | -0.211 |
| | ( 0.077) | ( 0.208) | ( 0.124) | ( 0.156) | ( 0.186) |
| 2016 | -0.673*** | -0.190 | 0.233* | -0.783*** | -0.203 |
| | ( 0.080) | ( 0.219) | ( 0.141) | ( 0.155) | ( 0.188) |
| 2021 | -0.684*** | -0.249 | 0.252 | -0.781*** | -0.189 |
| | ( 0.090) | ( 0.236) | ( 0.165) | ( 0.159) | ( 0.195) |
| *Panel B. With controls* | | | | | |
| 1980 | -0.550*** | -0.245 | 0.145 | -0.673*** | -0.408* |

*Continued on next page*

*Table B.1 – continued from previous page*

| | Math | Routine | Manual | Social | Contact |
|---|---|---|---|---|---|
| | ( 0.067) | ( 0.217) | ( 0.091) | ( 0.159) | ( 0.217) |
| 1990 | -0.516*** | -0.202 | 0.128 | -0.584*** | -0.269 |
| | ( 0.060) | ( 0.208) | ( 0.088) | ( 0.142) | ( 0.205) |
| 2000 | -0.488*** | -0.304* | 0.085 | -0.488*** | -0.123 |
| | ( 0.060) | ( 0.181) | ( 0.091) | ( 0.137) | ( 0.168) |
| 2006 | -0.492*** | -0.337* | 0.106 | -0.490*** | -0.055 |
| | ( 0.059) | ( 0.199) | ( 0.108) | ( 0.143) | ( 0.177) |
| 2009 | -0.485*** | -0.305 | 0.106 | -0.503*** | -0.061 |
| | ( 0.060) | ( 0.193) | ( 0.106) | ( 0.141) | ( 0.174) |
| 2012 | -0.476*** | -0.280 | 0.101 | -0.489*** | -0.034 |
| | ( 0.058) | ( 0.189) | ( 0.108) | ( 0.138) | ( 0.173) |
| 2016 | -0.476*** | -0.318 | 0.115 | -0.501*** | -0.014 |
| | ( 0.058) | ( 0.198) | ( 0.122) | ( 0.137) | ( 0.174) |
| 2021 | -0.486*** | -0.360* | 0.139 | -0.506*** | -0.012 |
| | ( 0.064) | ( 0.218) | ( 0.144) | ( 0.143) | ( 0.185) |

*Notes:* Entries are coefficients on a Black indicator from task-intensity regressions, so a negative entry means Black men work in occupations that require less of the task. Panel A adds no controls and is the mean difference the decomposition in Section 4.1 uses. Controls are age, age squared, years of education and state fixed effects. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year. Task intensities are min-max scaled from 0 to 10. Standard errors in parentheses are clustered by occupation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: Share of Men Aged 25 to 54 in a Full-Time Wage Job in a High-Task Occupation

| | White | | | Black | | |
|---|---|---|---|---|---|---|
| | 1980 | 2021 | Change | 1980 | 2021 | Change |
| Math | 0.331 | 0.377 | 0.046 | 0.142 | 0.213 | 0.070 |
| | (0.0004) | (0.0005) | (0.0006) | (0.0008) | (0.0012) | (0.0015) |
| Routine | 0.329 | 0.281 | -0.048 | 0.273 | 0.208 | -0.065 |
| | (0.0004) | (0.0005) | (0.0006) | (0.0010) | (0.0012) | (0.0016) |
| Manual | 0.317 | 0.303 | -0.013 | 0.340 | 0.317 | -0.023 |
| | (0.0004) | (0.0005) | (0.0006) | (0.0011) | (0.0014) | (0.0018) |
| Social | 0.327 | 0.405 | 0.078 | 0.154 | 0.266 | 0.112 |
| | (0.0004) | (0.0005) | (0.0006) | (0.0008) | (0.0013) | (0.0016) |
| Contact | 0.317 | 0.375 | 0.059 | 0.218 | 0.338 | 0.120 |
| | (0.0004) | (0.0005) | (0.0006) | (0.0009) | (0.0014) | (0.0017) |

*Notes:* Entries are the share of all men of that race aged 25 to 54 who held a full-time wage job in an occupation that is high in the task. The denominator is every man of that race in the age range, employed or not. An occupation is high in a task if its intensity exceeds the 1980 employment-weighted median of that task, and the cut is held fixed in every later year.

This table is not drawn from the paper's main analysis sample. It uses a population extract that retains men who hold no job, and it differs from the main sample in two ways. First, observations are weighted by the person weight rather than by labor supply. Second, self-employed men are included. Other sample restrictions are the same as the main analysis: Black and White male workers, aged 25 to 54, not in group quarters. Standard errors in parentheses are linearized.

Table B.3: Task Prices

| | Math | Routine | Manual | Social | Contact |
|---|---|---|---|---|---|
| *Panel A. Conditional on the other tasks* | | | | | |
| 1980 | 0.044** | 0.011* | 0.005 | 0.030* | -0.016* |
| | ( 0.020) | ( 0.006) | ( 0.009) | ( 0.016) | ( 0.009) |
| 1990 | 0.038** | 0.013*** | 0.001 | 0.050*** | -0.021** |
| | ( 0.018) | ( 0.005) | ( 0.008) | ( 0.016) | ( 0.008) |
| 2000 | 0.043*** | 0.012** | 0.002 | 0.058*** | -0.018** |
| | ( 0.016) | ( 0.006) | ( 0.009) | ( 0.015) | ( 0.009) |
| 2006 | 0.046*** | 0.014** | 0.000 | 0.066*** | -0.017* |
| | ( 0.016) | ( 0.006) | ( 0.010) | ( 0.014) | ( 0.009) |
| 2009 | 0.042** | 0.020*** | 0.004 | 0.075*** | -0.019** |
| | ( 0.016) | ( 0.006) | ( 0.011) | ( 0.015) | ( 0.010) |
| 2012 | 0.041*** | 0.021*** | 0.006 | 0.076*** | -0.020** |
| | ( 0.016) | ( 0.007) | ( 0.011) | ( 0.014) | ( 0.009) |
| 2016 | 0.045*** | 0.020*** | 0.006 | 0.079*** | -0.021** |
| | ( 0.015) | ( 0.007) | ( 0.011) | ( 0.014) | ( 0.010) |
| 2021 | 0.049*** | 0.021*** | 0.009 | 0.082*** | -0.020* |
| | ( 0.015) | ( 0.007) | ( 0.011) | ( 0.015) | ( 0.011) |
| *Panel B. One task at a time* | | | | | |
| 1980 | 0.060*** | 0.010* | -0.016* | 0.023*** | 0.002 |
| | ( 0.010) | ( 0.006) | ( 0.009) | ( 0.005) | ( 0.006) |
| 1990 | 0.067*** | 0.006 | -0.025** | 0.035*** | 0.007 |
| | ( 0.009) | ( 0.007) | ( 0.011) | ( 0.006) | ( 0.006) |
| 2000 | 0.080*** | 0.001 | -0.028** | 0.050*** | 0.013* |
| | ( 0.011) | ( 0.007) | ( 0.012) | ( 0.007) | ( 0.007) |
| 2006 | 0.090*** | -0.001 | -0.035*** | 0.060*** | 0.016** |
| | ( 0.011) | ( 0.008) | ( 0.014) | ( 0.006) | ( 0.008) |
| 2009 | 0.091*** | 0.002 | -0.033** | 0.061*** | 0.014* |
| | ( 0.011) | ( 0.008) | ( 0.015) | ( 0.006) | ( 0.008) |
| 2012 | 0.090*** | 0.003 | -0.031** | 0.061*** | 0.013 |
| | ( 0.011) | ( 0.008) | ( 0.016) | ( 0.006) | ( 0.008) |
| 2016 | 0.096*** | 0.002 | -0.035** | 0.066*** | 0.015* |
| | ( 0.011) | ( 0.009) | ( 0.015) | ( 0.006) | ( 0.009) |
| 2021 | 0.100*** | 0.000 | -0.038** | 0.070*** | 0.018* |
| | ( 0.012) | ( 0.009) | ( 0.015) | ( 0.007) | ( 0.010) |

*Notes:* Entries are coefficients on task intensity in a log hourly wage regression that also includes a race indicator. Panel A enters all five task measures together. Panel B enters one task measure at a time. Controls are age, age squared, years of education and state fixed effects. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year. Task intensities are min-max scaled from 0 to 10. Standard errors in parentheses are clustered by occupation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: The Decomposition under Three Reference Wage Structures

| | White | Black | Pooled with race indicator |
|---|---|---|---|
| *Panel A. Levels, 1980* | | | |
| Explained, all covariates | 0.123 | 0.153 | 0.127 |
| of which tasks | 0.059 | 0.044 | 0.058 |
| Unexplained | 0.192 | 0.163 | 0.189 |
| *Panel B. Levels, 2021* | | | |
| Explained, all covariates | 0.162 | 0.151 | 0.159 |
| of which tasks | 0.098 | 0.092 | 0.097 |
| Unexplained | 0.205 | 0.216 | 0.208 |
| *Panel C. Change in the task component, 1980–2021* | | | |
| Task sorting effect | -0.0208 | -0.0166 | -0.0203 |
| Task price effect | 0.0601 | 0.0644 | 0.0596 |

*Notes:* Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year. Each column values the racial difference in characteristics at a different set of returns. The first two columns use the coefficients from a wage regression run on White men alone and on Black men alone. The third column uses the coefficients from a single regression run on both races that includes a race indicator, so that the unexplained gap is the coefficient on the indicator; Elder et al. (2010) show that pooling without an indicator overstates the explained component, and that in Black–White comparisons the indicator-based measure is close to the estimate evaluated at White coefficients. Panel C follows the sorting and price definitions in equation 5, evaluated at each column's own coefficients. All entries are in log points.

Table B.5: Oaxaca-Blinder Decomposition of the Black-White Wage Gap

| | 1980 | 1990 | 2000 | 2006 | 2009 | 2012 | 2016 | 2021 |
|---|---|---|---|---|---|---|---|---|
| Total wage gap | 0.316*** | 0.265*** | 0.273*** | 0.314*** | 0.316*** | 0.318*** | 0.351*** | 0.367*** |
| | ( 0.018) | ( 0.021) | ( 0.020) | ( 0.022) | ( 0.022) | ( 0.023) | ( 0.023) | ( 0.024) |
| Explained | 0.123*** | 0.114*** | 0.127*** | 0.138*** | 0.134*** | 0.134*** | 0.155*** | 0.162*** |
| | ( 0.014) | ( 0.014) | ( 0.015) | ( 0.017) | ( 0.017) | ( 0.017) | ( 0.018) | ( 0.021) |
| Unexplained | 0.192*** | 0.151*** | 0.147*** | 0.176*** | 0.182*** | 0.184*** | 0.196*** | 0.205*** |
| | ( 0.009) | ( 0.013) | ( 0.013) | ( 0.015) | ( 0.015) | ( 0.015) | ( 0.015) | ( 0.018) |
| Explained by tasks | 0.059*** | 0.065*** | 0.072*** | 0.082*** | 0.085*** | 0.083*** | 0.091*** | 0.098*** |
| | ( 0.010) | ( 0.009) | ( 0.011) | ( 0.012) | ( 0.012) | ( 0.012) | ( 0.013) | ( 0.015) |
| Explained by education | 0.053*** | 0.050*** | 0.047*** | 0.052*** | 0.053*** | 0.053*** | 0.054*** | 0.053*** |
| | ( 0.009) | ( 0.007) | ( 0.007) | ( 0.007) | ( 0.007) | ( 0.007) | ( 0.007) | ( 0.008) |
| Explained by age | 0.004 | 0.003 | 0.009*** | 0.009*** | 0.003 | 0.003 | 0.011*** | 0.010*** |
| | ( 0.003) | ( 0.003) | ( 0.002) | ( 0.002) | ( 0.002) | ( 0.003) | ( 0.003) | ( 0.003) |
| Explained by state | 0.008** | -0.004 | -0.002 | -0.005** | -0.007*** | -0.006** | -0.001 | 0.002 |
| | ( 0.003) | ( 0.003) | ( 0.002) | ( 0.003) | ( 0.002) | ( 0.003) | ( 0.003) | ( 0.003) |

*Notes:* The table reports two-fold Oaxaca–Blinder decompositions of log hourly wage gaps using White coefficients as the reference wage structure. The task measures are min-max scaled from 0 to 10. Standard errors in parentheses are analytic delta-method standard errors clustered by occupation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Changes in the Task Component of the Explained Wage Gap

| | 1990 | 2000 | 2006 | 2009 | 2012 | 2016 | 2021 |
|---|---|---|---|---|---|---|---|
| Sorting effect | -0.010 | -0.018 | -0.021 | -0.022 | -0.023 | -0.021 | -0.021 |
| | ( 0.003) | ( 0.008) | ( 0.009) | ( 0.010) | ( 0.010) | ( 0.011) | ( 0.014) |
| Price effect | 0.016 | 0.031 | 0.044 | 0.048 | 0.047 | 0.053 | 0.060 |
| | ( 0.004) | ( 0.008) | ( 0.009) | ( 0.009) | ( 0.008) | ( 0.009) | ( 0.010) |
| Total task effect | 0.006 | 0.014 | 0.023 | 0.026 | 0.024 | 0.032 | 0.039 |
| | ( 0.004) | ( 0.013) | ( 0.013) | ( 0.014) | ( 0.013) | ( 0.015) | ( 0.018) |

*Notes:* Each column reports the change relative to the omitted base year, 1980. The sorting effect captures changes in racial differences in task means evaluated at current White returns; the price effect captures changes in White task returns evaluated at 1980 racial task gaps. Standard errors in parentheses are based on 500 occupation-cluster bootstrap replications.

Table B.7: Sorting and Price Effects by Task and Year, Relative to 1980

| | 1990 | 2000 | 2006 | 2009 | 2012 | 2016 | 2021 |
|---|---|---|---|---|---|---|---|
| *Panel: Math* | | | | | | | |
| Sorting effect | -0.004 | -0.006 | -0.007 | -0.007 | -0.007 | -0.008 | -0.008 |
| | ( 0.002) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.005) |
| Price effect | -0.005 | -0.001 | -0.000 | -0.003 | -0.004 | -0.001 | 0.002 |
| | ( 0.005) | ( 0.008) | ( 0.010) | ( 0.011) | ( 0.012) | ( 0.013) | ( 0.015) |
| *Panel: Routine* | | | | | | | |
| Sorting effect | 0.000 | 0.002 | 0.003 | 0.004 | 0.004 | 0.005 | 0.006 |
| | ( 0.001) | ( 0.002) | ( 0.002) | ( 0.003) | ( 0.003) | ( 0.003) | ( 0.004) |
| Price effect | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | ( 0.001) | ( 0.002) | ( 0.002) | ( 0.003) | ( 0.003) | ( 0.003) | ( 0.003) |
| *Panel: Manual* | | | | | | | |
| Sorting effect | -0.000 | 0.000 | -0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.002) | ( 0.002) | ( 0.002) |
| Price effect | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 | 0.001 | -0.000 |
| | ( 0.002) | ( 0.003) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) |
| *Panel: Social* | | | | | | | |
| Sorting effect | -0.011 | -0.021 | -0.026 | -0.029 | -0.031 | -0.030 | -0.032 |
| | ( 0.005) | ( 0.008) | ( 0.009) | ( 0.010) | ( 0.010) | ( 0.010) | ( 0.012) |
| Price effect | 0.024 | 0.032 | 0.042 | 0.052 | 0.054 | 0.057 | 0.062 |
| | ( 0.009) | ( 0.016) | ( 0.016) | ( 0.017) | ( 0.017) | ( 0.019) | ( 0.020) |
| *Panel: Contact* | | | | | | | |
| Sorting effect | 0.005 | 0.007 | 0.009 | 0.010 | 0.011 | 0.012 | 0.012 |
| | ( 0.003) | ( 0.004) | ( 0.005) | ( 0.006) | ( 0.006) | ( 0.006) | ( 0.007) |
| Price effect | -0.004 | -0.001 | -0.001 | -0.002 | -0.003 | -0.003 | -0.003 |
| | ( 0.003) | ( 0.007) | ( 0.007) | ( 0.007) | ( 0.007) | ( 0.008) | ( 0.009) |

*Notes:* Each column reports the change relative to the omitted base year, 1980. Within each task panel, entries decompose the change in that task's contribution to the explained Black–White wage gap into sorting and price effects. Standard errors in parentheses are based on 500 occupation-cluster bootstrap replications.

Table B.8: The Decomposition under a Later O*NET Vintage, 1980–2021

| | (1) Baseline, O*NET 1998 | | (2) O*NET 2023 | |
|---|---|---|---|---|
| Task | Sorting | Price | Sorting | Price |
| Math | -0.0083 | 0.0015 | -0.0182 | 0.0091 |
| Routine | 0.0058 | -0.0003 | 0.0008 | -0.0000 |
| Manual | 0.0006 | -0.0002 | 0.0007 | -0.0020 |
| Social | -0.0320 | 0.0622 | -0.0201 | 0.0656 |
| Contact | 0.0114 | -0.0032 | 0.0118 | -0.0127 |
| All tasks | -0.0225 | 0.0599 | -0.0250 | 0.0600 |
| Total task effect | 0.0374 | | 0.0350 | |

*Notes:* Each entry is a contribution to the 1980–2021 change in the Black–White log hourly wage gap, from the decomposition in equation 5. Column (1) uses the five task measures of the main text. Column (2) replaces *Math*, *Social* and *Contact* with the same composites measured on the 2023 O*NET, built from the same descriptor lists and the same occupation crosswalk. *Routine* and *Manual* come from the 1977 DOT, which has no later edition, so they are held at the DOT measure in both columns. Both columns use the occupations that appear in both vintages, and column (1) therefore differs from the main-text estimate only through that restriction. Task content is assigned at the occupation level and does not vary over time within a column, so the exercise asks whether the ranking of occupations by task content has moved enough to change the baseline results, not whether workers in 1980 faced 2023 job descriptions. Sorting effect is the change in the racial task gap valued at the 2021 White price, and price effect is the 1980 racial task gap valued at the change in the White price. Prices come from a log hourly wage regression on White men that enters all five tasks together, with age, age squared, years of education and state fixed effects. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year.

Table B.9: Wage variation explained by alternative summaries of the task space

| | | 5 dimensions | | | 10 dimensions | | 20 or more | |
|---|---|---|---|---|---|---|---|---|
| | (1) Baseline | (2) Pre-labeled tasks | (3) PCA 5 comp. | (4) $K$-means $K = 5$ | (5) PCA 10 comp. | (6) $K$-means $K = 10$ | (7) PCA 20 comp. | (8) All 187 descriptors |
| *Panel: 1980, with controls (age, age squared, education, state fixed effects)* | | | | | | | | |
| $R^2$ | 0.1403 | 0.1653 | 0.1666 | 0.1643 | 0.1791 | 0.1692 | 0.1863 | 0.2164 |
| Adjusted $R^2$ | 0.1403 | 0.1652 | 0.1665 | 0.1643 | 0.1791 | 0.1691 | 0.1862 | 0.2162 |
| $\beta_{\text{Black}}$ | -0.2287 | -0.1889 | -0.1846 | -0.1908 | -0.1782 | -0.1910 | -0.1724 | -0.1605 |
| | (0.0126) | (0.0098) | (0.0092) | (0.0097) | (0.0083) | (0.0092) | (0.0065) | (0.0063) |
| Observations | 1,162,019 | | | | | | | |
| *Panel: 2021, with controls (age, age squared, education, state fixed effects)* | | | | | | | | |
| $R^2$ | 0.2495 | 0.3202 | 0.3144 | 0.3220 | 0.3197 | 0.3250 | 0.3406 | 0.3760 |
| Adjusted $R^2$ | 0.2495 | 0.3202 | 0.3144 | 0.3220 | 0.3197 | 0.3250 | 0.3405 | 0.3759 |
| $\beta_{\text{Black}}$ | -0.2790 | -0.2075 | -0.2096 | -0.2125 | -0.2072 | -0.2126 | -0.1900 | -0.1659 |
| | (0.0164) | (0.0151) | (0.0163) | (0.0156) | (0.0149) | (0.0151) | (0.0126) | (0.0114) |
| Observations | 1,286,466 | | | | | | | |

*Notes:* Each column adds a different summary of the same 187 O*NET 1998 descriptors to a log hourly wage regression that always contains a Black indicator together with the controls named in the panel heading. Columns (3) and (5) use the first 5 and 10 principal components of the standardized descriptors; columns (4) and (6) use the corresponding $K$-means cluster scores. Columns (3) versus (4), and (5) versus (6), are therefore like-for-like comparisons at fixed dimensionality. Column (2) uses the five pre-labeled task measures, and column (8) uses all 187 descriptors with no reduction. Reported wage-gap coefficients are the coefficients on the Black indicator from the same regressions. Sample: Black and White men aged 25–54 working full time last year, weighted by labor supply, with standard errors clustered by occupation. The estimation sample is identical across every column within a panel.

Table B.10: Task List by Cluster (Sorted by Distance to Centroid)

| Cluster | Task Description | Distance |
|---|---|---|
| 1 | Dynamic Strength - Level | 16.37 |
| 1 | Bending or Twisting the Body - Frequency | 17.33 |
| 1 | Performing General Physical Activities - Level | 17.39 |
| 1 | Explosive Strength - Level | 17.43 |
| 1 | Static Strength - Level | 17.48 |
| 1 | Multilimb Coordination - Level | 18.04 |
| 1 | Extent Flexibility - Level | 18.09 |
| 1 | Dynamic Flexibility - Level | 18.62 |
| 1 | Trunk Strength - Level | 19.07 |
| 1 | Stamina - Level | 19.12 |
| 1 | Very Hot - Frequency | 19.73 |
| 1 | Speed of Limb Movement - Level | 19.87 |
| 1 | Kneeling, Crouching or Crawling - Frequency | 20.01 |
| 1 | Gross Body Coordination - Level | 20.39 |
| 1 | Cramped Work Space, Awkward Positions - Frequency | 20.93 |
| 1 | Contaminants - Frequency | 21.01 |
| 1 | Gross Body Equilibrium - Level | 21.14 |
| 1 | Handling and Moving Objects - Level | 21.15 |
| 1 | Hazardous Situations - Frequency | 21.16 |
| 1 | Sounds, Noise Levels Are Distracting, etc - Frequency | 21.26 |
| 1 | Extremely Bright or Inadequate Lighting - Frequency | 21.49 |
| 1 | Common Protective or Safety Attire - Frequency | 21.58 |
| 1 | Keeping or Regaining Balance - Frequency | 21.67 |
| 1 | Standing - Frequency | 22.23 |
| 1 | Hazardous Equipment - Frequency | 22.39 |
| 1 | Climbing Ladders, Scaffolds, Poles, etc - Frequency | 24.44 |
| 1 | Hazardous Conditions - Frequency | 26.99 |
| 1 | Outdoors - Frequency | 27.64 |
| 1 | Whole Body Vibration - Frequency | 28.04 |
| 1 | Walking or Running - Frequency | 28.76 |
| 1 | High Places - Frequency | 29.54 |
| 1 | Specialized Protective or Safety Attire - Frequency | 32.06 |
| 2 | Using Hands on Objects, Tools, Controls - Frequency | 17.74 |
| 2 | Finger Dexterity - Level | 18.72 |
| 2 | Arm-Hand Steadiness - Level | 18.81 |
| 2 | Making Repetitive Motions - Frequency | 19.03 |
| 2 | Manual Dexterity - Level | 19.08 |
| 2 | Wrist-Finger Speed - Level | 19.79 |
| 2 | Importance of Repeating Same Tasks - Importance | 22.49 |
| 2 | Near Vision - Level | 24.22 |
| 2 | Pace Determined by Speed of Equipment - Importance | 24.54 |
| 2 | Importance of Being Sure All Is Done - Importance | 25.00 |
| 2 | Importance of Being Exact or Accurate - Importance | 25.10 |
| 2 | Degree of Automation - Automation | 25.63 |
| 2 | Visual Color Discrimination - Level | 26.55 |
| 2 | Visualization - Level | 27.22 |
| 2 | Information Ordering - Level | 27.45 |
| 2 | Indoors - Frequency | 28.07 |
| 2 | Perceptual Speed - Level | 29.99 |
| 3 | Troubleshooting - Level | 18.09 |

Continued on next page

Table B.10 – continued from previous page

| Cluster | Task Description | Distance |
|---|---|---|
| 3 | Equipment Maintenance - Level | 18.09 |
| 3 | Repairing - Level | 19.82 |
| 3 | Operation Monitoring - Level | 19.90 |
| 3 | Repairing & Maintaining Mech Equip - Level | 20.25 |
| 3 | Inspecting Equipment,Structures,Material - Level | 20.53 |
| 3 | Installation - Level | 21.44 |
| 3 | Controlling Machines and Processes - Level | 21.82 |
| 3 | Operation and Control - Level | 21.90 |
| 3 | Control Precision - Level | 22.03 |
| 3 | Testing - Level | 23.03 |
| 3 | Equipment Selection - Level | 24.09 |
| 3 | Product Inspection - Level | 25.99 |
| 3 | Repairing & Maintaining Elect Equip - Level | 27.50 |
| 3 | Technology Design - Level | 27.74 |
| 3 | Monitor Processes, Material,Surroundings - Level | 30.60 |
| 3 | Consequence of Error - How Serious | 30.96 |
| 3 | Drafting & Specifying Tech Devices,etc - Level | 34.23 |
| 4 | Response Orientation - Level | 19.31 |
| 4 | Peripheral Vision - Level | 19.42 |
| 4 | Reaction Time - Level | 20.32 |
| 4 | Far Vision - Level | 22.40 |
| 4 | Sound Localization - Level | 22.98 |
| 4 | Depth Perception - Level | 23.04 |
| 4 | Rate Control - Level | 23.06 |
| 4 | Spatial Orientation - Level | 23.40 |
| 4 | Glare Sensitivity - Level | 23.80 |
| 4 | Night Vision - Level | 24.29 |
| 4 | Auditory Attention - Level | 26.07 |
| 4 | Time Sharing - Level | 26.95 |
| 4 | Hearing Sensitivity - Level | 27.35 |
| 4 | Selective Attention - Level | 27.70 |
| 4 | Operating Vehicles or Equipment - Level | 28.96 |
| 4 | Responsible for Others' Health & Safety - Responsible for Health & Safety | 30.51 |
| 4 | Frustrating Circumstances - Extent of Frustration | 32.33 |
| 5 | Deal With Physically Aggressive People - Frequency | 23.15 |
| 5 | Diseases/Infections - Frequency | 24.82 |
| 5 | Radiation - Frequency | 25.77 |
| 5 | Special Uniform - Frequency | 28.44 |
| 5 | Sitting - Frequency | 29.27 |
| 5 | Importance of Being Aware of New Events - Importance | 29.82 |
| 6 | Deductive Reasoning - Level | 23.52 |
| 6 | Inductive Reasoning - Level | 23.56 |
| 6 | Mathematical Reasoning - Level | 23.82 |
| 6 | Speed of Closure - Level | 25.00 |
| 6 | Number Facility - Level | 25.45 |
| 6 | Category Flexibility - Level | 26.55 |
| 6 | Flexibility of Closure - Level | 28.24 |
| 6 | Science - Level | 28.85 |
| 6 | Mathematics - Level | 29.65 |
| 6 | Problem Sensitivity - Level | 31.24 |

Continued on next page

Table B.10 – continued from previous page

| Cluster | Task Description | Distance |
|---|---|---|
| 6 | Memorization - Level | 31.95 |
| 7 | Analyzing Data or Information - Level | 17.30 |
| 7 | Processing Information - Level | 17.33 |
| 7 | Interpreting Meaning of Info to Others - Level | 18.49 |
| 7 | Getting Information Needed to Do the Job - Level | 19.07 |
| 7 | Making Decisions and Solving Problems - Level | 19.17 |
| 7 | Provide Consultation & Advice to Others - Level | 20.06 |
| 7 | Written Expression - Level | 20.63 |
| 7 | Writing - Level | 21.00 |
| 7 | Documenting/Recording Information - Level | 21.46 |
| 7 | Information Gathering - Level | 21.62 |
| 7 | Developing Objectives and Strategies - Level | 21.69 |
| 7 | Reading Comprehension - Level | 22.20 |
| 7 | Interacting With Computers - Level | 22.67 |
| 7 | Identifying Objects, Actions, and Events - Level | 22.73 |
| 7 | Communicating With Other Workers - Level | 23.28 |
| 7 | Updating & Using Job-Relevant Knowledge - Level | 23.75 |
| 7 | Organizing, Planning, and Prioritizing - Level | 24.00 |
| 7 | Judging Qualities of Things, Srvc, People - Level | 24.13 |
| 7 | Information Organization - Level | 24.34 |
| 7 | Performing Administrative Activities - Level | 25.20 |
| 7 | Written Comprehension - Level | 25.71 |
| 7 | Evaluating Info Against Standards - Level | 26.24 |
| 7 | Thinking Creatively - Level | 28.96 |
| 7 | Programming - Level | 29.09 |
| 7 | Estimating Needed Characteristics - Level | 30.81 |
| 7 | Implementing Ideas, Programs, etc - Level | 31.12 |
| 8 | Idea Evaluation - Level | 15.14 |
| 8 | Idea Generation - Level | 16.71 |
| 8 | Solution Appraisal - Level | 17.07 |
| 8 | Active Learning - Level | 17.24 |
| 8 | Visioning - Level | 17.92 |
| 8 | Implementation Planning - Level | 18.07 |
| 8 | Critical Thinking - Level | 18.79 |
| 8 | Identifying Downstream Consequences - Level | 19.22 |
| 8 | Identification of Key Causes - Level | 19.26 |
| 8 | Systems Evaluation - Level | 19.97 |
| 8 | Judgment and Decision Making - Level | 20.09 |
| 8 | Synthesis/Reorganization - Level | 20.26 |
| 8 | Systems Perception - Level | 23.01 |
| 8 | Learning Strategies - Level | 24.10 |
| 8 | Monitoring - Level | 25.90 |
| 8 | Fluency of Ideas - Level | 26.57 |
| 8 | Problem Identification - Level | 27.89 |
| 8 | Operations Analysis - Level | 28.27 |
| 8 | Originality - Level | 29.19 |
| 9 | Social Perceptiveness - Level | 16.77 |
| 9 | Job-Required Social Interaction - Amount of Contact | 17.56 |
| 9 | Deal With External Customers - Importance | 18.60 |
| 9 | Communicating With Persons Outside Org - Level | 18.92 |
| 9 | Active Listening - Level | 19.03 |

Continued on next page

Table B.10 – continued from previous page

| Cluster | Task Description | Distance |
|---|---|---|
| 9 | Establishing & Maintaining Relationships - Level | 19.05 |
| 9 | Speaking - Level | 19.22 |
| 9 | Performing for/Working With Public - Level | 19.92 |
| 9 | Service Orientation - Level | 21.08 |
| 9 | Deal With Unpleasant/Angry People - Frequency | 21.22 |
| 9 | Persuade Someone to a Course of Action - Importance | 21.30 |
| 9 | Oral Expression - Level | 21.67 |
| 9 | Persuasion - Level | 22.89 |
| 9 | Speech Clarity - Level | 22.96 |
| 9 | Frequency in Conflict Situations - Frequency | 23.75 |
| 9 | Selling or Influencing Others - Level | 24.02 |
| 9 | Oral Comprehension - Level | 24.99 |
| 9 | Provide a Service to Others - Importance | 25.53 |
| 9 | Speech Recognition - Level | 25.55 |
| 9 | Assisting and Caring for Others - Level | 25.64 |
| 9 | Objective or Subjective Information - Objective vs Subjective | 28.65 |
| 10 | Guiding, Directing & Motivating Subord - Level | 16.73 |
| 10 | Management of Personnel Resources - Level | 16.79 |
| 10 | Scheduling Work and Activities - Level | 18.60 |
| 10 | Coordinating Work & Activities of Others - Level | 18.86 |
| 10 | Developing and Building Teams - Level | 19.15 |
| 10 | Supervise, Coach, Train Others - Importance | 19.19 |
| 10 | Coordinate or Lead Others - Importance | 21.69 |
| 10 | Coaching and Developing Others - Level | 21.81 |
| 10 | Time Management - Level | 21.96 |
| 10 | Staffing Organizational Units - Level | 22.36 |
| 10 | Management of Financial Resources - Level | 23.17 |
| 10 | Negotiation - Level | 23.60 |
| 10 | Responsibility for Outcomes and Results - Responsibility | 23.92 |
| 10 | Resolving Conflict,Negotiating w/ Others - Level | 24.05 |
| 10 | Instructing - Level | 24.18 |
| 10 | Coordination - Level | 25.00 |
| 10 | Teaching Others - Level | 25.16 |
| 10 | Monitoring and Controlling Resources - Level | 25.35 |
| 10 | Management of Material Resources - Level | 27.74 |
| 10 | Take a Position Opposed to Others - Importance | 30.17 |

Table B.11: Sorting and Price Effects under Alternative Numbers of Clusters, 1980–2021

| | $K = 7$ | $K = 10$ | $K = 13$ |
|---|---|---|---|
| *Panel A. All clusters* | | | |
| Task sorting effect | -0.0202 | -0.0157 | -0.0207 |
| Task price effect | 0.0629 | 0.0589 | 0.0646 |
| Total task effect | 0.0427 | 0.0432 | 0.0439 |
| *Panel B. Clusters matched to Analytical Communication* | | | |
| Closest | Cluster-4 | Cluster-7 | Cluster-10 |
| Price effect | 0.0349 | 0.0856 | 0.0541 |
| Sorting effect | -0.0062 | -0.0153 | -0.0132 |
| Correlation with the $K = 10$ measure | 0.987 | 1.000 | 0.994 |
| Second closest | Cluster-5 | Cluster-8 | Cluster-11 |
| Price effect | 0.0386 | 0.0230 | 0.0391 |
| Sorting effect | -0.0147 | -0.0135 | -0.0146 |
| Correlation with the $K = 10$ measure | 0.937 | 0.937 | 0.942 |

*Panel C. Descriptors closest to the centroid of each cluster in Panel B*

| | |
|---|---|
| $K = 7$, Cluster-4 | Processing Information; Analyzing Data or Information; Getting Information Needed to Do the Job; Written Expression; Making Decisions and Solving Problems; Information Gathering |
| $K = 7$, Cluster-5 | Idea Evaluation; Idea Generation; Solution Appraisal; Active Learning; Visioning; Implementation Planning |
| $K = 10$, Cluster-7 | Analyzing Data or Information; Processing Information; Interpreting Meaning of Info to Others; Getting Information Needed to Do the Job; Making Decisions and Solving Problems; Provide Consultation & Advice to Others |
| $K = 10$, Cluster-8 | Idea Evaluation; Idea Generation; Solution Appraisal; Active Learning; Visioning; Implementation Planning |
| $K = 13$, Cluster-10 | Processing Information; Analyzing Data or Information; Interpreting Meaning of Info to Others; Getting Information Needed to Do the Job; Written Expression; Making Decisions and Solving Problems |
| $K = 13$, Cluster-11 | Idea Evaluation; Active Learning; Solution Appraisal; Idea Generation; Critical Thinking; Visioning |

*Notes:* Each entry is a contribution to the 1980–2021 change in the Black–White log hourly wage gap, from the decomposition in equation (5) with the five pre-labeled task measures replaced by the $K$-means cluster scores. The clusters are the machine-learning task classification described in Section 5, re-estimated at each $K$. Panel A sums over all clusters. Panel B reports, at each $K$, the two clusters whose scores correlate most strongly with the $K = 10$ *Analytical Communication* score across occupations. Panel C lists the 6 O*NET descriptors closest to each of those clusters' centroids, with the rating-scale suffixes removed. Within each column, clusters are numbered by their correlation with the pre-labeled *Social* composite.Sample: Black and White men aged 25–54, not self-employed, working full time.

Table B.12: Representative Occupations by Cluster (K=10)

| Cluster | Representative Occupations |
|---|---|
| C1 Heavy Manual | Roofers; Garbage and recyclable material collectors; Drywall installers; Insulation workers; Laborers, freight, stock, and material handlers, n.e.c. |
| C2 Routine - Fine Motor | Shoemaking machine operators; Data entry keyers; Tailors, dressmakers, and sewers; Textile sewing machine operators; Packers and packagers by hand |
| C3 Repair & Maint | Elevator installers and repairers; Small engine repairers; Sheet metal workers; Heating, air conditioning, and refrigeration mechanics; Repairers of household appliances and power tools |
| C4 Sensory - Reaction | Crossing guards; Taxi drivers and chauffeurs; Bus drivers; Drillers of earth; Locomotive operators: engineers and firemen |
| C5 Hazard Exposure | Garbage and recyclable material collectors; Ushers; Radiologic technologists and technicians; Payroll and timekeeping clerks; Mail carriers for postal service |
| C6 Pure Analytical | Actuaries; Mathematicians and statisticians; Agricultural and food scientists; Statistical clerks; Bookkeepers and accounting and auditing clerks |
| C7 Analytical Communication | Insurance underwriters; Social scientists and sociologists, n.e.c.; Mathematicians and statisticians; Actuaries; Operations and systems researchers and analysts |
| C8 Strategic Thinking | Operations and systems researchers and analysts; Vocational and educational counselors; Actuaries; Urban and regional planners; Economists, market and survey researchers |
| C9 Contact - Social | Clergy; Bill and account collectors; Vocational and educational counselors; Insurance sales occupations; Hotel clerks |
| C10 Managerial Coordination | Sales supervisors and proprietors; Managers of medicine and health occupations; Business and promotion agents; Religious workers, n.e.c.; Supervisors of cleaning and building service |

*Notes:* Occupations are `occ1990dd` codes. Within each cluster, occupations are ranked by the share of an occupation's total task score that the cluster accounts for, after dropping occupations whose score on that cluster falls below the median across occupations, and the five highest are listed. Cluster labels are the author's summaries of the cluster and are not inputs to the algorithm.

Table B.13: Black–White Differences in ML Cluster Task Intensity

| | Unconditional | | | With controls | | |
|---|---|---|---|---|---|---|
| | 1980 | 2021 | Change | 1980 | 2021 | Change |
| C1 Heavy Manual | 0.767*** | 0.414*** | -0.352*** | 0.295* | 0.132 | -0.163 |
| | ( 0.184) | ( 0.156) | ( 0.135) | ( 0.157) | ( 0.152) | ( 0.099) |
| C2 Routine–Fine Motor | 0.130 | -0.142 | -0.272*** | -0.043 | -0.196 | -0.153** |
| | ( 0.151) | ( 0.131) | ( 0.077) | ( 0.131) | ( 0.124) | ( 0.069) |
| C3 Repair & Maintenance | -0.151 | -0.286** | -0.135* | -0.297** | -0.351*** | -0.054 |
| | ( 0.142) | ( 0.126) | ( 0.080) | ( 0.126) | ( 0.121) | ( 0.067) |
| C4 Sensory–Reaction | 0.097 | 0.138 | 0.041 | 0.009 | 0.085 | 0.076 |
| | ( 0.108) | ( 0.138) | ( 0.076) | ( 0.094) | ( 0.128) | ( 0.077) |
| C5 Hazard Exposure | -0.129 | 0.082 | 0.210*** | 0.037 | 0.182 | 0.145** |
| | ( 0.100) | ( 0.117) | ( 0.059) | ( 0.088) | ( 0.114) | ( 0.059) |
| C6 Pure Analytical | -0.882*** | -0.761*** | 0.121 | -0.556*** | -0.545*** | 0.011 |
| | ( 0.094) | ( 0.111) | ( 0.103) | ( 0.068) | ( 0.077) | ( 0.077) |
| C7 Analytical Communication | -1.199*** | -0.945*** | 0.253* | -0.667*** | -0.605*** | 0.062 |
| | ( 0.147) | ( 0.134) | ( 0.141) | ( 0.106) | ( 0.098) | ( 0.090) |
| C8 Strategic Thinking | -1.282*** | -1.034*** | 0.248* | -0.773*** | -0.709*** | 0.064 |
| | ( 0.150) | ( 0.144) | ( 0.149) | ( 0.112) | ( 0.109) | ( 0.105) |
| C9 Contact–Social | -1.088*** | -0.562*** | 0.526*** | -0.550*** | -0.273* | 0.277*** |
| | ( 0.223) | ( 0.164) | ( 0.140) | ( 0.183) | ( 0.152) | ( 0.098) |
| C10 Managerial Coordination | -1.293*** | -1.008*** | 0.285* | -0.806*** | -0.721*** | 0.085 |
| | ( 0.245) | ( 0.195) | ( 0.160) | ( 0.199) | ( 0.179) | ( 0.121) |

*Notes:* The ten clusters are the machine-learning task classification described in Section 5. Entries are coefficients on a Black indicator from cluster-intensity regressions, so a negative entry means Black men work in occupations that require less of the tasks in the cluster . The first block adds no controls and is the mean difference the decomposition uses. Controls are age, age squared, years of education and state fixed effects. The change is estimated on the two survey years stacked with every regressor interacted with a 2021 indicator, so the 1980 and 2021 entries are those of the separate-year regressions and the standard error of the change carries the covariance between the two years that clustering on occupation induces. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year. Task intensities are min-max scaled from 0 to 10. Standard errors in parentheses are clustered by occupation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.14: Task Prices by ML Cluster, White Men

| | All clusters together | | | One cluster at a time | | |
|---|---|---|---|---|---|---|
| | 1980 | 2021 | Change | 1980 | 2021 | Change |
| C1 Heavy Manual | -0.030** | -0.001 | 0.029* | -0.011 | -0.039*** | -0.028*** |
| | ( 0.014) | ( 0.017) | ( 0.015) | ( 0.007) | ( 0.010) | ( 0.008) |
| C2 Routine–Fine Motor | 0.014 | 0.035** | 0.021 | 0.022** | 0.022* | -0.000 |
| | ( 0.012) | ( 0.014) | ( 0.015) | ( 0.011) | ( 0.013) | ( 0.011) |
| C3 Repair & Maintenance | 0.011 | -0.007 | -0.018 | 0.024*** | 0.021* | -0.003 |
| | ( 0.012) | ( 0.014) | ( 0.013) | ( 0.008) | ( 0.011) | ( 0.009) |
| C4 Sensory–Reaction | 0.021 | 0.000 | -0.020 | 0.005 | 0.002 | -0.003 |
| | ( 0.018) | ( 0.023) | ( 0.020) | ( 0.011) | ( 0.014) | ( 0.010) |
| C5 Hazard Exposure | -0.019 | -0.008 | 0.011 | -0.011 | 0.014 | 0.025** |
| | ( 0.014) | ( 0.016) | ( 0.017) | ( 0.009) | ( 0.013) | ( 0.011) |
| C6 Pure Analytical | 0.005 | -0.025 | -0.030 | 0.053*** | 0.104*** | 0.050*** |
| | ( 0.044) | ( 0.038) | ( 0.030) | ( 0.010) | ( 0.011) | ( 0.012) |
| C7 Analytical Communication | -0.011 | 0.060 | 0.071** | 0.041*** | 0.096*** | 0.054*** |
| | ( 0.031) | ( 0.038) | ( 0.030) | ( 0.005) | ( 0.007) | ( 0.007) |
| C8 Strategic Thinking | 0.036 | 0.054** | 0.018 | 0.044*** | 0.091*** | 0.047*** |
| | ( 0.025) | ( 0.027) | ( 0.024) | ( 0.004) | ( 0.007) | ( 0.007) |
| C9 Contact–Social | -0.024 | -0.001 | 0.023 | 0.007 | 0.045*** | 0.038*** |
| | ( 0.019) | ( 0.024) | ( 0.015) | ( 0.006) | ( 0.009) | ( 0.007) |
| C10 Managerial Coordination | 0.018 | -0.000 | -0.019* | 0.027*** | 0.058*** | 0.030*** |
| | ( 0.012) | ( 0.016) | ( 0.010) | ( 0.004) | ( 0.008) | ( 0.007) |

*Notes:* The ten clusters are the machine-learning task classification described in Section 5. Entries are coefficients on cluster intensity in a log hourly wage regression estimated on White men, which is the return the decomposition values the racial gap at. The first block enters all ten cluster measures together and is the price the decomposition uses; the second enters one at a time. Controls are age, age squared, years of education and state fixed effects. The change is estimated on the two survey years stacked with every regressor interacted with a 2021 indicator, so the 1980 and 2021 entries are those of the separate-year regressions and the standard error of the change carries the covariance between the two years that clustering on occupation induces. Sample is Black and White male workers aged 25 to 54, not self-employed, working at least 30 hours per week and reporting at least 48 weeks of work in the prior year. Task intensities are min-max scaled from 0 to 10. Standard errors in parentheses are clustered by occupation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.15: K-Means Task-Cluster Sorting and Price Effects by Year

| | 1990 | 2000 | 2006 | 2009 | 2012 | 2016 | 2021 |
|---|---|---|---|---|---|---|---|
| *Panel: C1 Heavy Manual* | | | | | | | |
| Sorting effect | -0.003 | -0.002 | -0.001 | 0.001 | 0.001 | 0.001 | -0.000 |
| | ( 0.003) | ( 0.005) | ( 0.005) | ( 0.005) | ( 0.006) | ( 0.006) | ( 0.007) |
| Price effect | -0.007 | -0.018 | -0.020 | -0.025 | -0.025 | -0.025 | -0.022 |
| | ( 0.005) | ( 0.009) | ( 0.009) | ( 0.010) | ( 0.010) | ( 0.011) | ( 0.012) |
| *Panel: C2 Routine–Fine Motor* | | | | | | | |
| Sorting effect | 0.001 | 0.006 | 0.007 | 0.007 | 0.007 | 0.008 | 0.009 |
| | ( 0.002) | ( 0.003) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.005) | ( 0.005) |
| Price effect | -0.001 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.003 |
| | ( 0.002) | ( 0.003) | ( 0.003) | ( 0.003) | ( 0.003) | ( 0.003) | ( 0.004) |
| *Panel: C3 Repair & Maintenance* | | | | | | | |
| Sorting effect | 0.000 | -0.001 | -0.001 | -0.001 | -0.000 | -0.000 | -0.001 |
| | ( 0.001) | ( 0.002) | ( 0.002) | ( 0.002) | ( 0.002) | ( 0.002) | ( 0.002) |
| Price effect | -0.000 | -0.002 | -0.002 | -0.002 | -0.002 | -0.002 | -0.003 |
| | ( 0.001) | ( 0.003) | ( 0.003) | ( 0.003) | ( 0.003) | ( 0.003) | ( 0.004) |
| *Panel: C4 Sensory–Reaction* | | | | | | | |
| Sorting effect | -0.000 | -0.000 | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 |
| | ( 0.001) | ( 0.001) | ( 0.001) | ( 0.002) | ( 0.001) | ( 0.002) | ( 0.002) |
| Price effect | 0.002 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.002 |
| | ( 0.002) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) |
| *Panel: C5 Hazard Exposure* | | | | | | | |
| Sorting effect | 0.000 | 0.001 | 0.001 | -0.000 | -0.001 | 0.001 | 0.002 |
| | ( 0.002) | ( 0.003) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) | ( 0.004) |
| Price effect | 0.002 | 0.002 | 0.002 | 0.003 | 0.003 | 0.002 | 0.001 |
| | ( 0.002) | ( 0.003) | ( 0.003) | ( 0.003) | ( 0.004) | ( 0.003) | ( 0.003) |
| *Panel: C6 Pure Analytical* | | | | | | | |
| Sorting effect | 0.002 | 0.001 | 0.001 | 0.003 | 0.003 | 0.003 | 0.003 |
| | ( 0.007) | ( 0.007) | ( 0.007) | ( 0.007) | ( 0.008) | ( 0.007) | ( 0.008) |
| Price effect | -0.015 | -0.008 | -0.008 | -0.019 | -0.023 | -0.022 | -0.026 |
| | ( 0.012) | ( 0.019) | ( 0.020) | ( 0.022) | ( 0.024) | ( 0.026) | ( 0.028) |
| *Panel: C7 Analytical Communication* | | | | | | | |
| Sorting effect | 0.001 | -0.003 | -0.005 | -0.009 | -0.012 | -0.012 | -0.015 |
| | ( 0.008) | ( 0.011) | ( 0.012) | ( 0.012) | ( 0.013) | ( 0.012) | ( 0.014) |
| Price effect | 0.007 | 0.028 | 0.033 | 0.052 | 0.061 | 0.068 | 0.086 |
| | ( 0.020) | ( 0.026) | ( 0.028) | ( 0.030) | ( 0.031) | ( 0.035) | ( 0.039) |
| *Panel: C8 Strategic Thinking* | | | | | | | |
| Sorting effect | -0.012 | -0.017 | -0.020 | -0.020 | -0.020 | -0.016 | -0.013 |
| | ( 0.006) | ( 0.009) | ( 0.010) | ( 0.010) | ( 0.010) | ( 0.010) | ( 0.011) |
| Price effect | 0.029 | 0.030 | 0.042 | 0.043 | 0.036 | 0.033 | 0.023 |
| | ( 0.013) | ( 0.024) | ( 0.025) | ( 0.026) | ( 0.026) | ( 0.029) | ( 0.033) |
| *Panel: C9 Contact–Social* | | | | | | | |
| Sorting effect | 0.004 | -0.001 | -0.003 | -0.000 | 0.001 | -0.000 | 0.000 |
| | ( 0.006) | ( 0.009) | ( 0.012) | ( 0.012) | ( 0.013) | ( 0.013) | ( 0.013) |
| Price effect | 0.009 | 0.028 | 0.031 | 0.026 | 0.023 | 0.026 | 0.025 |
| | ( 0.005) | ( 0.013) | ( 0.014) | ( 0.015) | ( 0.015) | ( 0.017) | ( 0.018) |
| *Panel: C10 Managerial Coordination* | | | | | | | |
| Sorting effect | -0.002 | 0.000 | 0.002 | 0.001 | 0.001 | 0.000 | 0.000 |
| | ( 0.003) | ( 0.004) | ( 0.005) | ( 0.005) | ( 0.005) | ( 0.005) | ( 0.006) |
| Price effect | -0.007 | -0.024 | -0.030 | -0.028 | -0.026 | -0.026 | -0.024 |
| | ( 0.006) | ( 0.010) | ( 0.011) | ( 0.011) | ( 0.011) | ( 0.013) | ( 0.014) |

*Notes:* C1–C10 denote the ten k-means task clusters. Each year is compared with 1980. Entries decompose the change in the task-cluster component of the explained Black–White wage gap into sorting and price effects. Standard errors in parentheses are based on 500 occupation-cluster bootstrap replications.

## Appendix C. Gelbach's Decomposition

Gelbach (2016) writes the change in a coefficient between a base and a full regression as a sum of covariate-specific terms. Let $G^{base}$ be the racial wage gap net of age, schooling and state, and let $G^{full}$ be the gap that remains once the five task measures also enter, each priced at $\beta_k$ in the same regression.[17] Let $\tilde{\tau}_k$ be the White–Black difference in task $k$ net of the same controls, taken from a regression of task $k$ on a race indicator and those controls. Least squares imposes

$$G^{base} - G^{full} \;=\; \sum_{k} \beta_k \, \tilde{\tau}_k. \tag{6}$$

The left-hand side is the portion of the gap that the task measures account for, and $\beta_k \tilde{\tau}_k$ is the contribution of task $k$, a racial difference in task exposure multiplied by the price of that task. The assignment does not depend on the order in which the tasks are added, because every $\tilde{\tau}_k$ comes from a regression on the base covariates alone while every $\beta_k$ comes from the full equation.

Equation (6) has the same structure as the task component of the explained gap in Section 4.1, where task $k$ contributes $\beta_k^W(\bar{\tau}_k^W - \bar{\tau}_k^B)$. Both are a task price multiplied by a racial difference in task exposure, and they differ in how each factor is measured. In the main text, task prices are estimated with a White men sample, and the estimated task gap is the raw mean difference in task exposure. Equation (6) takes one price from a pooled regression that includes a race indicator, and measures task gap net of age, schooling, and state.

Equation (6) decomposes the gap in a single period, while the object of this paper is the change in the gap between 1980 and 2021. I run Gelbach's decomposition separately in each year and apply the base-year algebra of Section 4.2 to the resulting series, so that the sorting effect is the change in the task gap valued at the 2021 price and the price effect is the change in the price valued at the 1980 task gap. Table C.1 reports the results beside the main text figures.

Both column blocks agree on what the main text draws from the decomposition. The sorting effect is negative and the price effect is positive for all tasks taken together, *Social* is the largest in both effects, and the *Social* price effect alone exceeds the total task contribution. The magnitudes differ, however, and differ most for *Social* and for the all-task totals, where the sorting effect falls from −0.021 to −0.006 and the price effect from 0.060 to 0.038. The pooled price is not the reason. Panel C of Table B.4 runs the same decomposition on a pooled regression that includes a race indicator and returns a sorting effect of −0.020 and a price effect of 0.060, within a thousandth of the White-specific values. What differs is the gap. Holding age, schooling and state fixed cuts the *Social* exposure gap from 1.15 to 0.67 in 1980 and from 0.78 to 0.51 in 2021, and both terms of the decomposition scale with that gap.

[17] Both come from pooled regressions of log hourly wages on a race indicator and the controls, estimated on the same sample and weights. $G^{base}$ is the negative of the race coefficient when the task measures are excluded and $G^{full}$ the negative of that coefficient when they are included, so each is written as a White–Black difference. The identity below is exact in any such pair of regressions; see Gelbach (2016) for the general case.

Table C.1: Baseline and Gelbach Decompositions of the Change in the Racial Wage Gap, 1980–2021

| | Baseline (main text) | | Gelbach-style | |
|---|---|---|---|---|
| Task | Sorting | Price | Sorting | Price |
| Math | −0.0078 | 0.0017 | −0.0031 | 0.0027 |
| Routine | 0.0062 | −0.0002 | 0.0024 | 0.0025 |
| Manual | 0.0004 | −0.0002 | 0.0001 | −0.0006 |
| Social | −0.0316 | 0.0618 | −0.0137 | 0.0351 |
| Contact | 0.0119 | −0.0029 | 0.0079 | −0.0017 |
| All tasks | −0.0208 | 0.0601 | −0.0064 | 0.0380 |
| Total task effect | 0.0392 | | 0.0316 | |

*Notes.* Baseline columns take the task price from a wage regression fitted on White men and the task gap as the raw racial difference in task exposure, and reproduce column V1 of Table D.1. Gelbach columns take the task price from one pooled wage regression of log hourly wage on a race dummy, the five tasks and controls, and the task gap from the race coefficient in a regression of each task on race and the same controls, so the gap is net of age, schooling and state. Both column blocks apply the same base-year algebra, with sorting the change in the task gap valued at the 2021 price and price the change in the price valued at the 1980 gap. Sample and controls are identical across the two.

The main text reports the Oaxaca–Blinder decomposition because the accounting question concerns the racial difference in task exposure that exists, not the difference that would remain if Black and White men matched on age, schooling and state. Schooling shapes which occupations workers enter, so holding schooling fixed removes part of what the decomposition is meant to measure. The Gelbach columns assign less of the widening to tasks in total, and they raise rather than lower the margin by which the price effect exceeds the sorting effect, from a factor near three to a factor near six.

## Appendix D. The Index-Number Choice in the Decomposition

Equation (5) splits the change in the explained gap into a task sorting effect and a task price effect. That split is not unique. Taking a single task, and writing $\bar{X}_W^{(t)} - \bar{X}_B^{(t)}$ for the racial gap in exposure to that task in period $t$ and $\beta_W^{(t)}$ for its price, the change between periods 0 and 1 satisfies the algebraic identity

$$\begin{aligned}\big(\bar{X}_W^{(1)} - \bar{X}_B^{(1)}\big)\beta_W^{(1)} - \big(\bar{X}_W^{(0)} - \bar{X}_B^{(0)}\big)\beta_W^{(0)} = {} & \underbrace{\Big[\big(\bar{X}_W^{(1)} - \bar{X}_B^{(1)}\big) - \big(\bar{X}_W^{(0)} - \bar{X}_B^{(0)}\big)\Big]\beta_W^{(0)}}_{\text{sorting}} \\ & + \underbrace{\big(\beta_W^{(1)} - \beta_W^{(0)}\big)\big(\bar{X}_W^{(0)} - \bar{X}_B^{(0)}\big)}_{\text{price}} \\ & + \underbrace{\Big[\big(\bar{X}_W^{(1)} - \bar{X}_B^{(1)}\big) - \big(\bar{X}_W^{(0)} - \bar{X}_B^{(0)}\big)\Big]\big(\beta_W^{(1)} - \beta_W^{(0)}\big)}_{\text{interaction}}.\end{aligned} \tag{7}$$

The interaction term arises because quantities and prices both change. The interaction is the part of the change that cannot be attributed to sorting or to price alone, and any two-way decomposition must assign the interaction to the sorting term or to the price term.

There are three ways to attach the interaction.

(V1) Attach the interaction to the sorting term, so that quantity changes are valued at *end-period* prices and price changes at *base-period* quantities:

$$\Big[\big(\bar{X}_W^{(1)} - \bar{X}_B^{(1)}\big) - \big(\bar{X}_W^{(0)} - \bar{X}_B^{(0)}\big)\Big]\beta_W^{(1)} + \big(\beta_W^{(1)} - \beta_W^{(0)}\big)\big(\bar{X}_W^{(0)} - \bar{X}_B^{(0)}\big).$$

This is the specification used in the main text, equation (5), and follows Blau and Kahn (2017).

(V2) Attach the interaction to the price term, valuing quantity changes at base-period prices and price changes at end-period quantities:

$$\Big[\big(\bar{X}_W^{(1)} - \bar{X}_B^{(1)}\big) - \big(\bar{X}_W^{(0)} - \bar{X}_B^{(0)}\big)\Big]\beta_W^{(0)} + \big(\beta_W^{(1)} - \beta_W^{(0)}\big)\big(\bar{X}_W^{(1)} - \bar{X}_B^{(1)}\big).$$

(V3) Report all three terms of (7) separately.

Table D.1 reports all three. Two points follow.

Table D.1: Sorting and price effects under alternative assignments of the interaction term, 1980–2021

| | (V1) Main text | | (V2) Alternative | | (V3) Three-way | | |
|---|---|---|---|---|---|---|---|
| | Sorting | Price | Sorting | Price | Sorting | Price | Interaction |
| Math | -0.0078 | 0.0017 | -0.0075 | 0.0013 | -0.0075 | 0.0017 | -0.0003 |
| Routine | 0.0062 | -0.0002 | 0.0030 | 0.0030 | 0.0030 | -0.0002 | 0.0032 |
| Manual | 0.0004 | -0.0002 | 0.0004 | -0.0001 | 0.0004 | -0.0002 | 0.0000 |
| Social | -0.0316 | 0.0618 | -0.0117 | 0.0418 | -0.0117 | 0.0618 | -0.0199 |
| Contact | 0.0119 | -0.0029 | 0.0097 | -0.0007 | 0.0097 | -0.0029 | 0.0022 |
| All tasks | -0.0208 | 0.0601 | -0.0061 | 0.0453 | -0.0061 | 0.0601 | -0.0148 |
| Total task effect | 0.0392 | | 0.0392 | | 0.0392 | | |

*Notes:* Each entry is a contribution to the 1980–2021 change in the Black–White log hourly wage gap. Writing $\bar{X}_W^{(t)} - \bar{X}_B^{(t)}$ for the racial gap in task exposure in period $t$ and $\beta_W^{(t)}$ for the task price, the three-way identity in equation (7) means any two-way split must assign the interaction to one component. V1 attaches it to sorting (quantity changes valued at end-period prices), V2 attaches it to price, and V3 reports it separately. The total task effect of 0.0392 log points is identical across columns; only its division differs. The main text uses V1. Sample: Black and White men aged 25–54, not self-employed, working full time.

First, the interaction is not negligible, and it is interpretable. Across all five tasks the interaction contributes −0.015 log points, roughly 38 percent of the total task-related change

of +0.039; for *Social* alone it is −0.020. The interaction for *Social* is negative because Black workers converged in the task whose price was rising. That is, convergence, $\bar{X}_W^{(1)} - \bar{X}_B^{(1)} < \bar{X}_W^{(0)} - \bar{X}_B^{(0)}$ for *Social*, coincided with repricing, $\beta_W^{(1)} > \beta_W^{(0)}$.

Second, the main text uses (V1) because it matches the questions the decomposition is meant to answer. The sorting term asks what the observed convergence in task allocation is worth in the labor market as it exists at the end of the period, and therefore values the change in quantities at end-period prices. Valuing the reallocation achieved by 2021 at 1980 prices would understate what that reallocation is worth to workers today. The price term asks how much the wage gap changed because the market repriced tasks, given the existing pattern of segregation across tasks, and therefore values the change in prices at base-period quantities. The alternatives redistribute the interaction and so change the magnitudes: the sorting effect is −0.021 under (V1) and −0.006 under (V2) and (V3), and the price effect is +0.060 under (V1) and (V3) and +0.045 under (V2). The qualitative pattern is common to all three. The sorting effect is negative and the price effect is positive in every column, and because (7) is an identity the total task contribution of +0.039 log points is invariant across them. Only the division between sorting and price changes. And all three assignments of the interaction show that the price effect dominates the sorting effect, and most of the effects are from *Social*.

## Appendix E. Oaxaca–RIF Decomposition

The Oaxaca–Blinder (OB) decomposition is widely used to separate observed wage gaps and is suited to mean comparisons. It cannot answer whether the same forces matter equally at different points of the wage distribution, nor can it explain whether convergence (or divergence) is concentrated at the bottom, middle, or top of the distribution. To address this limitation, I adopt the Oaxaca–RIF framework, which extends the OB decomposition to arbitrary distributional statistics, such as percentiles or inequality measures (Firpo et al., 2009, 2018).

The extension builds on the concept of an *influence function* (IF). Let $v(F)$ denote a statistic of interest that is a functional of the distribution $F$ of wages $Y$ (for example, the mean, median, or a given percentile). The influence function $IF(y; v, F)$ measures the effect of an infinitesimal perturbation in $F$ at the observation $y$ on the statistic $v(F)$. Formally,

$$IF(y; v, F) = \lim_{\epsilon \to 0} \frac{v\big((1-\epsilon)F + \epsilon\, \delta_y\big) - v(F)}{\epsilon}, \tag{8}$$

where $\delta_y$ is the degenerate distribution at $y$. Intuitively, the IF describes how sensitive the statistic $v(F)$ is to the presence of an observation $y$ in the sample.

Since the IF has mean zero, Firpo et al. (2009) propose the *recentered influence function* (RIF), defined as

$$RIF(y; v, F) = v(F) + IF(y; v, F). \tag{9}$$

By construction, $\mathbb{E}[RIF(Y; v, F)] = v(F)$. This recentering step transforms a nonlinear

statistic of the distribution into the expectation of a transformed outcome. For example, when $v(F)$ is the $\tau$-th quantile $q_\tau$, the associated RIF is

$$RIF(Y; q_\tau, F) = q_\tau + \frac{\tau - \mathbb{1}\{Y \leq q_\tau\}}{f_Y(q_\tau)}, \tag{10}$$

where $f_Y(q_\tau)$ is the density of $Y$ at $q_\tau$. This expression provides a linearized outcome whose conditional expectation can be modeled with standard regression methods.

The advantage of this construction is that it allows Oaxaca-type decompositions to be carried out for any distributional statistic, not only the mean. In practice, the wage outcome $Y$ in a regression is replaced by its recentered influence function $RIF(Y; v, F)$, and the relationship between worker characteristics $X$ and distributional statistics such as quantiles is estimated using ordinary least squares. This approach allows me to quantify, for each percentile of the wage distribution, how much of the change in the racial wage gap is driven by changes in racial differences in task-related characteristics versus changes in task prices. Formally, the change in the racial wage gap at statistic $v$ can be written as the change in the difference in average recentered influence functions between White and Black workers; the analysis below focuses on the explained component of this change.

$$\underbrace{\left(\bar{\mathbf{X}}_W^{(1)} - \bar{\mathbf{X}}_B^{(1)}\right)\beta_W^{(1)}(v) \; - \; \left(\bar{\mathbf{X}}_W^{(0)} - \bar{\mathbf{X}}_B^{(0)}\right)\beta_W^{(0)}(v)}_{\text{Change in Explained Gap (via OB-RIF)}} = \underbrace{\left[\left(\bar{\mathbf{X}}_W^{(1)} - \bar{\mathbf{X}}_B^{(1)}\right) - \left(\bar{\mathbf{X}}_W^{(0)} - \bar{\mathbf{X}}_B^{(0)}\right)\right]\beta_W^{(1)}(v)}_{\text{Effect of Changing Means}}$$
$$+ \underbrace{\left(\beta_W^{(1)}(v) - \beta_W^{(0)}(v)\right)\left(\bar{\mathbf{X}}_W^{(0)} - \bar{\mathbf{X}}_B^{(0)}\right)}_{\text{Effect of Changing Coefficients}} \tag{11}$$

Equation (11) applies the OB–RIF framework to the change in a distributional statistic $v$ between two periods. The left-hand side represents the change in the explained gap in statistic $v$, such as a given percentile of the wage distribution. The first term on the right captures the task-sorting channel (how changes in racial differences in task content affect the gap at percentile $v$); the second term captures the task-price channel (how changes in the valuation of tasks affect the gap at percentile $v$).

## Appendix F. Details of the K-means Clustering Procedure

This appendix provides methodological detail for the data-driven task classification introduced in Section 5. I describe the input variables, the standardization procedure, the $K$-means optimization, the choice of $K$, the label-stabilization routine, and robustness checks.

### F.1 Input Variables

The clustering input is the O*NET 1998 database directly downloaded from the replication package from (Deming, 2017). I retain 187 descriptors drawn from four domains: skills, abilities, work activities, and work contexts. I exclude the knowledge domain, because those items reflect fields of expertise—e.g., psychology, medicine, geography—rather than

on-the-job tasks, and the wage regressions in the main text already control for educational attainment. I use the O*NET "level" rating as the primary score when a descriptor is evaluated along both "level" and "importance" dimensions. Table B.10 lists every included descriptor.

## F.2 Standardization

O*NET ratings are pre-processed in two steps before clustering.

*Ipsative (within-occupation) standardization.* For each occupation $o$ and descriptor $j$, let $r_{oj}$ denote the raw O*NET importance rating, and let $\bar{r}_o$ and $s_o$ be the mean and standard deviation of $\{r_{oj}\}_{j=1}^{187}$ within occupation $o$. The ipsative-standardized score is

$$\tilde{r}_{oj} \;=\; \frac{r_{oj} - \bar{r}_o}{s_o}.$$

This removes occupation-level differences in overall rating intensity, so that $\tilde{r}_{oj}$ captures the relative emphasis of descriptor $j$ within occupation $o$ rather than the occupation's overall complexity.

*Descriptor-level standardization.* For each descriptor $j$, I then compute the cross-occupation $Z$-score

$$z_{oj} \;=\; \frac{\tilde{r}_{oj} - \bar{\tilde{r}}_{\cdot j}}{\mathrm{sd}(\tilde{r}_{\cdot j})}.$$

This puts every descriptor on a common unit-variance scale, so that high-variance descriptors do not mechanically dominate the distance metric used by $K$-means.

## F.3 K-means Optimization

I apply $K$-means to the transposed matrix $Z$, in which the 187 descriptors are units of observation and the occupations are features. The algorithm partitions the 187 descriptors into $K$ non-overlapping clusters $\{C_1, \ldots, C_K\}$ so as to minimize the within-cluster sum of squared Euclidean distances to cluster centroids (WCSS):

$$\mathrm{WCSS}(K) \;=\; \sum_{k=1}^{K} \sum_{j \in C_k} \left\| z_{\cdot j} - \mu_k \right\|^2, \qquad \mu_k \;=\; \frac{1}{|C_k|} \sum_{j \in C_k} z_{\cdot j}.$$

Because $K$-means is sensitive to the random initialization of centroids, I run the algorithm across 10,000 random initializations and retain the solution with the lowest WCSS.

## F.4 Choice of K

I set $K = 10$ in the main analysis. Ten clusters are enough to separate distinct task dimensions and few enough that each cluster can be read as a recognizable type of work. I repeat the analysis with $K = 7$ and $K = 13$, and the main results remain unchanged.

## F.5 Label Stabilization

The $K$-means output determines cluster *compositions*, but the labels themselves (cluster 1, 2, 3, ...) are assigned in arbitrary order by the algorithm. I therefore sort the clusters by their correlation with the pre-labeled *Social* composite, so that cluster $C_1$ is the cluster with the lowest correlation with *Social* and cluster $C_{10}$ is the cluster with the highest. This affects only how clusters are labeled, not which descriptors belong to which cluster, and it is used purely to refer to the same cluster consistently across Section 5.