Tasks and Black-white Inequality over the Long Twentieth Century *

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Abstract

We present new evidence on the long-run evolution of occupational task content by race in the United States, 1900-2021. Black workers began the transition to better paid, cognitive-intensive modern jobs at least a generation after white workers; substantial convergence only occurred after 1960. Longitudinal data suggests that task transitions were racially biased: Black men moved to jobs with lower rewarded task content than white men, conditional on initial tasks, though gaps decreased after 1940. Routine-intensive Black workers were less likely to move up into non-routine analytic work in all periods. The results suggest that task-displacement shocks widen Black-white inequality.

JEL codes: N31, N32, J24, J62

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I. Introduction

The trajectory of Black labor market outcomes relative to those of white Americans has been well- documented across the second half of the twentieth century. Wages displayed strong convergence in the 1940-80 period, followed by a notable stagnation or even divergence after 1980 (Juhn, Murphy, and Pierce 1991; Jaynes 1990; Bayer and Charles 2018). The pre-World War II (WWII) era has received less attention due to limited wage data availability, but was characterized by substantial racial occupational segregation and wage gaps (Collins and Wanamaker 2022; Margo 2016; Myrdal 1996; Sundstrom 1994). In this paper, we show that the task composition of occupations plays an important role in perpetuating Black-white labor market disparities for American men.

We identify the task concentrations of Black men relative to white men to provide new insights into why Black progress stalled at various points over the past 120 years. The task-based approach is a powerful framework for explaining trends in wage inequality (Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011; Acemoglu and Restrepo 2022), but, until recently, it has not been linked to racial inequality (Cavounidis et al. 2021; Hurst, Rubinstein, and Shimizu 2024). In this paper, we use a new long-run task dataset that maps task intensities onto census occupations. We identify trends in both racial differences in task intensity and in average wages by task. Finally, we document persistent racial disparities in workers' task trajectories both across their own careers and across generations, even for those in the same narrowly defined labor market. Overall, our approach provides a richer understanding of Black-white inequality over the long twentieth century and complements prior work that focused on other factors such as discrimination (Aizer et al. 2022), schooling (Carruthers and Wanamaker 2017a), and institutional changes in the labor market (Derenoncourt and Montialoux 2021).

To measure long-run changes in tasks by race, we develop a new series of occupational task content between 1900 and 2021. We focus on three key tasks that describe the nature of work—routine-manual, physical, and non-routine analytic—using task measures from the pre- and post-WWII editions of the *Dictionary of Occupational Titles* (DOT). After developing these

measures by occupation, we merge them into United States Census and American Community Survey (ACS) data between 1900 and 2021, which allows us to trace how occupational task content has changed over time for low-, middle-, and high-paid tasks. We further use longitudinal data (linked censuses from 1900-40 and post-WWII survey data) to document transitions for workers over their lifecycle and across generations. We find differences in these transitions to be important in explaining racial task gaps and their persistence even today.

First, we sketch overall task trends to provide a benchmark for the subsequent Black-white analysis. By extending task data back to 1900, we show the uninterrupted decline in physical tasks, almost exactly mirrored by a rise in non-routine analytic tasks.[1] These latter occupations, which involve complex thinking and problem solving, were consistently at the upper end of the wage distribution over the last 80 years, while workers in brawn-intensive jobs were always the lowest paid. In contrast, our final task measure, routine-manual, experienced a rise and fall in intensity over the past 120 years. Its decline since 1960 has been well-documented since (Autor, Levy, and Murnane 2003), but the longer view here allows us to show that the decades of rapid industrial development in the early twentieth century, fueled by electricity and the production line, created an increase in the routineness of American work (Gray 2013; Gaggl et al. 2021).[2] These findings are similar within each census region and are not driven by the shift out of agriculture. Altogether, this suggests that working in cognitively-, not physically-, intensive tasks was broadly predictive of higher earnings and more stable employment.

Second, we identify three distinct eras in racial disparities in occupational task content: stalled progress from 1900 to 1940, significant convergence from 1940 to 1980, and renewed stagnation from 1980 to today. In the first era (1900–40), racial gaps barely shifted: white men in 1900 already held roles more intensive in non-routine analytic tasks—a marker of modern work—than Black men did even by 1950. During these decades, Black men became further concentrated in physical labor, while white workers transitioned toward routine-manual and non-routine analytic tasks, preserving the racial divide. In the second era (1940–80), there was significant progress as task gaps by race narrowed. The gap in routine-manual tasks completely converged over these four

decades, and the gap in non-routine analytic and physical tasks closed by more than half. However, in the third era (1980–2021), progress has stalled again, resembling the early 20th century trend. These patterns hold when controlling for education (which was first recorded in 1940) or when dropping agricultural workers, which we take as evidence that Black workers were less likely to benefit from increases in demand for non-routine analytic tasks and were more subject to long-run declines in demand for other tasks.

Third, we illustrate substantial convergence in the observational labor market returns to each task by race. In 1940, Black and white workers' relative earnings varied substantially by task on average, perhaps reflecting discrimination in these jobs, particularly in the manufacturing sector (Sundstrom 1992, 1994). These racial differences then converged strongly between 1940 and 1980 such that today there is a nearly perfect correlation between Black and white workers' average earnings for performing each of the tasks of interest. However, our decomposition exercise shows that Black-white task gaps remain substantial enough to explain 30 percent of the lingering Black-white income gap.

Fourth, we investigate the persistence of Black and white task gaps using a longitudinal approach. Building on the income mobility literature (Chetty et al. 2020; Collins and Wanamaker 2022) — which attributes cross-sectional racial income gaps to racial gaps in mobility—we extend this logic to occupational tasks. For instance, because, conditional on parental income, Black children end up with lower income than white children, racial income gaps are expected to persist across generations and over time (Chetty et al. 2020). We similarly test whether the disparities in task content we documented have persisted because Black workers transition into lower-paid tasks, conditional on initial task content, or there is simply a slow transition to a steady-state where there are no Black-white gaps. These estimates on racial gaps in transitions are important given the changing demand for tasks over time and resulting labor market polarization (Autor and Dorn 2013).

We find that, conditional on initial task content, Black workers have consistently been more likely to remain in physically intensive tasks and exit non-routine analytic tasks over the past 120

years. Before WWII, we estimate that Black men at the 75th percentile of the non-routine analytic task distribution fell 20 ranks lower ten years later than white men starting at the same rank in the same census. The opposite was true of physical work, where Black men were more likely than white men to remain in an occupation that was physically intensive. By 1980, these gaps had halved for routine-manual and non-routine analytic work. However, later decades erased some of this progress such that Black men in the 1910s and 2010s experienced similarly elevated chances of remaining in physically intensive tasks. We find similar results when we look at father-son gaps in racial mobility, suggesting that Black men are more likely to remain in low-paid tasks and less likely to persist in the highest return task over long time horizons.

We also find that transitions out of routine-manual work pushed Black workers down the skill ladder at higher rates than white workers. When we examine workers' tasks ten years after working a routine-manual intensive job (i.e. being at the 75th percentile in routine-manual), we find that Black workers disproportionately enter physically intensive work and exit routine-manual tasks compared to their white peers. If anything, the routine-manual to physical task transition gap is *larger* now, amidst the automation-driven hollowing out of the skill distribution, than in the past. These effects also persist over decades and are robust to alternative measures of routineness.

We do not estimate the impact of technology on tasks in a causal way in this paper because it is difficult to construct a consistent framework to do that across 120 years. Our preferred hypothesis is that task change is primarily driven by technology, given its strong role in the existing literature and the pervasive labor market impacts of general-purpose technologies such as electricity and computers across locations and sectors. We instead investigate whether the racial task mobility and transition effects can be explained by factors such as location-specific shocks (like structural transformation), differences in observables such as education, or initial occupation. We add successively more detailed fixed effects to our task mobility and transition results in our linked intragenerational data, which are sufficiently powered in the historical census for county-industry-occupation-year quadruplet fixed effects. All our results remain, indicating that Black and white workers in the same location with the same job in the same year experience vastly different

task outcomes by the next census wave. Black workers, both over their own lifetimes and across generations, repeatedly moved down the task ladder instead of up, which is consistent with racial heterogeneity in the face of task displacement, as in the case of technological change.

There are two limitations to our approach. The most important limitation is that the trend in task content is primarily based on across-occupation shifts in tasks without incorporating most within-occupation changes. Within-occupation changes in tasks and the emergence of new jobs have certainly been identified (Autor et al. 2024; Atalay et al. 2020), and we can only account for changing measures reflected in different editions of the DOT between 1939 and 1991. However, there is evidence that we are accurately capturing trends in the early 1900s since many job descriptions are correlated, both quantitatively and qualitatively, between editions of the DOT.[3] A second limitation is that, due to the absence of wage data prior to 1940, we are unable to explicitly link changes in task measures to changes in wage inequality in all years. We note though that the compositional changes we identify are in line with the research on modern technological change (Autor, Levy, and Murnane 2003; Acemoglu and Restrepo 2022).

This study thus contributes a long-run perspective to both the growing literature on workplace tasks and the literature on racial gaps in outcomes. Our approach takes a broader perspective than others who research specific cases of technology change, such as automated telephone operation, electrification, and the more general move from hand to machine production (Feigenbaum and Gross 2024; Gray 2013; Atack, Margo, and Rhode 2019). We contribute a more comprehensive depiction of task employment over the past 120 years, yielding a new understanding of the timing of the rise of modern, cognitive-intensive, work. By covering three major task quantities (physical, routine-manual, and non-routine analytic) and earnings for a long time frame, this paper provides a unified analysis of tasks from the structural transition out of agriculture and subsequent urbanization (for example, Gaggl et al. 2021) through the invention of the computer and the rise of the services sector whose impacts have been identified post-1960 (Autor, Levy, and Murnane 2003; Autor and Dorn 2013).

By focusing on tasks, a fine-level description of the nature of work, we complement and extend previous important research on extreme racial segregation in the American labor market through the civil rights era (Aneja and Avenancio-León 2020; Bayer and Charles 2018; Collins and Wanamaker 2022; Derenoncourt and Montialoux 2021; Derenoncourt et al. 2024; Margo 2016; Sundstrom 1994). Presenting trends and transitions for three major tasks allows us to see clearly how relative demand for different types of work shifted during successive waves of general-purpose technologies and its implications for racial gaps. Previous research grouped occupations by status or skill levels and could identify racial segregation across occupations. The task dataset helps to uncover new implications beyond the contemporaneous skill differentials– that Black workers remained in lower paid, less complex tasks and jobs for a half-century longer than whites, hampering individual and intergenerational mobility for generations.

Task data has been used to analyze racial gaps since 1960, either emphasizing different task premia across Black and white workers (Hurst, Rubinstein, and Shimizu 2024) or differences in employment shares across tasks (Dicandia 2022), providing intuition behind current racial differences in automation exposure (Lerch 2025; Mason 2022; Aizer et al. 2022). Other work notes the disparate impacts of technological change by race more broadly (Gould 2021; Acemoglu and Restrepo 2022). By following workers' intensity of low-, medium-, and high- return tasks over time, we extend the long-run racial task gap trends back before the automation era to show that the racial wage gap could have been reduced at least 25% in every decade since 1960 if Black workers had the same task content as white workers.

Another key contribution is to examine how Black and white tasks differ not just in the cross-section, but also in longitudinal data. This relates to the small literature that has used modern-day panel data to uncover task content across the life cycle (Cortes 2016; Ross 2017; Yamaguchi 2018; Golan, Sanders, and James 2024). Not only do we extend this literature by comparing historical linked data to modern data, we also separately estimate differences in task mobility and transitions by race both over one's own career but also across generations. This latter point provides a task perspective to the literature on long-run measures of intergenerational economic mobility, which

has only recently started to include Black men (Collins and Wanamaker 2022; Jácome, Kuziemko, and Naidu 2025; Ward 2023). We show that Black and white workers move down and up the skill ladder, respectively, even if they start in the same position, suggesting changing task demand can slow racial labor market convergence.

II. Data

A. Task Definitions

Our historical occupation-based task measures come from the original version of the *Dictionary of Occupational Titles* (DOT) (US Dept. of Labor, 1956), which was based on task ratings of 4,000 jobs observed by employment experts from 1939 to 1949 (US Employment Service, 1949). The data, first compiled in Gray (2013), estimate worker traits required for different jobs, such as a worker's aptitudes (for example, verbal skill, motor coordination, finger dexterity), temperament (for example, work situations involving repetition, isolation, or dealing with people), and physical capabilities (for example, amount of lifting or climbing). Ratings are sometimes on a one to five scale, such as the variable for strength which classifies work into sedentary, light, medium, heavy or very heavy categories.[4] In other cases, variables that describe work are dichotomous such as whether the job involves repetitive tasks.

We create three composite measures that reflect the changes in task content over time: routine-manual, non-routine analytic, and physical, broadly following the definitions used in Autor, Katz, and Kearney (2006, 2008), adapted for the slightly different set of task measures available in different DOT editions.[5] These measures allow us to quantify the long-run shifts away from traditional tasks such as physical strength (often viewed as substituting for capital), towards more cognitive-skill intensive work, typically considered capital-complementary in the modern period. We included routine-manual as a key variable of interest because of the large literature documenting the hollowing out of the labor force in developed countries since 1960, with the replacement of routine work by computers and automated machine tools (Autor, Levy,

and Murnane 2003; Boustan, Choi, and Clingingsmith 2022). Our longer run trends support the existing findings, while showcasing that the rise of factory-work and electricity in the first half of the century increased routineness to a peak around 1960 before its decline.

The full definitions of all underlying variables are given in Online Appendix C; here we explain how our composite measures were constructed. Routine-manual is defined as the average of finger dexterity, manual dexterity, motor skills and form perception. The first three measure manipulation of parts and goods, often in a factory floor or production line setting, while form perception ranks jobs based on the degree to which they require comparison of parts and goods in a standardized way. Tool makers, medical technicians, and blacksmiths score highly on this measure. Non-routine analytic averages a measure of the education level required to do a job, the intensity with which a job involves numerical skills, and whether evaluating situations based on measurable criteria is a key feature of a job. Occupations associated with intensive use of non-routine analytic work are chemists, inspectors, and engineers. Lastly, physical tasks are the average of how much strength is required in a job and requirements for climbing, reaching, and stooping. Plumbers, welders, and baggage handlers are all physically intensive occupations by this measure. As a robustness check, we also compute the routine task intensity (RTI) measure used in Autor and Dorn (2013), calculated as the difference between log routine-manual and the sum of log non-routine analytic and log physical tasks. We show that this singular measure of relative routine-intensity rose and fell over the century, but much earlier for whites than for Blacks, consistent with our preferred task specification.[6]

After creating the composite task measures by DOT code, we map them into 3-digit occupation codes (*occ1950*) following the process in Gray (2013) and create an average task measure by occupation. We then merge these measures into a 1% sample of the 1950 US Census by occupation code (Ruggles et al. 2023).[7] Because the three tasks are measured on different ordinal scales but we wish to make comparisons across measures, we percentile rank each occupation based on their position in the 1950 Census – this means that any changes in the task variables are changes from the 1950 baseline.[8]

To describe task content for recent decades, we follow the modern-day literature and use information from the 1977 DOT (Autor, Levy, and Murnane 2003; Autor and Price, 2013).[9] There was a revision to the 1977 DOT released in 1991, but updates were limited such that the correlation of task measures across versions was high (Peri and Sparber 2009). We compute the same three composite task measures described above using the 1977 DOT, which we also merge to the 1950 Census to percentile rank them. Based on these measures, we do find some intra-occupational change: the correlation of task content by occupation is about 0.78-0.83 across versions (Figure A1). Figure A2 demonstrates the implications of using a historical DOT are particularly important for capturing the shift in routine-manual work over time. Hence, for our main results, we will use the historical DOT for the period between 1900 and 1950, a weighted average of the two measures in 1960, and then use the 1977 DOT for census years 1970 onwards.[10] Our approach thus yields an updating measure of task content for a consistent set of occupational categories for a wider range of tasks over a longer window than other methods such as those that rely on text analysis of job descriptions (Atalay et al. 2020; Michaels, Rauch, and Redding, 2018; Kogan et al. 2021).

An important thing to note is that the data include ratings for farmers, who represented a large share of the economy in the early 20th century (though declining from 20% in 1900 to 10% in 1940). Therefore, our methodology allows us to capture the structural shift away from agriculture. In the early DOTs, farmers were ranked at the 67-70th percentile in physical and routine-manual tasks, as well as for non-routine analytic. These ratings show that our measures paint farming as a complex combination of "high-skill" non-routine analytic tasks and "low-skill" physical/routine-manual tasks. Our primary results include farming, but we also show that many results are robust to dropping farmers, as well as farm laborers. More generally, we show that our results are robust to sectoral changes and that overall task evolution was a result of both industry shifts and the within-industry technological changes such as electrification and computerization that are so often the focus in the literature.

B.Census Data

After creating task content measures at the occupation level (*occ1950*), we merge them to cross- sectional census data between 1900 and 2021 using data from IPUMS (Ruggles et al. 2023; Ruggles et al. 2021). We use the full-count censuses between 1900 and 1940, 5 percent or 1 percent samples from 1950 to 2000, and the 2010 and 2021 American Community Survey (ACS). We aim to measure task content for the entire occupational distribution, so we place limited restrictions on the sample: we include all men of prime age (18-55) who listed an occupation and were not living in group quarters. We follow Alston and Ferrie (2005) and re-code Black southern farmers as laborers since most Black farmers were sharecroppers whose tasks were more similar to laborers than farmers.

In addition to the cross-sectional census data, we use longitudinal data to measure how occupational task content changes across the life cycle or across generations. Tracking men over time is possible in historical censuses by searching for combinations of name, birthplace, and birth year, characteristics which should be stable across censuses. We use the links created by the Census Linking Project (Abramitzky et al. 2021), which are then merged into full-count data from IPUMS (Ruggles et al. 2021). For intragenerational data, we limit the sample to men aged 18-55 in the 1900-30 US censuses and then link them ten years later. For intergenerational data, we link sons aged 0-14 to the 1920-40 US Censuses 20, 30, or 40 years later.[11] The data are weighted for representativeness using inverse probability weights (Bailey et al. 2020). Full details on linking, weighting and representativeness are given in Online Appendix D.

C. PSID Data

We use longitudinal data from the PSID to compare with linked historical data. As in the census data, we exclude men not in the labor force or who are living in group quarters. We create two different datasets from the PSID: an intragenerational dataset that tracks male occupations over an individual's life cycle, and an intergenerational dataset that compares the occupations of fathers and sons. We aim to make the PSID sample as comparable to the historical census data as possible: for example, we limit it to males in the same age ranges. For the intragenerational dataset, we compare occupations ten years apart, similar to historical censuses. For the intergenerational dataset, we use the same sample constructed by Ward (2023), where the son's occupation is taken at the mid-point of the life cycle and the father's occupation is recorded at two separate points. Occupations are also recorded at a 3-digit level in the PSID, which we crosswalk to 1950 occupation codes and then merge into the task data. We weight the PSID data in a similar manner as the historical data in case selective attrition biases results.[12]

There are a few limitations to keep in mind when comparing estimates from linked historical census data to estimates from the PSID. First, measurement error when recording occupations is likely different across sources, where there is greater error in historical census data, perhaps due to less careful enumerators (Ward, 2023). Such error would bias estimates toward greater mobility in the historical data. Moreover, due to the lack of unique identifiers in historical census data, a person may be incorrectly linked to the next Census, which would also lead to error and a higher mobility estimate (Bailey et al. 2020). One way to address this error is to use multiple reports of the father's task content, but this method can only be applied for intergenerational estimates and not intragenerational estimates. For this reason, we focus more on the trend in the *gap* in mobility across Black and white men, rather than the absolute level of mobility.

To investigate racial gaps in task mobility in the period between the historical census and the PSID, we turn to the Occupational Changes in a Generation (OCG) survey. These data were

collected in 1962 and 1973 by the Census Bureau as a supplement to the March Current Population Survey. Respondents were asked about their own occupation and what type of occupation their father held when they were age 16, facilitating an intergenerational task analysis. We follow Collins and Wanamaker (2022) and restrict the sample to men who report living with a parent at age 16. All other sample selections (aged 18-55, Black or white, with an occupation) are consistent with our other analyses. The intergenerational results in Figures A3 and 8 are the only places where OCG data are used. Unfortunately, because the respondents were only surveyed in one period, we cannot use this sample for intragenerational analysis.

III. 120 Years of Task Trends

A. Long-run Task Content

Mapping workers' occupations to task content allows us to summarize the overall impact of 120 years of labor demand shifts. Using our dataset, we first describe the evolution of task content from 1900 to 2021. Figure 1 shows the broad trends in the three main task measures: routine-manual, physical labor, and non-routine analytic. Note that while we measure an occupation's task intensity based on their location in the 1950 census, because the occupational distribution is lumpy, the 1950 measure is not exactly equal to the 50th percentile.

Over the course of the 20th century the economy shifted towards occupations that were less physical such that the physical task measure halved in intensity, while non-routine analytic tasks gradually increased in importance. In 1900 a typical worker in terms of physical task intensity was employed as a baker, machinist, or excavating machine operator. By 2020, the typical worker was employed in jobs with much lower physical intensity, such as photographer, librarian, and chemist. A long-run decline in occupations specialized in physical tasks offset by a steady rise in non-routine analytic work is consistent with both within-sector skill-biased technological change as well as urbanization and structural transformation pushing labor towards services and away from

brawn-intensive manufacturing and agriculture (Kogan et al. 2021; Autor, Levy, and Murnane 2003; Michaels, Rauch, and Redding 2018; Goldin and Katz 2009; Deming 2017). Workers changed task intensity at similar rates over time, both within their own lifetimes and intergenerationally, suggesting that labor market dynamics have remained stable across such structural shifts and are more likely primarily driven by technological change (Figure A7).

We show that routine-manual work experienced two distinct eras of change. First, there was a rise in routine intensity between 1900 and 1960, briefly interrupted by the Great Depression and high (routine-intensive) manufacturing unemployment. The second phase began about 1960 when routineness began to decline. Early in the 20th century, routine-manual work first rose slowly, as steam-powered and then electric-powered machinery helped to replace tasks performed by hand (Atack, Margo, and Rhode 2019, 2022).[13] Contemporaries observed these trends in technological change followed by job change, expressing concern that particular types of workers might be replaced *en masse* (Jerome 1934). The postwar period saw a sustained rise in routine-manual intensity to a peak around 1960 before the modern period of hollowing out began (Autor, Levy, and Murnane 2003). While our data rely more on the earliest versions of the DOT, we capture the same trends in the latter half of our period that others have shown exclusively based on later versions and our results are robust to using only the 1977 DOT, as shown in Figure A2. For instance, the late 20th century story of the peak and long-term fall of routine jobs is visible, which partially reflects automation from computerization and robots (Autor, Levy, and Murnane 2003; Acemoglu and Restrepo 2019). We also find that non-routine analytic tasks continued to expand (Michaels, Rauch, and Redding 2018).

In other words, regardless of sector (Figure 1b) or location (Figure A4), occupational task content shifted from physical to analytically-oriented work. We see this also in the non-monotonic trends in routine-manual tasks, despite the fairly steady movement out of agriculture and towards manufacturing and then services. We go further, in Figure A5, to show our basic task trends accounting for shifts in broad industry category. We found that about two thirds of the century-

wide trends in physical and analytic tasks were explained by industry shifts, while the remainder were within-industry. For routine-manual tasks, the trend is the same no matter whether we control for industry, and most of the trend comes from within-industry changes. Thus structural transformation is an important part of the story in explaining how work has changed over time, consistent with historical (Gaggl et al. 2021) and modern (Autor and Dorn 2013) findings, but it is certainly not the only determinant that we have uncovered, extending recent research (for example, Bhagia and Bryson 2023) to indicate labor demand is the dominant driver of these trends.

B. Observational Task Returns Over Time

While the overall task content of American labor has changed remarkably over the last 120 years, it is unclear whether the relative return to task content has also changed. We might expect that increased educational attainment has pushed wages up, and that, along with labor demand shocks, this might have changed the returns to different tasks (Goldin and Katz 2009). To examine this question, we estimate observational task premia by regressing the log of weekly wages on the task intensity measure, a quadratic in age, and years of educational attainment for male wage workers aged 30-45:[14]

$$(1) \qquad log(WeeklyWage_i) = \beta_0 + \beta_1 Rank(Task_i) + \beta 2 YearsEd_i + \beta_3 A_i + \beta_4 A^2{}_i + \varepsilon_i$$

We estimate the regression for each cross section between 1940 and 2021. Note that the wage premia do not account for business or farm income due to data definitions, nor are they separable from individual-level controls uncorrelated with education or experience. We emphasize these regression results are not causal but provide some indication of the relative status associated with task intensities.[15] We then plot the ranking of these task premia over time in Figure 2.

First, Figure 2 shows that the relative ranking of task premia are similar throughout the 80-year

period. In 1940, non-routine analytic tasks were the highest-rewarded task, with routine-manual in the middle and physical labor the lowest. The same pattern holds in 2021. However, there were important movements of task premia across those 80 years. The Great Compression, as Goldin and Margo (1992) termed the fall in the skill premium between 1940 and 1950, shows up as a large fall in the non-routine and routine-manual task premia and an increase in the physical task premium. Since 1980, however, the gulf between physical and non-routine analytic tasks' average wages has become larger than at any point in our sample.

Although routine-manual work has remained the middle return task over time, its relative remuneration has fallen consistently from 1940 to today. There is no evidence of a post-Great Compression reversal. Instead, during the postwar rise in routine-manual task intensity, its relative wages *fell*– routine-manual tasks are no longer associated with high incomes, denoted by a positive coefficient in this approach. This downward trend in routine-manual remuneration happened at the same time as these jobs were being "hollowed out" from the American labor force, while since 1960 nonroutine-analytic tasks have seen their demand continue to grow with their wage premium mostly intact.

Although we focus in this paper on three summary task measures, the changes in the 21 underlying task components are also indicative of shifts in relative demand related to technological change. Across these finer task intensity variables, Figure A6 shows that there was remarkable stability in premia between 1940 and 2021. A simple regression between task premia across years yields an R-squared of 0.71. The overall steadiness of relative task premia indicates that task quantities likely played a particularly important role in shaping income disparities over time and, given the stark differences in task composition by race, suggests that this channel might explain a significant portion of racial wage gaps. We investigate various aspects of this hypothesis below.

The 45-degree line clarifies which tasks' observational returns have changed over time. For example, routine-manual is to the right of the line, illustrating that it was higher paid in 1940 than in 2021. We see particularly steep declines in the relative returns to tasks like *repetitive* and *reaching*, which are closely associated with physical and routine work. Specialization in routine and physical

work has become less well-paid over time, so below we will investigate whether both race-based task premia and task intensities contribute to trends in racial inequality in labor market outcomes.

IV. Tasks' Role in Racial Labor Market Gaps

A. Black-White Task Content Disparities

Understanding Black-white labor market disparities through a task lens requires we first document the changes in task content by race since 1900, which spans Jim Crow, the civil rights era, and the post-civil rights slowdown in income convergence (Margo 2016). We present differences in task intensity by race for male workers from 1900 to 2021 in Figure 3.[16] Positive numbers indicate that the average Black worker has a higher task intensity than the average white worker. For example, Black workers held jobs that were more physically demanding than white workers in 1900. For comparison with the existing literature, we also plot the difference in occupational income in every cross-section.

The overall economy moved out of physically intensive work and towards non-routine analytic work starting in 1900 but this masks tremendous racial differences. At the start of our sample in 1900, Black workers held jobs that were more physically demanding than white workers. The gap was at least 10 percentiles in 1900 and widened to 20 percentiles by 1940. In occupation terms, the 1900 percentile gap is equivalent to the difference between a farm laborer (a common occupation for Black workers, at the 87th percentile) and a mechanic (77th percentile). By 1940, the gap is more similar to the physicality gap between farm laborers and tool makers (67th percentile). White workers transitioned toward jobs with fewer physical demands immediately and continuously since 1900. It was not until 1960 that the physical content for Black workers matched the physical content for white workers in 1900 – a 60-year lag.[17] As a result of this marked racial divergence in task trends, the typical pre-WWII Black worker was a farm laborer or wood sawyer while white workers were far more likely to work as carpenters, salesmen, and cabinetmakers.

In contrast, a period of rapid convergence after WWII led to greater similarities in exposure

to the 1940-80 rise and post-1980 fall in routine-manual tasks by race. The rapid advancement in Black occupational outcomes before 1980 can partially be attributed to an increased propensity of Black men to do routine-manual work. After 1940, as routine-manual work became less well-paid but increased in quantity, Black workers' routineness converged towards the level of white workers. White workers' routine-manual task intensity peaked in 1960, just as the modern hollowing out period began but after the relative remuneration of routine-manual work had started to fall. Both white and Black workers experienced similar declines in routineness after 1980, when task displacement due to automation and computerization grew (Autor and Salomons 2018). The fourth panel of Figure A9 reinforces this result, using the RTI measure of Autor and Dorn (2013) which condenses our task measures into one measure capturing relative routine intensity. It clearly shows the rise and fall of relative routine intensity for white workers, around the 1960 peak. This also indicates that Black workers diverged from whites in RTI up to 1940 before rapidly entering jobs with increased RTI up to a peak in 1970. The timing of this convergence occurred well after the premium to routineness had begun to decline, representing bad timing for Black men who were finally gaining access to what had been stable and fairly well-paid, often unionized, manufacturing jobs.

Substantial variation by race in task allocation still exists in 2021, despite sustained institutional and cultural change. The largest racial gaps remain in non-routine analytic work, indicating stalled convergence at the top of the wage distribution. As the century progressed and the aggregate share of these innovation-complementary jobs increased (for example, Autor et al. 2024), Black workers increased their intensity in non-routine analytic tasks, but did not fully converge to white workers' intensity.

Certainly some of the convergence observed in Figure 3 was due to the prohibition of outright discrimination based on race in 1964 with the passage of the Civil Rights Act, which opened up jobs in new sectors and occupations for Black workers (Donohue and Heckman 1991; Aneja and Avenancio-León 2020). Over time, taste-based discrimination also appears to have decreased, prompting Black workers' entry to factory work in the 1940s and 1950s, and later,

public-facing service employment (Aizer et al. 2022; Ferrara 2022; Hurst, Rubinstein, and Shimizu 2024). We note, however, that controlling for state of residence, age, and educational attainment does little to close the Black-white gaps on their own over time. However, the limited human capital controls in census data make it difficult to precisely measure gaps conditional on skill level (Neal and Johnson 1996).[18] Some of the convergence since the 1940s likely reflects reductions in unobserved skill gaps, for example, as disparities in Black-white school quality decreased (Card and Krueger 1992; Carruthers and Wanamaker 2017a; Cook and Evans 2000; Page, Murnane, and Willett 2008). Nevertheless, as modern innovations tend to substitute for physical and routine labor and complement complex problem-solving skills, these results reveal the century-long roots of Black workers' higher exposure to technological substitution (and not complementarity) in the modern era (Cavounidis et al. 2021; Wrigley-Field and Seltzer 2020; Hurst, Rubinstein, and Shimizu 2024; Lerch 2025).

B. Relative Task Premia By Race

We investigate here whether the gulf in task quantities by race identified above was exacerbated by differences in observational task returns by race. Many studies of Black-white wage differences have examined the role of differences in individuals' observable human capital, which we build on to show how differences in the return to these investments have evolved across the skill distribution.[19] We re-estimate Equation 1 separately by race and plot the results in Figure 4. Now the task premia reflect whether specializing in a task was associated with a higher wage within-race. In 1940, for instance, physically demanding jobs signaled higher average wages within the Black population but signaled lower wages within the white population. The opposite was true for routine-manual or non-routine manual average task wages.

Some striking differences remained in returns by race after WWII despite the rapid narrowing in task quantity gaps shown in Figure 3. Unlike white workers, Black workers' returns to routine-manual work rose from 1940 to 1960, indicating that routine-manual work was a path for Black workers to gain higher relative wages in the postwar period compared to other tasks. On the

other hand, the premium associated with non-routine analytic work was smaller for Black workers over the entire sample, perhaps because discrimination limited large wage gains in occupations intensive in those tasks (for example, Hurst, Rubinstein, and Shimizu 2024). These observational racial return disparities indicate that Black and white men received different average earnings across tasks before 1980.

Over time, the gap between Black and white observational task returns has been bridged. In the bottom right of Figure 4, we plot the correlation between white and Black specific task premia for our underlying task components. In 1940, the Black and white premia for the same task were very different. Black workers received lower relative earnings in non-routine analytic and higher relative earnings in physical tasks. After 1950 we see rapid increases in this correlation, especially in the civil rights era, with near total convergence in racial task premia occurring by 2000.

C. A Task Decomposition of the Racial Wage Gap

These Black-white occupational task content differences can explain a significant portion of the racial wage gap after 1940. Here we conduct a thought experiment to predict the size of the racial income gap in each period if we assign Black workers the same task content as white workers, in a Oaxaca-style decomposition.[20]

Figure 5 displays the contributions of occupational task differences to average racial wage gaps over the last 80 years where wage data is available. Task content differences were at their zenith in 1940 (Figure 3), at which point they explained 45 percent of the Black-white wage gap. After 1945, the share explained nearly halved, though even in 1980 task content differences could explain almost a quarter of the racial income gap when controlling for age and education. If task content was equalized across race now, it would lower the racial wage gap by 30 percent, suggesting lingering task differences may play a role in the stagnating racial income gap since 1980 (Daly, Hobijn, and Pedtke 2017).

V. The Black-White Gap in Task Mobility

A. Estimating Mobility Gaps

Task content, like income, has failed to converge completely for Black and white men over the past century. The remaining racial task gaps in the cross-section suggest that Black and white workers experience different long-run transitions across tasks. We estimate mobility in task content, as in the income mobility literature:[21]

$$Rank(Task_{i,t}) = \alpha_r + \beta_r Rank(Task_{i,t-j}) + \epsilon_{i,t} \quad (2)$$

where the subscript r denotes race-specific (white or Black) intercepts and slopes. Within-generation estimates regress the current individual's current percentile rank on the percentile rank from 10 years prior, while across-generation estimates regress the son's percentile rank on the father's percentile rank. A high value of β_r suggests that within-race differences in initial task content are preserved over time (within a lifetime) or across generations. As in the income mobility literature using ranks, we use percentile rank by age to account for life cycle effects (Chetty et al. 2014).

To fix ideas, Figure 6 plots the intergenerational results from estimating Equation 2 for non-routine analytic tasks across generations using the PSID. There are large racial gaps in intercepts but similar slopes, meaning that that the rank-rank line for Black individuals is always below that for white individuals. As a result, racial mobility gaps exist across the entire distribution. Black sons, on average, end up in occupations with lower non-routine analytic task content than white sons, even when their fathers had similar task intensities. It is precisely this gap that we want to document from 1900 to 2021, which helps to uncover whether Black and white workers transition differently in the face of changing labor demand.

While we can estimate mobility gaps across the entire distribution, we focus on comparing Black and white individuals who start at relatively high task intensities, defined as the 75th percentile. This

choice aligns with Chetty et al. (2024), who report racial income gaps for children from families at the same percentile, which they classify as "high-income." This gap helps us to understand what happens to workers and children if a labor demand shock impacts occupations high in the task distribution, such a declining demand for occupations that are high intensity in routine manual. As shown in Figure 6, Black men end up 9.6 ranks lower than white men in non-routine analytic task content, despite their fathers having similarly high task intensity. Beyond estimating this gap conditional on the starting point, we also add control variables, when available, to examine whether Black-white mobility gaps stem from differences in observable characteristics.

Figure 6 also plots the intersection of each race's rank-rank line with the 45-degree line, where the initial rank equals the ending rank. This intersection, calculated as $\frac{\alpha_r}{1-\beta_r}$, represents the race-specific steady-state rank: individuals starting above this rank are expected to have lower ones, while those below it are expected to rise (see Chetty et al. 2020). These steady-state gaps correspond to the cross-sectional gaps in average rank we showed in the prior section. If we find a steady-state rank gap (as we find a gap of 12.2 in Figure 6), then we would not expect the Black-white gaps observed in the Census or ACS to ever converge.

We emphasize that racial convergence could still occur with differences in these slopes or intercepts even if the racial mobility gap existed at the 75th percentile. That is, there could be a racial gap at the 75th percentile of the routine-manual distribution, such that a labor demand shock to those high in the distribution leads to different outcomes by race. At the same time, there may be no steady-state gap, such that any gap caused by the labor demand shock disappears as Black and white workers eventually converge back to equal steady states. This is not the case, however, in Figure 6, as the slopes are quite similar. Therefore, we transform our estimates into the steady-state gap for each task in our intergenerational dataset to investigate how task mobility informs long-run Black-white convergence.

B. Racial Gaps in Task Mobility over the Last 120 Years

Using the intragenerational data, we find that the 20th century began with large racial mobility gaps for those starting at the 75th percentile for each task measure (see Figure 7a).[22] By 1940 gaps had widened in ways consistent with white men exiting low-paid tasks more than Black men and Black men leaving high-paid tasks more frequently. In the historical period, Black men were more likely to end up in a physical-intensive job, but less likely to remain in a routine-manual job than white men engaged in similar work previously. The largest disparities before WWII were in non-routine analytic work such that Black men fell 25 percentiles below white men at the 75th percentile in the prior census. This is also consistent with the large occupational income gaps displayed in Figure 7a, but demonstrates that the direction of task mobility repeatedly pushed Black men out of higher-paid jobs and kept them in physical tasks over time.

Between 1940, our last historical observation, and 1980, our first PSID observation, all of the racial mobility gaps shrink substantially. During this forty-year window, we find that the Black-white differences in our two higher-return tasks fell. The non-routine analytic mobility differences halved, while the routine-manual equivalent became indistinguishable from zero. Without additional longitudinal data, however, we cannot rule out that this trend began in 1940.

Like the racial income gap, convergence in mobility measures stalled after 1980. Despite the similarity of Black and white returns for non-routine analytic work, Black men who started in high-intensity analytic work still fell by 10 ranks relative to white men. A similar narrowing of the physical mobility gap also occurred, but this trend did not continue towards total convergence. Instead, the most recent census wave has the same magnitude gap as in 1910, suggesting little cumulative progress over time. Despite reductions in other labor market disparities, Black men are still less likely to remain in the highest return, continually expanding, and most technology-complementary task (non-routine analytic) while being more likely to remain in the lowest paid, least technologically advanced, and continually shrinking task (physical).

C. The Transition out of Routine-Manual Work By Race

Routine-manual tasks have undergone substantial intensity and remuneration changes over the past century, even compared to physical and non-routine analytic work. As demand for this middle-skill task has fallen, workers' labor market outcomes have become more polarized (Autor, Katz, and Kearney 2006). Though there has been substantial Black-white routine-manual convergence in both cross-sectional (Figure 3) and mobility (Figure 7a) terms, there remains a possibility that workers' transitions out of routine-manual work vary by race.

To measure racial differences in the movement out of routine-manual work, we estimate the predicted task percentile of an individual who started at the 75th percentile of the routine-manual task distribution in the previous census or an earlier wave of the PSID.[23] We do this for each task in the second census/PSID wave and run the regression separately by race. Figure 7b plots where Black and white routine-manual workers end up on the task distribution separately for historic and modern eras.

This exercise reveals that Black and white workers transition into very different work from the same starting point of routine-manual intensity. Both groups experience a fall in routine-manual content over the decade but the similarities stop there. No matter the time period, white routine workers are far more likely to end up in occupations with more analytic tasks than Black routine workers. Instead, Black routine workers are more likely to enter jobs that are more physically intensive. Gaps in most of these transition measures have narrowed over time, but Black workers are actually *more* likely to move into the lowest-paid task now than either modern white workers or historical Black workers.

Our results remain robust across different measures of routineness and additional controls. An alternative approach to measuring routine-ness is RTI, which classifies occupations based on the relative prevalence of routine tasks Autor, Levy, and Murnane (2003). We find using this measure yields similar results (Figure A14).[24] Another issue is while we purposely do not include controls in order to describe overall transitions, the patterns may differ when conditioning on observables

Adding controls for educational attainment and state in the base period *t* (Figure A15) preserves the sign of the gaps, though they are smaller in magnitude for non-routine analytic and physical tasks.[25] We also present results on movements out of other core task measures, assessing whether Black workers are more likely to transition into lower-paid task occupations (Figure A11). In each period and task, white men move up (or fail to move down) the skill ladder more frequently and Black men tend to move down (or fail to move up) the skill ladder.

We take this as evidence that task transitions compound the racial divides in task mobility illustrated in the previous subsection. In both the modern and historical periods, Black workers exit high-return work more, remain in low-return work more, and move out of the middle-return task into the low-return task more than white men. Despite some convergence, differential task transitions continue to contribute to racial disparities in labor market experience. Given the recent decades of significant technological change and labor market displacements, differential task transitions can have a significant impact on labor market outcomes by race.

D. Intergenerational Gaps in Task Mobility

Changes in workers' task content may further slow racial income convergence by carrying over to the next generation. We test for the intergenerational transmission of task content by regressing an individual's task rank on their father's task rank. We estimate this both for those whose fathers started at the 75th percentile of the distribution and for the steady-state gap. A positive value indicates that Black sons have higher task ranks than white sons after controlling for their fathers' labor market experiences.

Intergenerational gaps in task mobility have narrowed substantially over time for all tasks, as shown in Figure 8. In and before 1940, we find estimates in line with the own lifetime correlation: Black men with fathers at the 75th percentile were far more likely to be in physical work, and far less likely to be in any other task. These differences in task mobility corroborate the lack of upward occupational mobility for Black men over time highlighted elsewhere (Collins and Wanamaker 2022).

After WWII, we observe some, but not complete, convergence as all 3 task mobility gaps fall by ten points, although later estimates are noisy due to a limited PSID sample size. Most of the convergence in intergenerational task mobility over the past 120 years occurred in the 1960s and 1970s, periods associated with both reductions in labor market barriers for Black men and convergence in labor market returns by race.[26] By 1990, the mobility gap had fallen for all tasks but we find some evidence that intergenerational mobility has not fully converged for non-routine analytic and physical tasks.[27]

The mobility gap at the 75th percentile may differ in both level and trend from the steady-state gap in average ranks. This would occur if the slopes of the Black and white rank-rank lines were significantly different, but that does not appear to be the case. Figure 8b shows the steady-state gap between Black and white workers over the last 100 years.[28] We find that steady-state gaps decrease over time, meaning the steady state itself is not truly stable across generations. However, statistically significant gaps remain for non-routine analytic and physical tasks. Without further shifts in mobility rank-rank lines, full convergence is not expected to occur in task content.

E. Explanations for the Racial Gap in Task Mobility

The above analyses illustrate that Black males have consistently been less likely to work in, and remain in, non-routine analytic-intensive jobs compared to white males, instead entering and remaining in low-return tasks. Task-based labor demand theories suggest that workers stay in jobs based on demand for the tasks they perform. When demand declines—often due to technological advances that make tasks easier to automate—workers are more likely to leave those jobs (Acemoglu and Autor 2011). For example, electricity reduced the need for physically intensive labor by 1900 (Katz and Margo 2014), and automation began replacing routine-manual jobs in the latter half of the 20th century (Autor, Katz and Kearney 2006). In this subsection, we examine whether racial disparities in the effects of task demand changes can explain Black workers' higher probability of remaining in physical work and exiting non-routine analytic work.

Certainly, Black and white workers may experience different employment trajectories without

this being due to task demand shocks. Both historical and modern research emphasize that both overt and indirect discrimination kept Black workers from higher-paying jobs, even within the same firm (Dewey 1952; Sundstrom 1994; Maloney 1995; Foote, Whatley, and Wright 2003; Charles and Guryan 2008; Borghans, Ter Weel, and Weinberg 2014; Fan, Wei, and Zhang 2017; Hurst, Rubinstein, and Shimizu 2024). Differences in location likely played a role, especially early in our historical sample, because Black workers were disproportionately concentrated in the rural South, which had markedly different labor market institutions and job mix than the rest of the nation (Wright 1986).[29] Other work suggests that there may be racial differences in workers' job transitions more generally, as Black men have long experienced more unemployment and longer unemployment spells than white men (Bound and Freeman 1992; Sundstrom 1992; Fairlie and Sundstrom 1997; Daly, Hobijn, and Pedtke 2020).

Investigating whether Black and white men experience different task mobility from the same task demand shock requires we adjust for these long-standing differences. To do so, we saturate our task mobility equation with successively more detailed time-dependent fixed effects which capture geographical and occupational sorting. We use finer fixed effects in the historical dataset than in the PSID due to dataset detail and size limitations in the latter. We regress worker i's task content rank in $t + 10$ on their rank in time t, a race indicator, and a range of fixed effects using the following specification for each of our baseline task measures:

$$(3) \qquad y_{io\,jc,t+10} = \beta_0 + \beta_1 Black_i + \beta_2 Black_i \times (y_{i,t} - 75) + \gamma_{o\,jc,t} + \varepsilon_{io\,jc,t+10}$$

where the fixed effects are based on the interaction of occupation o, industry j, county (region in the PSID) c, and year t indicators. We recenter the prior rank at the 75th percentile so that the coefficient on the Black indicator (β_1) captures the Black-white mobility gap conditional on starting at the 75th percentile, although the direction of results does not depend on this interaction. Figure 9a displays the β_1 coefficient. The first set of results in each panel replicates Figures 7a and 8 through 1940 in a pooled fashion. The next three sets to the right add successively more detailed

fixed effects.

First, we find that controlling for initial occupation using *OCC*1950 and year causes the Black coefficient on physical tasks to fall, while the coefficients on non-routine analytic and routine-manual jobs are stable. This specification more flexibly controls for occupation-specific shocks, such as declining demand for agricultural laborers, blacksmiths, or other artisans, though at a national level. Next, we interact these effects with *IND*1950, leveraging variation within year, occupation, and industry. This approach accounts for variation within occupation by industry, such as for general laborers or operatives in different industries. Still, there is little movement in the Black-white gap.

Then we interact year, occupation, industry, and county categories, absorbing variation in both geographic and occupational sorting, following prior work on technologically-based local labor market shocks and structural change (Gaggl et al. 2021; Feigenbaum and Gross 2024; French 2024; Cockriel 2024). In this case, Black and white workers are in the same occupation, industry, year, and county. Even with this demanding specification Black workers' end up in physical tasks that are 6.2 percentiles higher, only 2 percentiles higher than the baseline without these controls (Figure 9a). The gaps are even larger for the other two tasks when estimated within narrowly defined occupation-industry-county groups than at baseline. The routine-manual coefficient becomes slightly more negative after adding the controls (-14 to -16 percentiles) and the non-routine analytic gap is slightly less negative than the baseline (-24 to -23 percentiles). This implies that even within narrowly defined occupation-industry-county groups, similar Black and white workers end up in starkly occupations that are intensive in different tasks. Figure A16 includes education-level controls where available (only between 1930-1940), and still finds these same patterns, further strengthening our confidence that Black and white men's tasks evolve differently even when they start with the same observables.

Similarly, father-based fixed effects only slightly alter Black-white gaps in transitions in the historical period (Figure 9c). We find that using precise information on a father's labor market

outcome decreases the Black-white gap in physical tasks by 2 percentiles (14 to 12), but it does not eliminate it. The mobility gaps for the other tasks slightly widen when including the controls, once again confirming our baseline results, showing that they are not biased by differences in initial industry or location.

The fineness of the comparison group in Figures 9a and 9c suggests that Black and white workers' task mobility diverged even within a occupation, industry, and county and year. We extend this analysis, with less-detailed geographic fixed effects due to data limitations to the PSID in Figures 9b and 9d, and find the same patterns hold. Adding controls attenuates our estimated gaps but they remain in both physical and non-routine analytic tasks within and across workers' lifetimes. Over the past century, then, we repeatedly find that Black workers and their sons were far more likely to stay in physical tasks and exit non-routine analytic tasks as demand for the former rose steadily and the latter fell.

Finally, we provide evidence that these racial mobility gaps occurred when technological change lowered routine-manual task demand. We apply the same approach to estimate how the recent "hollowing-out" of routine-manual tasks has affected Black and white workers, but where always regress on initial routine manual intensity, and add occupation-region-year fixed effects in Figure A18. Our analysis reveals that Black workers were disproportionately pushed into low-skill physical jobs (for example, labor or cleaning), while white workers more often transitioned to high-skill non-routine analytic roles (for example, data analysis or management). This pattern holds true both within individual careers and across generations in both the pre-1940 and PSID data, indicating that technological shifts disproportionately harmed Black workers—even when they began in comparable roles to white workers. Though not conclusive, these results are consistent whether examining long-term declines in physical work or short-term technology-driven disruptions. Together, they suggest that racial differences in adapting to changing job markets contribute to persistent Black-white labor gaps, a mechanism often missing from models of workplace inequality.

VI. Conclusion

In this paper, we harmonize task measures over the last 120 years and use them to document changes in aggregate task content and task content by race. We find significant Black-white gaps in task content in the early 20th century. Starting from 1900, white workers transitioned toward modern jobs with higher analytical skills, leaving lower-paid physical-intensive positions to Black workers. In turn, Black workers followed the same trends for these tasks, albeit a full half-century later. White workers' intensity in routine-manual tasks followed closely their relative demand trends, while Black workers were still entering those jobs at least a decade after their relative demand began to fall, and two to three decades after their remuneration peaked.

We argue that racial differences in task mobility, both within and across workers' lifetimes, have contributed to the lingering economic disparities between Black and white men. We find that Black men were more likely to remain in physical tasks and, at the other end of the task compensation spectrum, less likely to remain in non-routine analytic work compared to white workers. These task barriers existed historically and persist even today. Our findings provide a new perspective on the stalled convergence of racial labor market outcomes since 1980, one that links to the broad waves of technological change that have been found to have pervasive labor market impacts, through the channel of differential task transitions. They further suggest that future research that uses task-based approaches to understand labor market inequality should factor in race-based heterogeneity in the response to technologically-driven task shocks. Another valuable question for future work is to investigate further why task transitions look so different for Black workers, in the context of large technological upheavals– in order to imagine a world with full convergence of outcomes we need to understand the factors driving upward versus downward moves following displacements.

Notes

[1]These findings are consistent with other research on occupational change which uses broad occupation categories (Katz and Margo 2014) and are also in line with Autor et al. (2024) on post-1940 employment in new work and Kogan et al. (2021) on historical patent descriptions and recent earnings.

[2]The rise and fall in routineness is most clearly shown in Figure A9 which uses the Autor and Dorn (2013) composite routine task intensity index measure. This figure shows that Black men were delayed in their entry into routine-intensive jobs until after 1940, when they experienced rapid catch-up. Their routineness peaked in 1970, after routine-intensive jobs began to see their relative demand decline. Black men remain in more routine-intensive jobs by this measure.

[3]Gray (2013) showed that descriptions from the 1939 DOT are similar to those in a 1918 US Army job description publication (Swan 1918).

[4]Contrast strength with the clerical variable which measures the clerical competency required to perform an occupation on a scale from one to five. A stenographer would rate low on the strength variable, as it is mostly a sedentary job, and it receives the second highest score in the clerical variable (proofreader ranks highest for clerical accuracy). In contrast, a machinist receives the lowest possible clerical accuracy score.

[5]Another composite measure, communication, was constructed as an alternate representation of modern work, as described in Michaels, Rauch, and Redding (2018) and Deming (2017). Results using that variable are available and are similar to those for non-routine analytic tasks and are in line with the findings of Michaels, Rauch, and Redding (2018) on urbanization's role in the growth of interactive tasks.

[6]We also constructed an Abstract measure, following Hurst, Rubinstein, and Shimizu (2024) as

closely as possible given limitations in long-run DOT definition continuity. Abstract has a relatively flat trajectory– the racial gap was initially smaller than that for non-routine analytic, though the stalled convergence since 1980 is similar. Abstract contains more managerial tasks so we assume that Black men could be sole-proprietors in Black neighborhoods historically more readily than they could enter occupations intensive in non-routine analytic tasks. This is supported by Hurst, Rubinstein, and Shimizu (2024) who argue that interpersonally interactive tasks converged more due to falling discrimination.

[7]The sample is limited to men ages 18-55 with an occupation.

[8]The normalization was conducted such that, in 1950, a value of 0.34 indicates that 34% of the population in 1950 worked in an occupation which was equally or less intensive in the use of that task.

[9]The update to the DOT measures, O*NET, has been used elsewhere (for exambole, Peri and Sparber 2009). However, Autor and Handel (2013) note that the O*NET measures are more complex than DOT measures such that it is difficult to merge measures over time, the focus of our study.

[10]For example, one of the largest shifts in ratings between the two DOTs was for farmers, which dropped from the 87th percentile in routine-manual to 18th, perhaps due to mechanization. Cashiers also fell in non-routine from the 84th to the 44th percentile, which reflects a shift from a clerical job (as classified in 1950 occupation codes) to a sales job (as classified in 1980 occupation codes) as technology made barcode-based payment systems feasible (Basker 2016).

[11]These are the same data as in Ward (2023). Ward takes children ages 0-14 in the 1850-1920 censuses and uses their links to censuses 20, 30, and 40 years onwards, keeping those between 25 and 55 years of age. Fathers are also linked to a second observation 10 years earlier or later. Conservative links are used (exact first and last name strings that are unique within plus/minus 2-years of birth) to address issues of false positives (Bailey et al. 2020).

[12]We pool the PSID with the 1980-2020 CPS-ASEC. We then use a probit model to determine which observable characteristics are associated with appearing in the PSID relative to the CPS-ASEC. This method is the same suggested by Bailey et al. (2020). The observable characteristics are age (in 10-year bins), race (Black or white), region of residence interacted with Black, occupational category interacted with Black, (white collar, farmer, unskilled or skilled). All of these are interacted with five-year dummy variables in case selection into the PSID varies over time. We winsorize weights at the 5th and 95th percentiles to reduce outliers biasing results. This weighting method is the same as that in Ward (2023), who shows that estimates of intergenerational mobility are similar when using these weights or PSID-provided weights.

[13]Increases in routine manual occupations likely would be larger with data going back into the 1800s to capture the rise of steam-powered machinery and operatives in place of artisans (Goldin and Sokoloff 1984; Atack, Bateman, and Margo 2008).

[14]Weekly wages are reported annual wage and salary income divided by weeks worked. Wages are adjusted for inflation using CPI measures from MeasuringWorth.com.

[15]Due to data constraints, we are unable to recover causal returns leveraging individual-level variation over time as in (Cortes 2016; Böhm 2020). However, household-level unobservables are unlikely to drive these average earnings results, as results are largely unchanged in a sibling fixed effects approach using linked historical censuses 1900–1940 and the PSID microdata for 1969–2015. Results are available upon request.

[16]See Figure A9 for the levels of Black and white task percentiles.

[17]Note again that the higher prolonged Black concentration in agriculture pre-1960 cannot fully explain this difference. If one drops farmers and farm laborers, then Black-white task differentials widened by less in the early 20th century but still remained (Figure A10a). Both Black workers'

migration out of the rural South and technological advances in agriculture (e.g. the mechanical cotton picker reducing stooping and picking by farm laborers) likely contributed to the reduction of farm labor and physical work among Black workers (Derenoncourt 2022; Collins and Wanamaker 2014; Ward 2023; Hornbeck and Naidu 2014).

[18]Information on human capital is scarce in the 1900-1930 census records, where only the ability to read or write was recorded. However, between 1940 and 2021 we can observe educational attainment. Figure A10b shows the trend of the Black-white gap when conditioning not only on educational attainment, but also on age and state of residence. Task gaps are smaller when conditioning on education, but the historical gaps between 1940-80 do not close by much. Further, gaps remain for non-routine analytic and physical jobs today when controlling for education.

[19]See, for example, the discussion of these methods in Carruthers and Wanamaker (2017b).

[20]We follow Fortin (2008) to decompose mean wage gaps in each survey wave.

[21]The main sample requires males to claim an occupation in both periods, which misses differential exit out of the labor force (Bayer and Charles 2018). We find that there is a racial difference in exit, where Black males were 1.2 to 1.9 percentage points less likely to have no occupation conditional on initial task content, further lowering their ability to move up the task ladder. Golan, Sanders, and James (2024) also provide some recent evidence that Black workers begin their working lives in jobs requiring less complex tasks.

[22]We recenter the data to be on the 75th percentile rank, regress the second task rank on the first rank, an indicator for Black, and the interaction between the indicator and first task rank. We plot the Black indicator. Research such as Collins (2000) showed the start of increased mobility for Black Americans from WWII onwards. However, consistent with our results for the earlier era, he still found that Black workers in wartime production experienced more downward mobility in terms of occupations compared to whites, upon transitioning back to civilian production.

[23]We run the regression $task_{i,t+10} = \beta_0 + \beta_1 routinemanual_{i,t} + \varepsilon_i$ for Black and white workers, and plot the predicted percentile for those at the 75th routine-manual percentile.

[24]There is one difference: when we use routine task intensity historically, we do not find a racial gap at the 75th percentile of RTI. However, we do find racial gaps for entering non-routine analytic and physical work for those starting at the 75th percentile of RTI.

[25]We can only add education as a control in the historical data for the 1930-40 linked dataset, where we assume that the value recorded in 1940 is stable in 1930.

[26]See, for example, related work by Donohue and Heckman (1991).

[27]When using the IV method, we find that 0 is within the 95 percent confidence interval for our intergenerational mobility estimates but still reject the null of total convergence at a 10% level. See Figure A12.

[28]We estimate this by re-centering the ranks of Black and white fathers based on their race-specific intersection with the 45-degree line. We then regress the son's rank on a Black indicator, the father's re-centered rank, and the interaction between the father's re-centered rank and the Black indicator. The figure plots the Black indicator.

[29]We note, however, that Figures A10a and A10b show that our results are robust to dropping farming or controlling for state, respectively.

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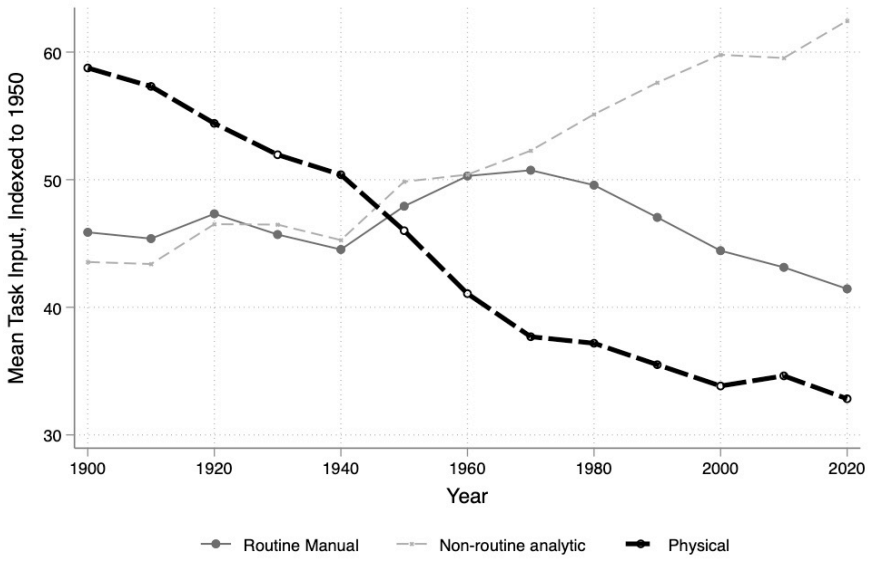
VII. Figures

(a) Level of task content, all industries



(b) Level of task content, excluding agriculture

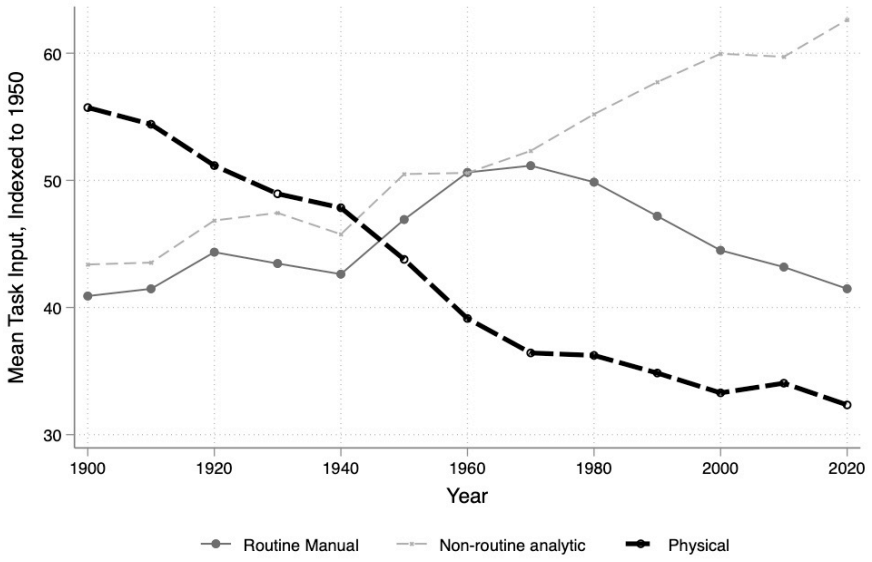


Figure 1: National trends in task content

Notes: Data are from the 1900-2000 censuses, and the 2010 and 2021 ACS (Ruggles, Flood, Foster, Goeken, Pacas, Schouweiler and Sobek, 2023). Sample is 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table C6 for task definitions. Panel B drops farmers and farm laborers.

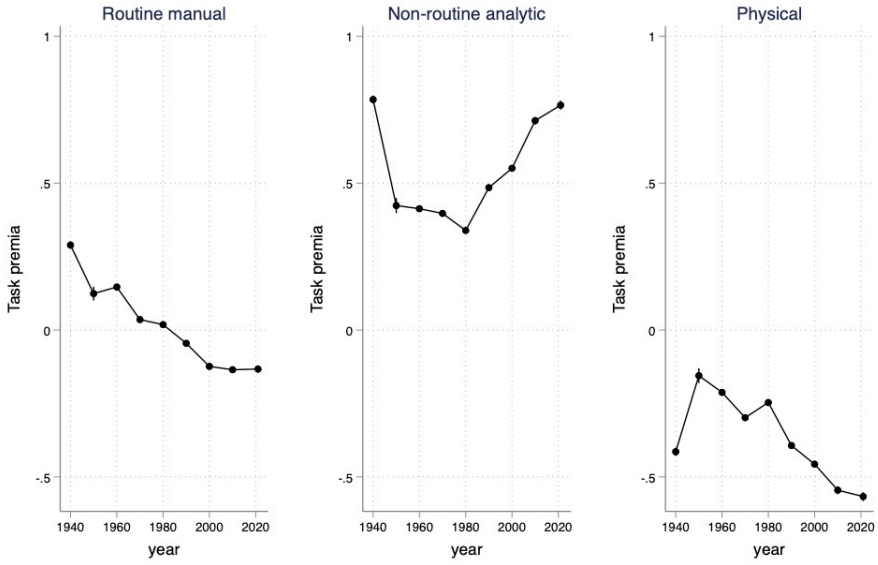


Figure 2: Observational task returns over time

Notes: Data are from the 1940 IPUMS and the 2021 ACS (Ruggles et al. 2021). Sample is 30–45-year-old male wage workers with an occupation. Task premia are estimated by regressing the log of weekly wage income on percentile rank of task, a quadratic in age, and years of education and are plotted along with 95% confidence intervals. See Tables C1-C6 for definitions. Full regression results are in Online Appendix table B1.

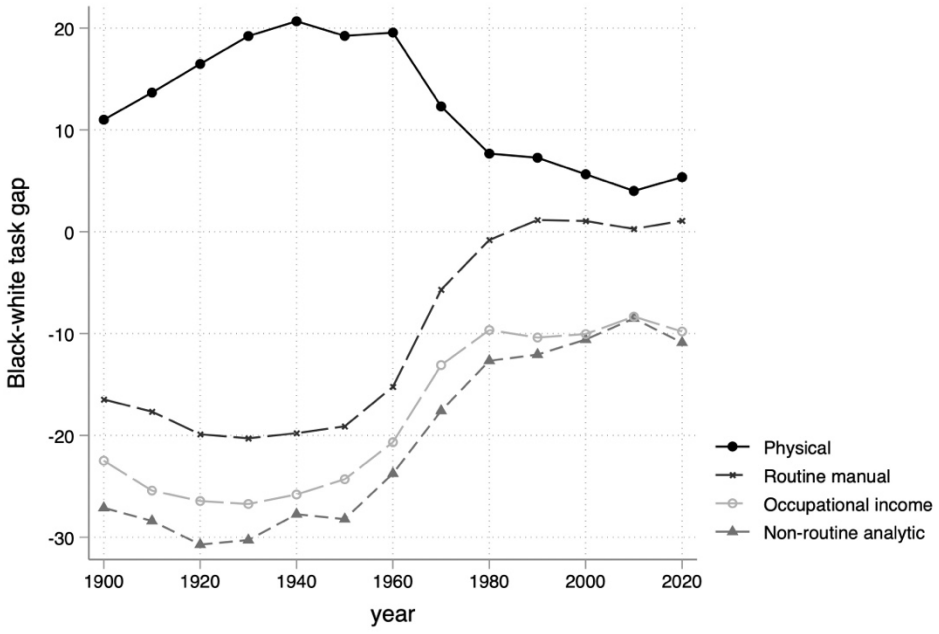


Figure 3: Black-white differences in tasks over time

Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Data are of 18–55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table C6 for task definitions.

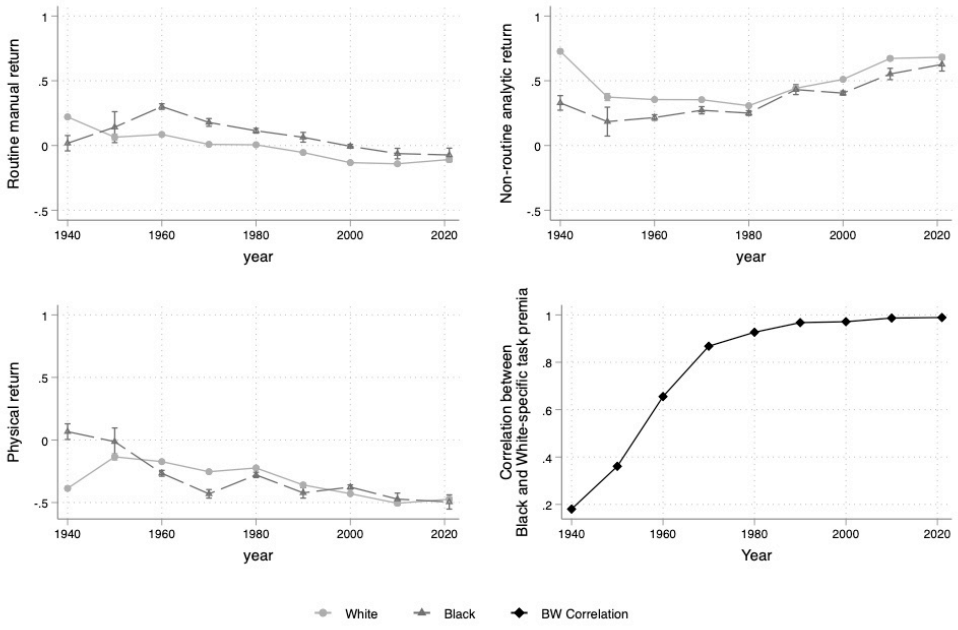


Figure 4: Racial differences in observational task returns over time

Notes: Data are from the 1940-2000 Censuses, 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Sample is male wage workers aged 30-45 with an occupation. Average task returns are observational and are estimated by regressing the log of weekly wage income on percentile rank of task, a quadratic in age, and years of education separately by reported race in each census wave and are shown with 95% confidence intervals. See Tables C1-C6 for definitions. Full regression results are in Online Appendix table B2.

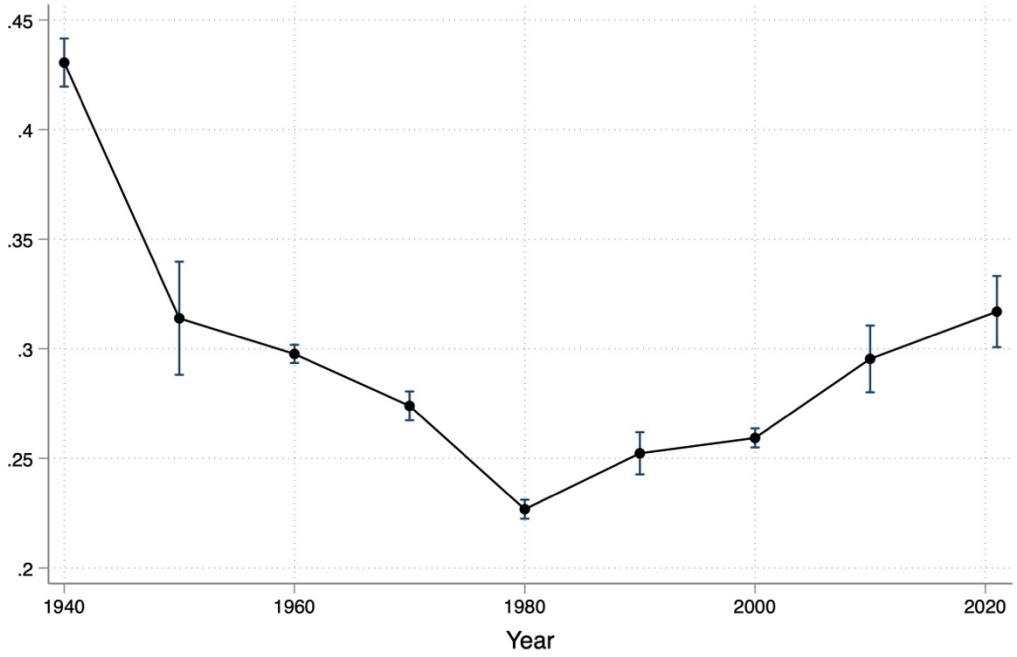


Figure 5: Tasks and the Black-white wage gap

Notes: This figure plots the percent of Black-white wage differences that can be explained by differences in task intensities in each cross-section, as well as 95% confidence intervals. The decomposition includes controls for education and age (not reported in the figure). Data are from the 1900–2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Data are men aged 30-45 with an occupation who are not self-employed. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950.

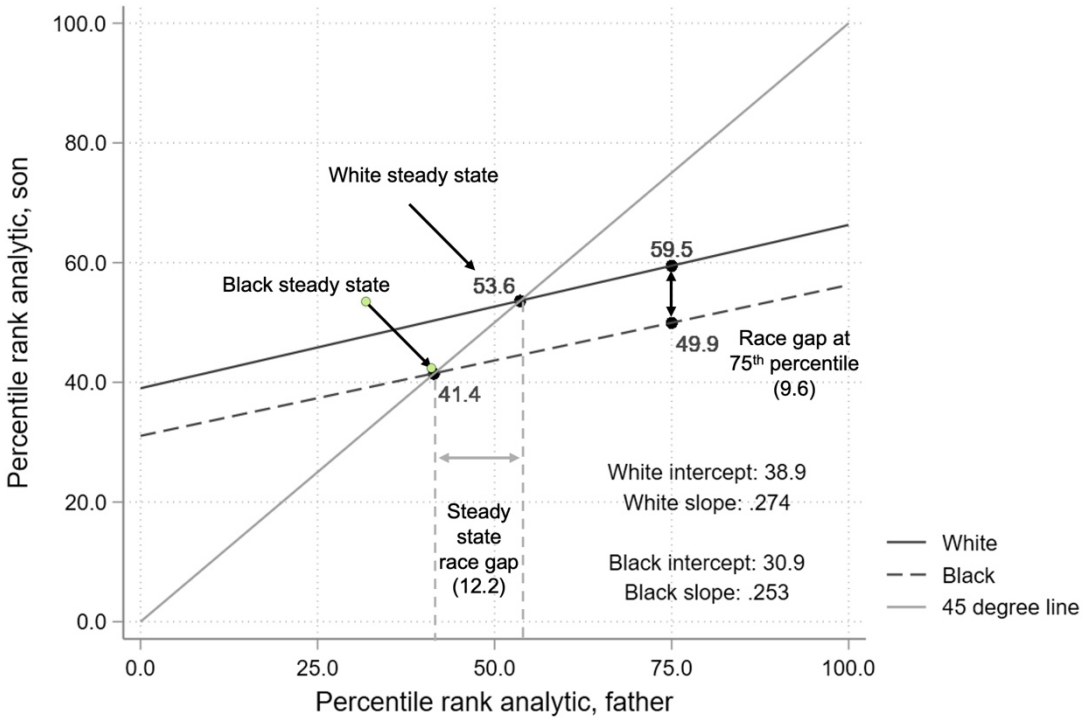
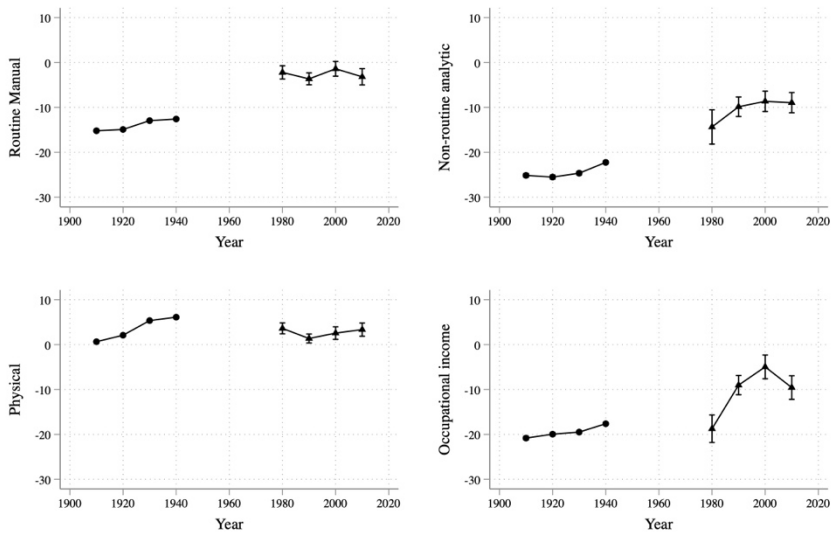


Figure 6: Black-white task mobility gaps: Nonroutine-analytic

Notes: This figure shows an example of rank-rank slopes by race using our data from the PSID. In this paper, we estimate the Black-white gap at the 75th percentile, examining whether, conditional on the father being relatively concentrated in that task, Black men end up in different ranks. We also estimate steady-state gaps in task ranks, which represent the difference where the race-specific line meets the 45-degree line. This figure is based on Chetty et al. (2020), which readers can consult for a more in-depth discussion.

(a) Own lifetime



(b) Movement out of Routine-Manual

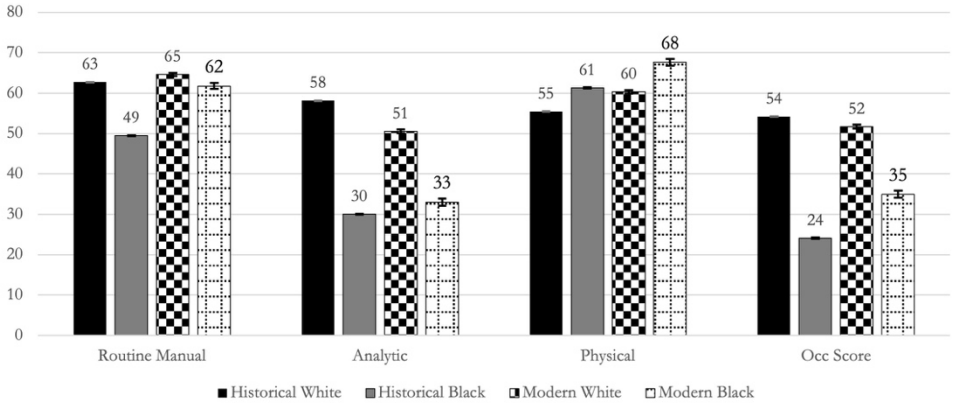
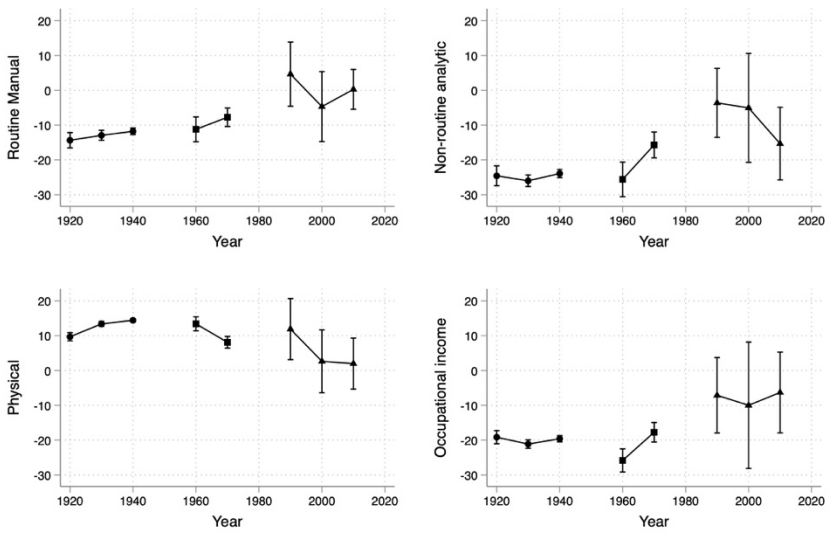


Figure 7: Black-white mobility gaps across the 20^{th} century

Notes: Underlying data are from the PSID (1980-2010), and the United States Censuses (1900-1940) (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2021) in Panel A and Ward (2023) in Panel B. Panel A plots the Black-white mobility gap for those initially at the 75th percentile of the task distribution along with corresponding 95% confidence intervals. Standard errors are robust. Panel B plots the predicted percentile on the dependent variable for those who start at the 75th percentile of routine-manual in the first Census or an earlier PSID wave. Regression results are available in Online Appendix tables B3 and B4.

(a) Intergenerational mobility gaps at the 75th percentile



(b) Steady-state race gaps

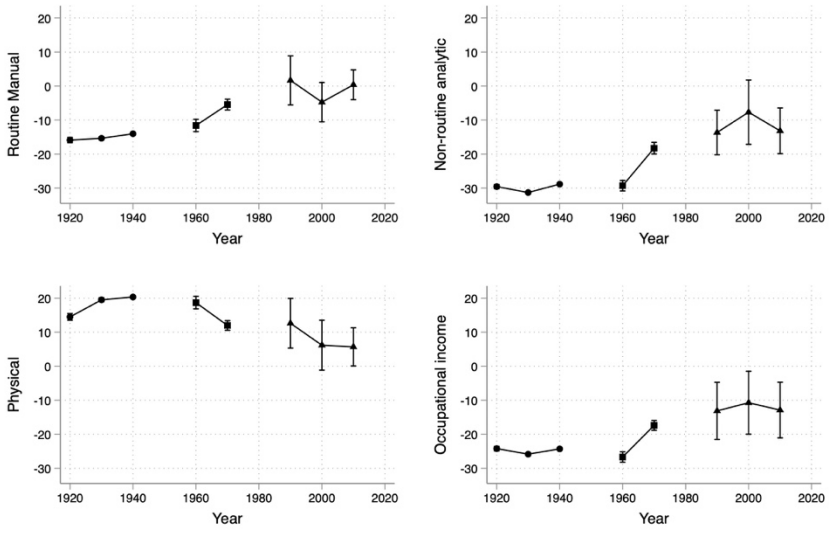
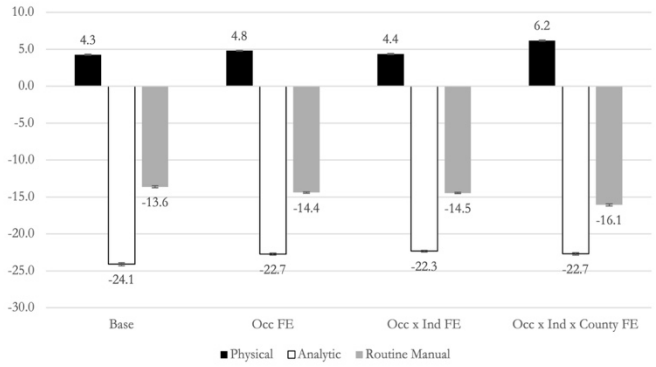


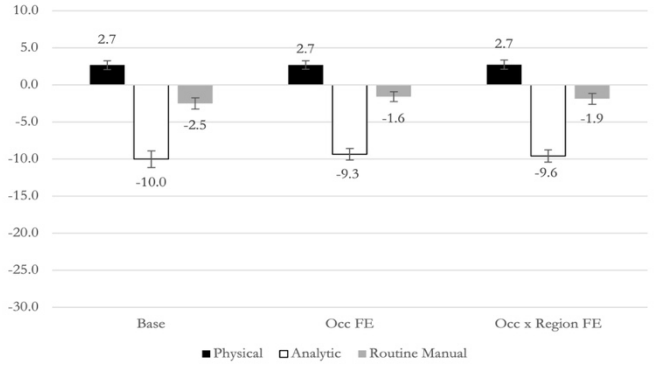
Figure 8: Black-white intergenerational gaps in task mobility

Notes: Underlying data are from the PSID (triangle), OCG (square), 1900-1940 Censuses (circle) (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2021). Panel A shows the Black-white difference in expected rank conditional on having a father at the 75th percentile of that task, along with corresponding 95% confidence intervals. All measures are percentile ranked. Occupational income is a 0-100 percentile ranked measure that imputes income by occupation. Panel B plots the Black-white difference in the intersection with the 45 degree line, which plots the steady-state gap (see Figure 6). Regression results are in Online Appendix tables B5 and B6.

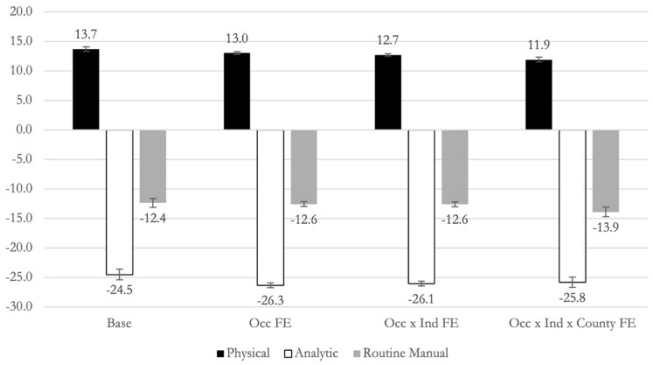
(a) Intragenerational gaps, 1900-1940



(b) Intragenerational gaps, PSID



(c) Intergenerational gaps, 1900-1940



(d) Intergenerational gaps, PSID

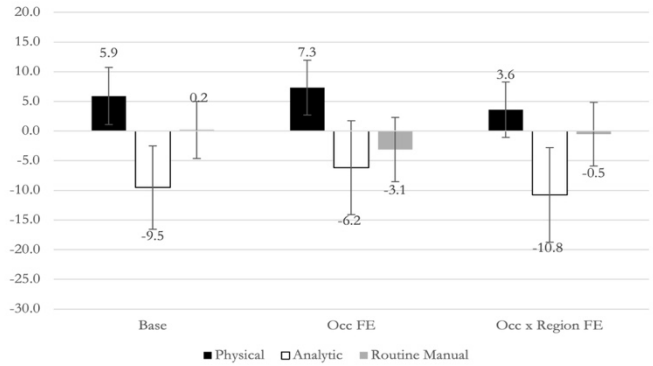


Figure 9: Effects of local labor market factors on Black-white task mobility gaps

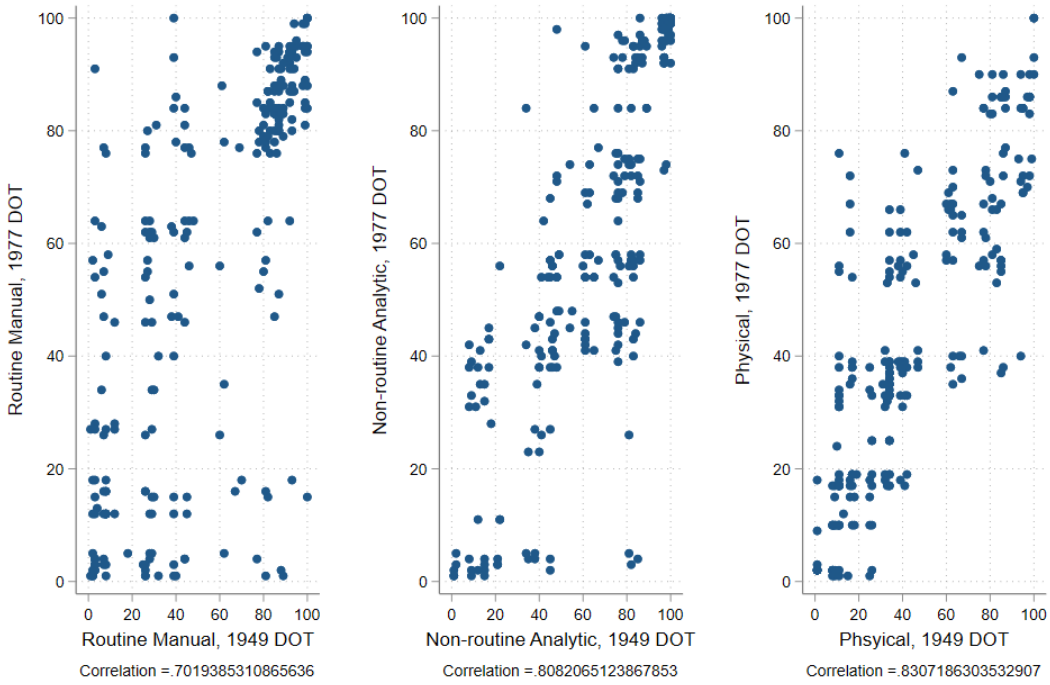
Notes: Underlying data are from the PSID (right) and 1900-1940 Censuses (left) (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2021). This figure presents the Black-white mobility gap for individuals who themselves (top) or their fathers (bottom) were initially at the 75th percentile of the task distributions, adding successively more detailed fixed effects measured in time *t*, along with corresponding 95% confidence intervals. Year is additionally controlled for in the fixed effects. Regression results are in Online Appendix tables B7 and B8.

ONLINE APPENDIX

"Tasks and Black-white Inequality over the Long Twentieth Century"
by Rowena Gray, Siobhan O'Keefe, Sarah Quincy, and Zachary Ward

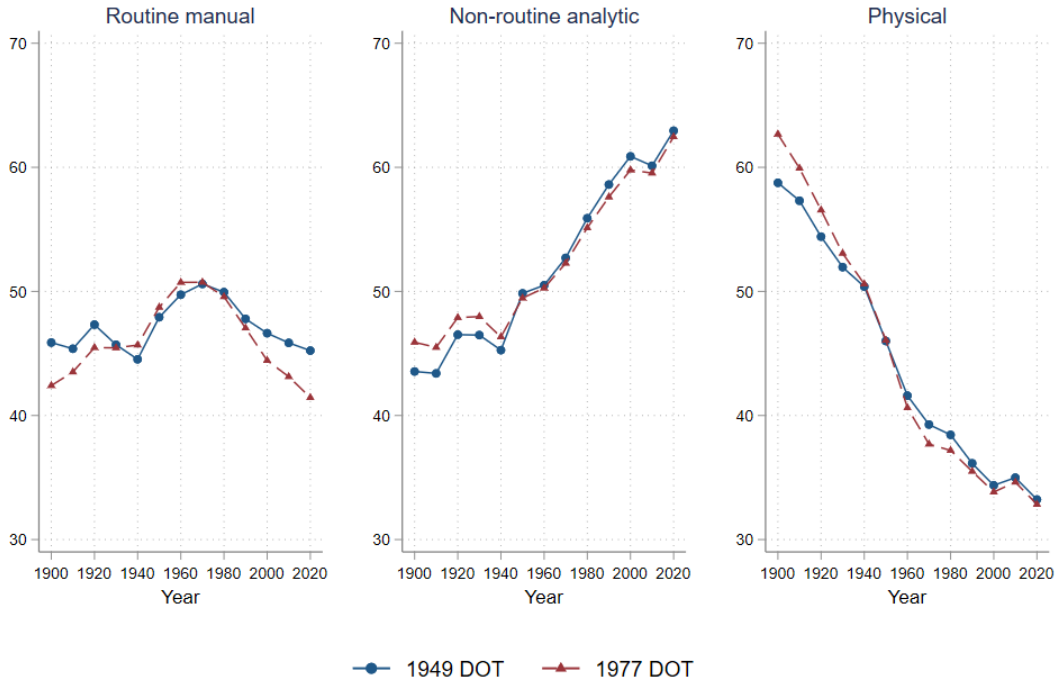
A. Additional Figures

Figure A1: Correlation between 1949 and 1977 Dictionary of Occupational Titles Data



Notes: The unit of observation is an occupation (occ1950 code). This figure plots the percentile ranking of each occupation in 1949 against its percentile rank in 1977.

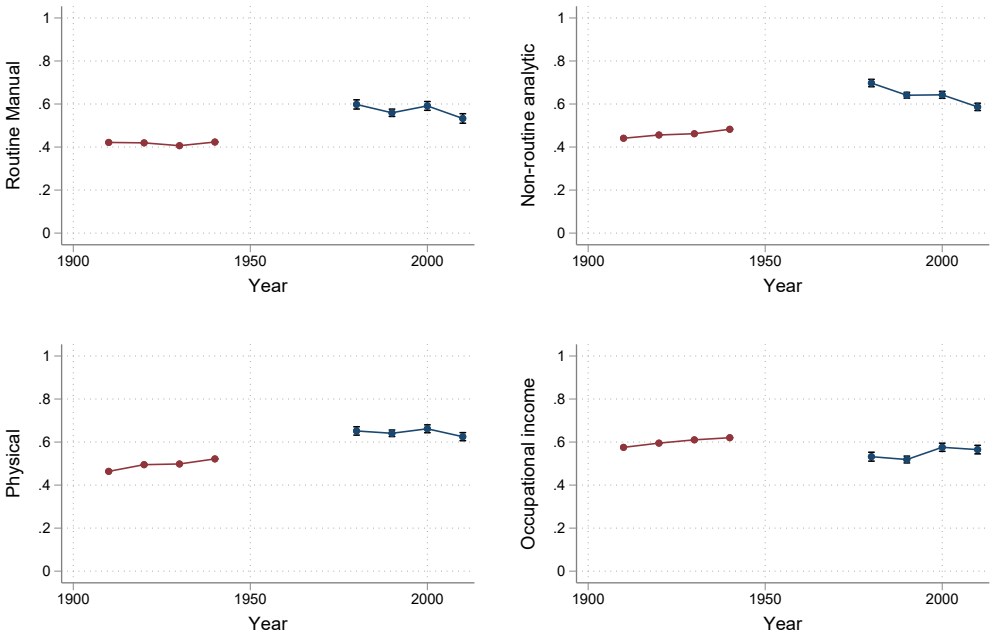
Figure A2: Trends in occupational task content using the 1977 DOT



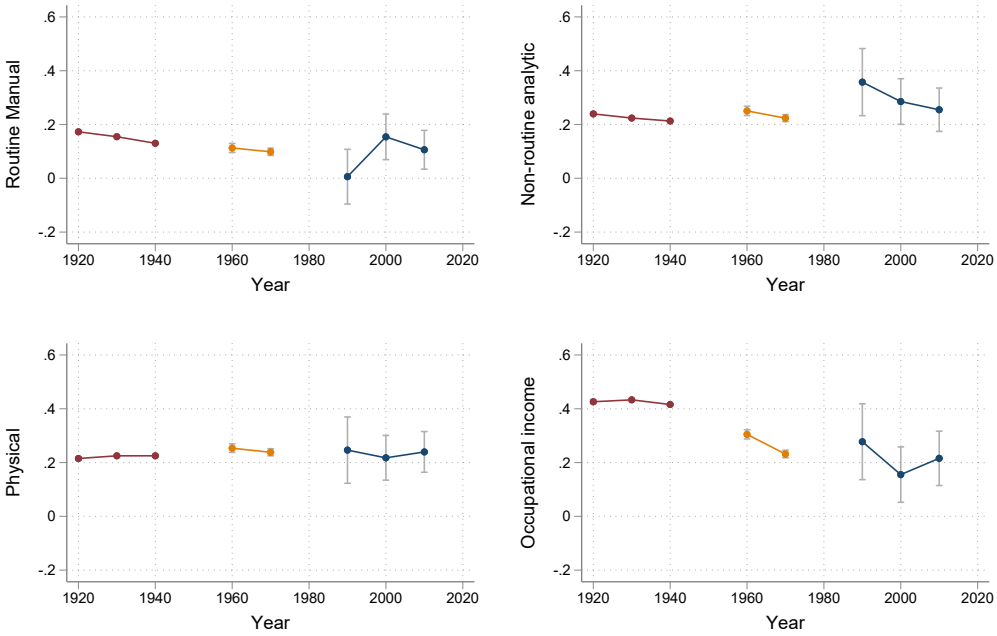
Notes: This figure compares the trend in routine-manual, non-routine analytic and physical when using the task intensity measures based on the 1949 Dictionary of Occupational Titles, versus the task content based on the 1977 Dictionary of Occupational Titles.

Figure A3: Task mobility, then and now

(a) Within one generation

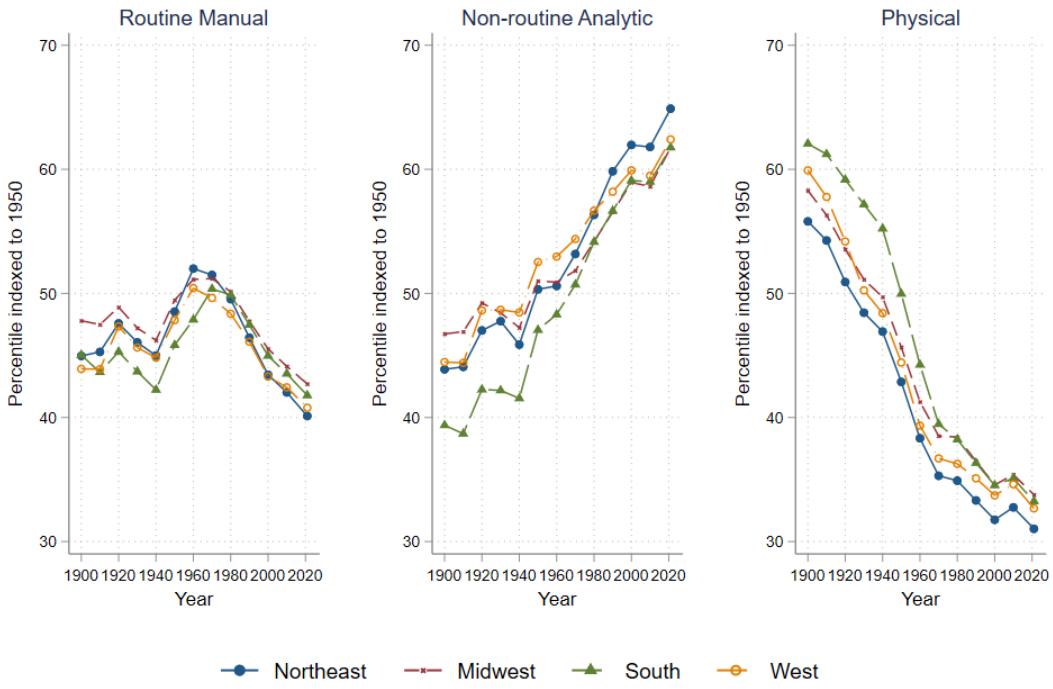


(b) Across generations from father to son



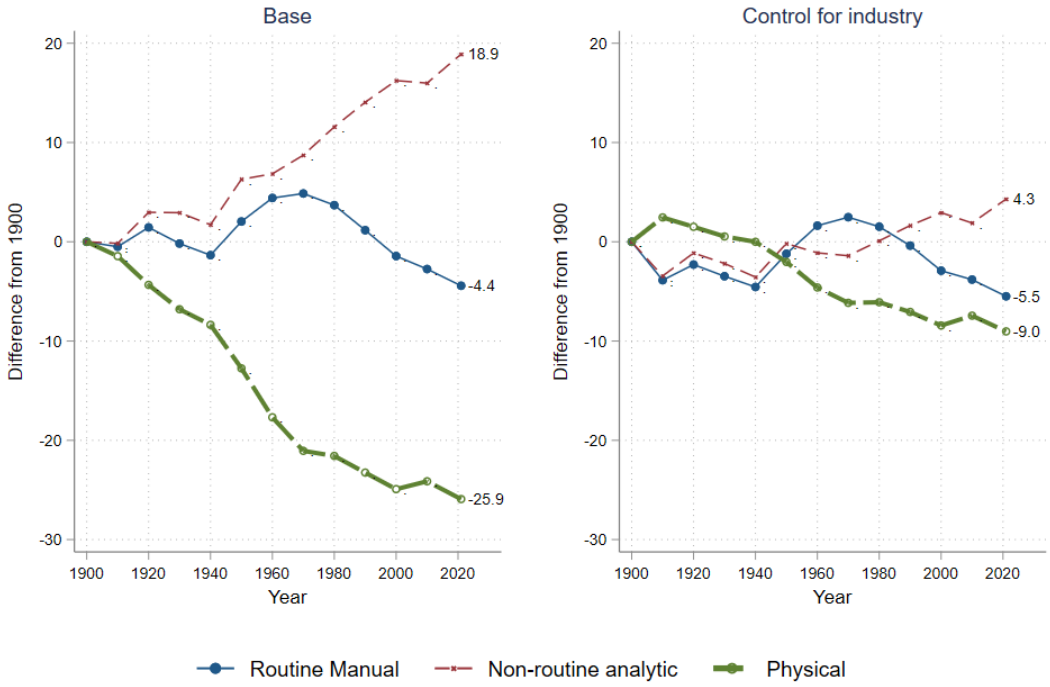
Notes: Underlying data are from the PSID (blue), OCG (orange), and 1900-1940 Censuses (red), (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2021) in Panel A and Ward (2023) in Panel B. Panel A shows the point estimate from a regression of the outcome in census t+10 on the outcome in census t along with its 95% confidence interval. Panel B shows the point estimate from an OLS regression of the son's outcome on the father's along with its 95% confidence interval. Standard errors are robust. All measures are percentile ranked.

Figure A4: Task measures by census region



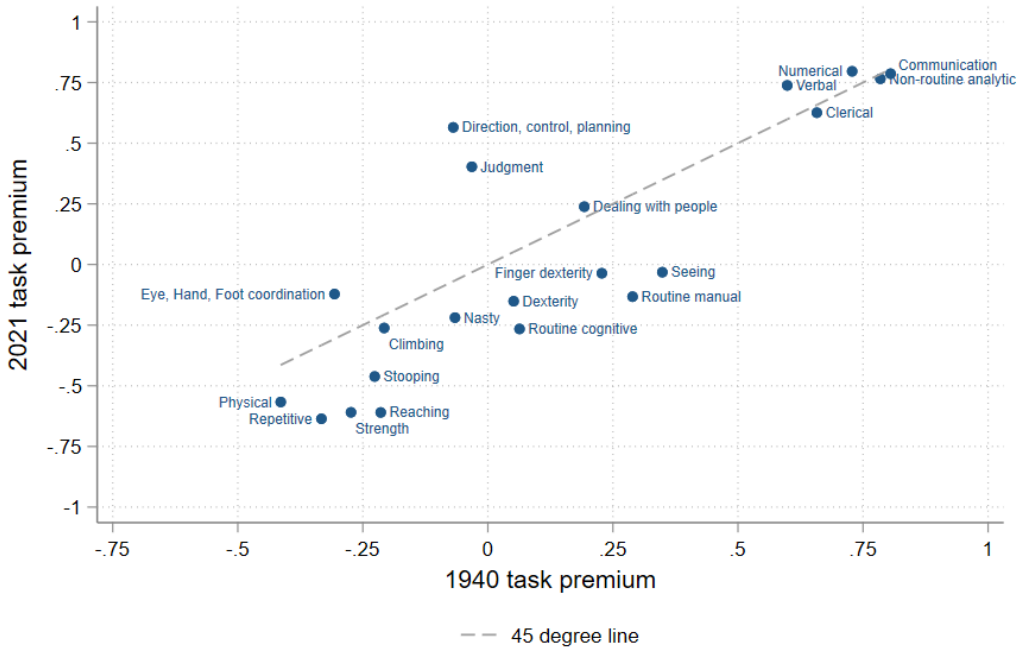
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table C6 for task definitions.

Figure A5: National trends in task content, adding industry fixed effects



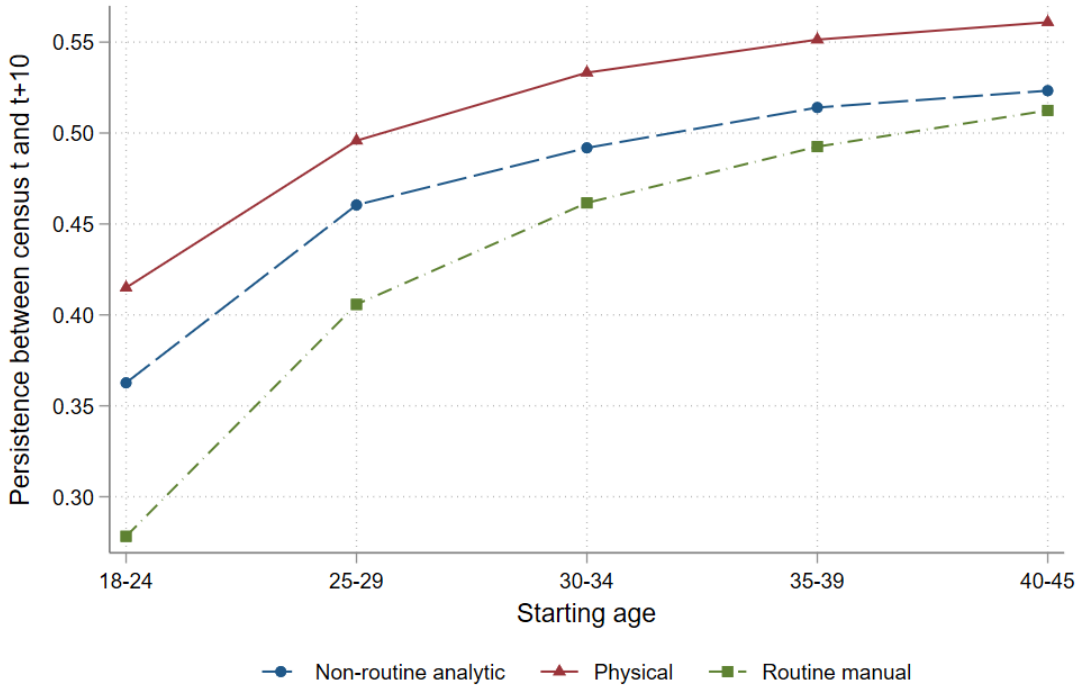
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles, Fitch, Goeken, Hacker, Nelson, Roberts, Schouweiler and Sobek, 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table C6 for task definitions. We categorize the data into 12 different industry categories based on the *ind*1950 variable from IPUMS. They are split by Agriculture, Forestry and Fishing [105, 126]; Mining [206, 239]; Construction [246]; Manufacturing Durables [306, 399]; Manufacturing Nondurables [406, 499]; Transportation, Communication and Other Utilities [508, 598]; Wholesale and Retail Trade [606, 699]; Finance, Insurance, and Real Estate [716, 756]; Business and Repair Services [806, 817]; Personal Services [826, 849]; Professional and Related Services [868, 899]; Public Administration [906, 946].

Figure A6: Stability of observational task premia 1940 and 2021



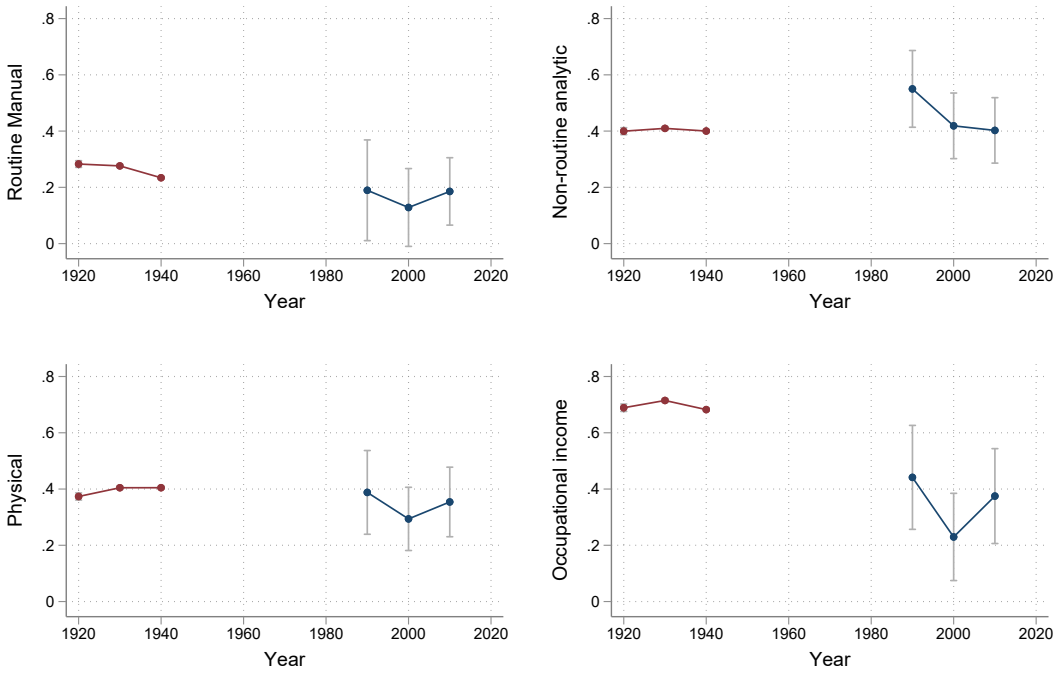
Notes: Data are from the 1940 IPUMS and the 2021 ACS (Ruggles et al. 2021). Sample is 30–45-year-old male wage workers with an occupation. Task premia are estimated by regressing the log of weekly wage income on percentile rank of task, a quadratic in age, and years of education. See Tables C1-C6 for definitions.

Figure A7: Task mobility throughout the life cycle



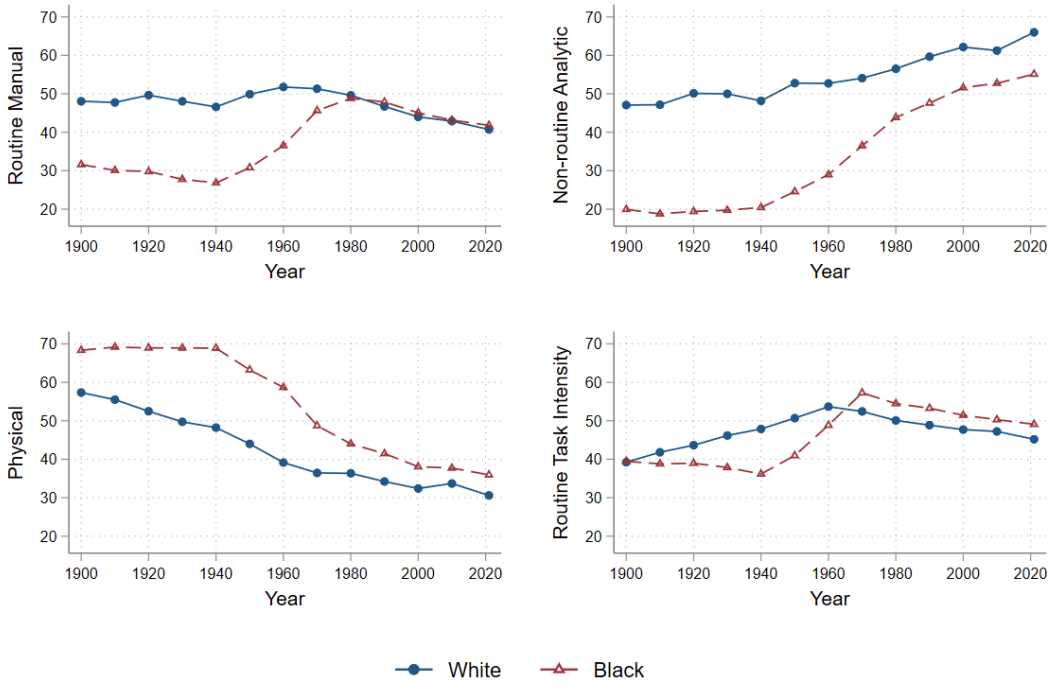
Notes: Data are from the 1900-1940 censuses (Ruggles et al. 2021). Each point plots a separate regression of the task content in time t+10 on the task content in census t by age and task. The main point of the figure is that the occupational task content was more persistent across a 10-year period throughout the life cycle.

Figure A8: Transmission of task content from father to son, IV method



Notes: Data are from the 1900-1940 censuses (Ruggles et al. 2021). Each point plots a separate regression of the task content for the son on the father, after instrumenting the father with a second occupation observation, along with corresponding 95% confidence intervals.

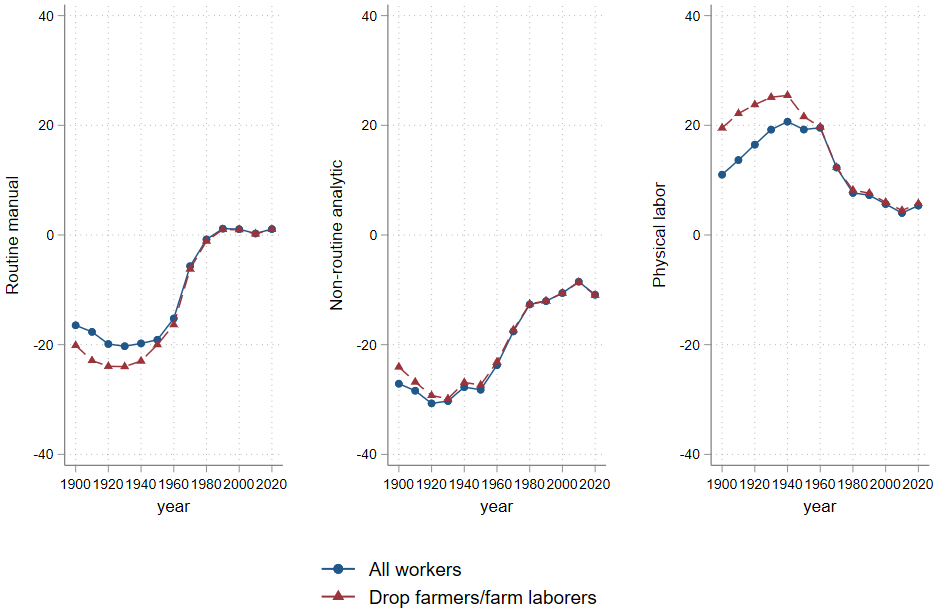
Figure A9: Black-white trends in levels



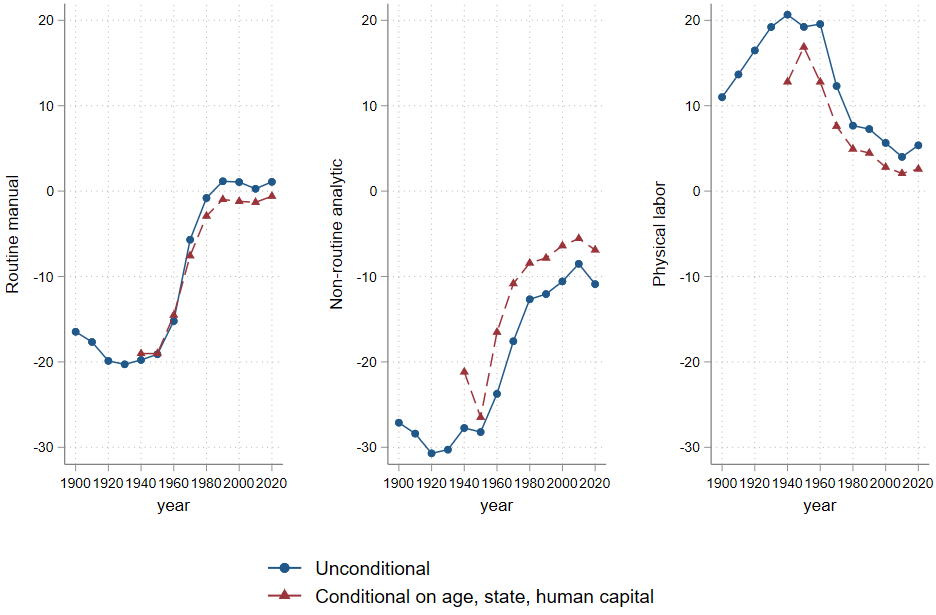
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table C6 for task definitions.

Figure A10: Black-white trends accounting for observable differences

(a) With and without agricultural workers



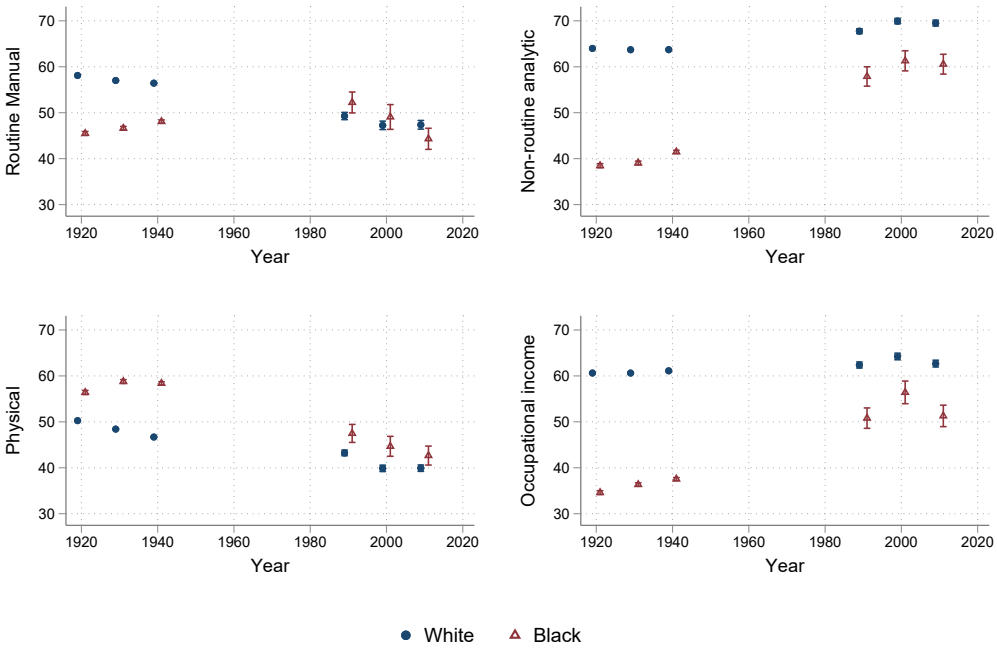
(b) Conditional on observables



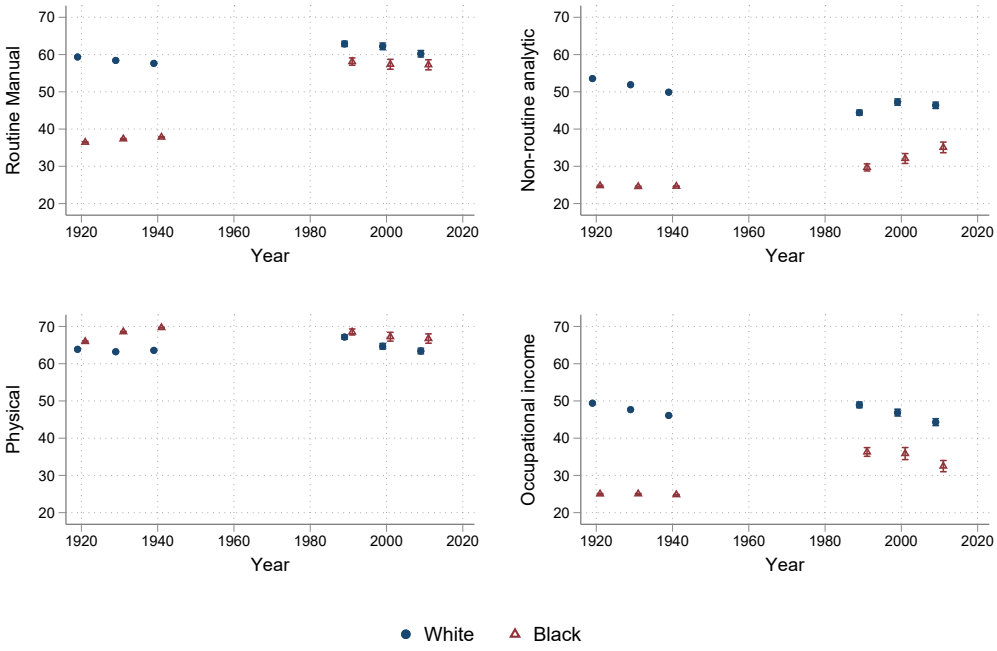
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table C6 for task definitions. The red lines in Panel B condition on educational attainment (which has 11 categories), starting in 1940, age, and state of residence.

Figure A11: Black-white mobility gaps across the 20^{th} century, additional tasks

(a) Movement out of Non-Routine Analytic

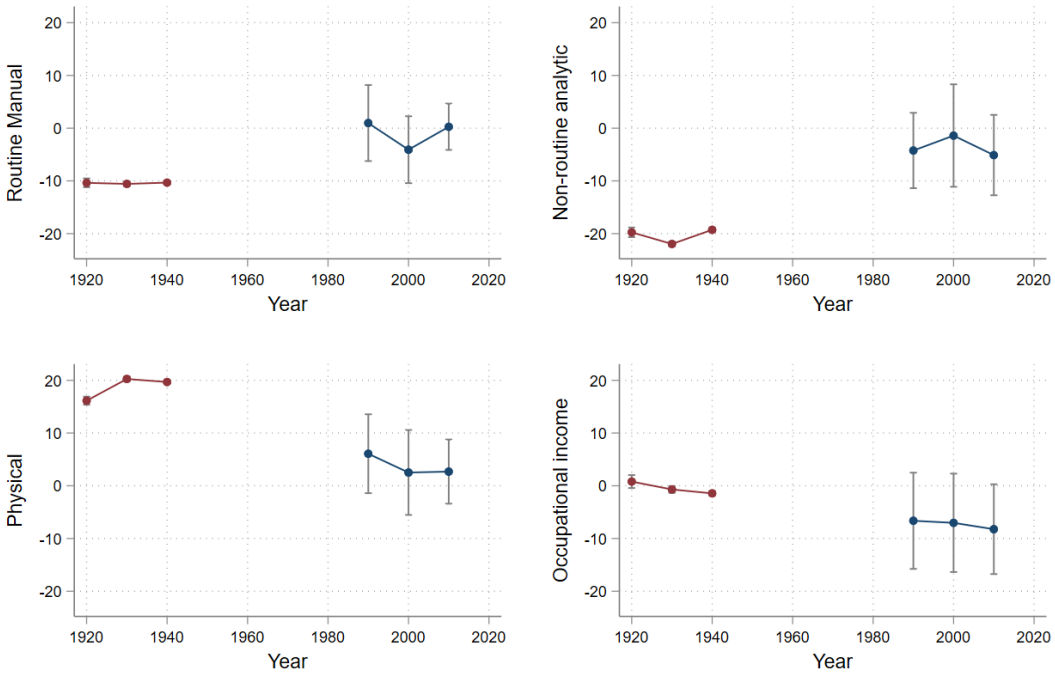


(b) Movement out of Physical



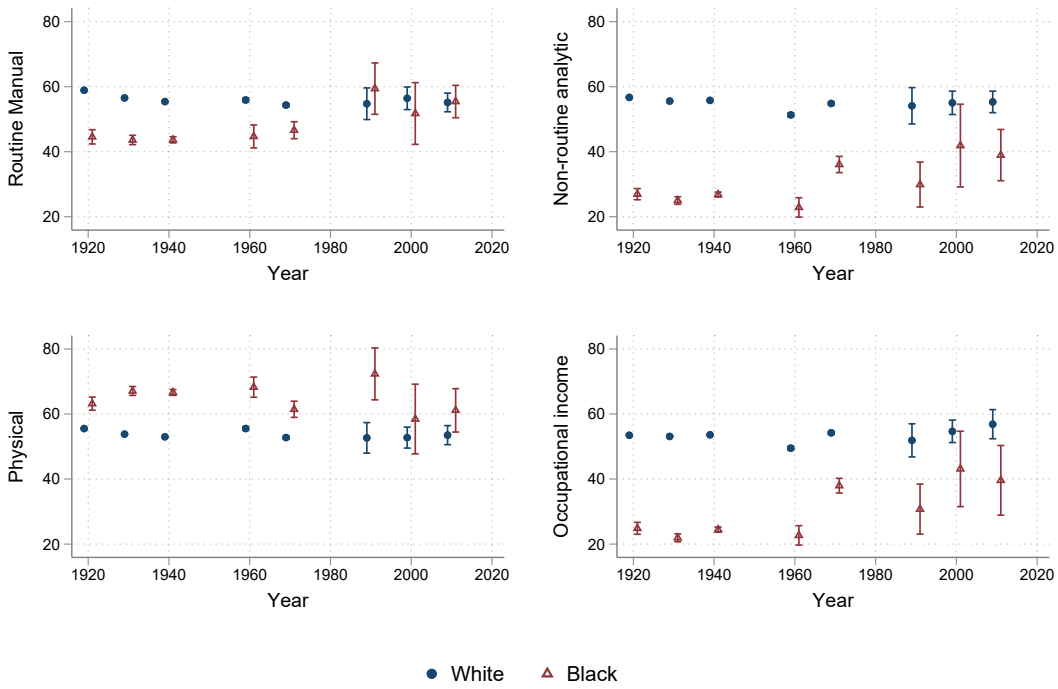
Notes: Underlying data are from the PSID (1980-2010), and the United States Censuses (1900-1940) (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2021) in Panel A and Ward (2023) in Panel B. Each panel plots the predicted percentile on the dependent variable for those who start at the 75th percentile of the designated task in the first observation period, along with corresponding 95% confidence intervals.

Figure A12: Black-white differences in intergenerational mobility, IV estimates



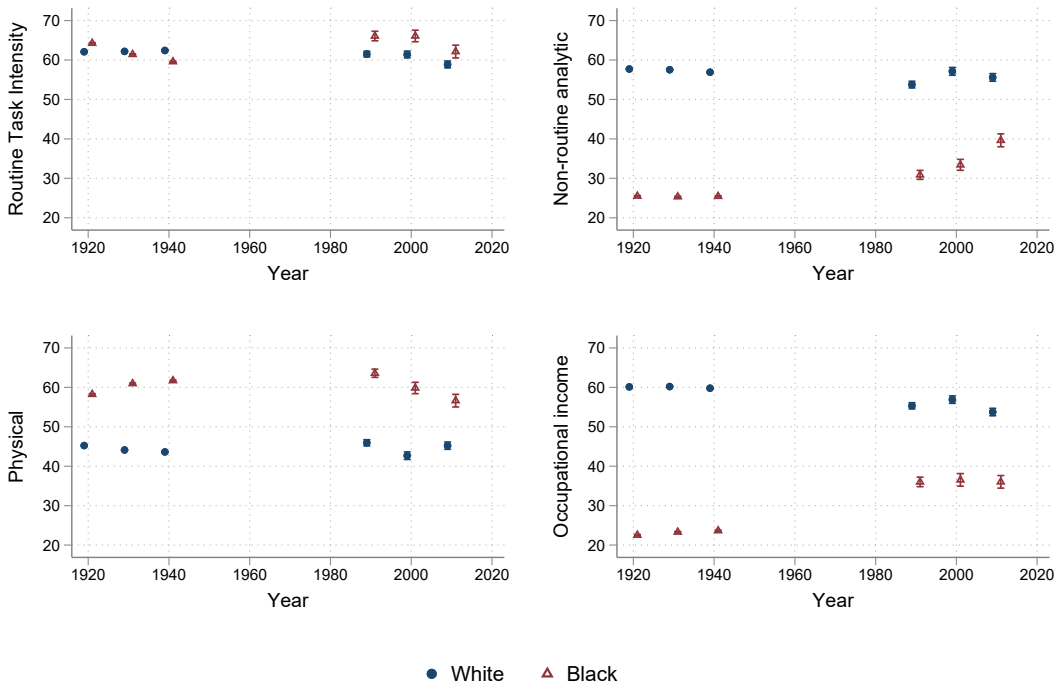
Notes: Underlying data are from the PSID and 1900-1940 US Censuses (Ruggles et al. 2021) and links from Ward (2023). Each panel shows the point estimate on the Black indicator variable after using an IV regression of the son's outcome on the father's, where the father's outcome is instrumented with a second occupation observation to address potential measurement error, per Ward (2023). Each coefficient is displayed with its corresponding 95% confidence interval.

Figure A13: Black-white intergenerational transitions, father starting in routine-manual



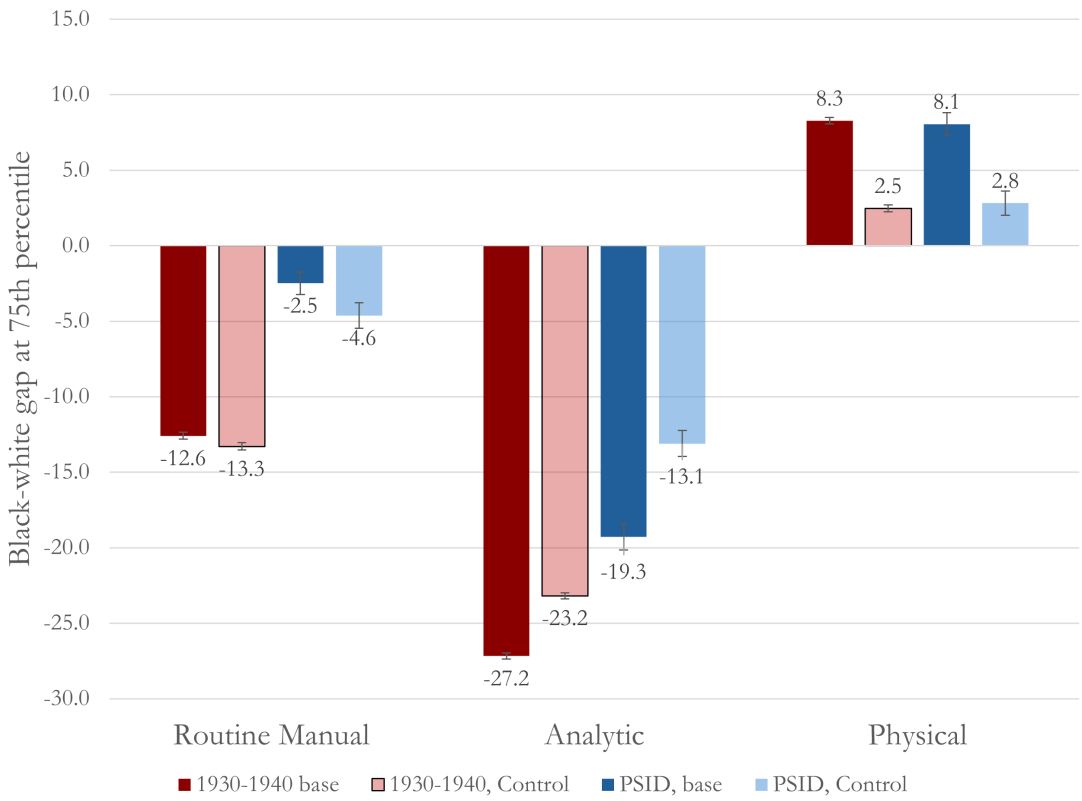
Notes: Underlying data are from the PSID (1980-2010), OCG (1960-1970), and the United States Censuses (1900-1940) (Ruggles et al. 2021) with links from the Census Linking Project (Abramitzky et al. 2021) and Ward (2023). Each panel plots the predicted percentile of the dependent variable for those whose fathers were observed at the 75th percentile of the routine-manual task, along with corresponding 95% confidence intervals.

Figure A14: Black-white intragenerational transitions, using routine task intensity



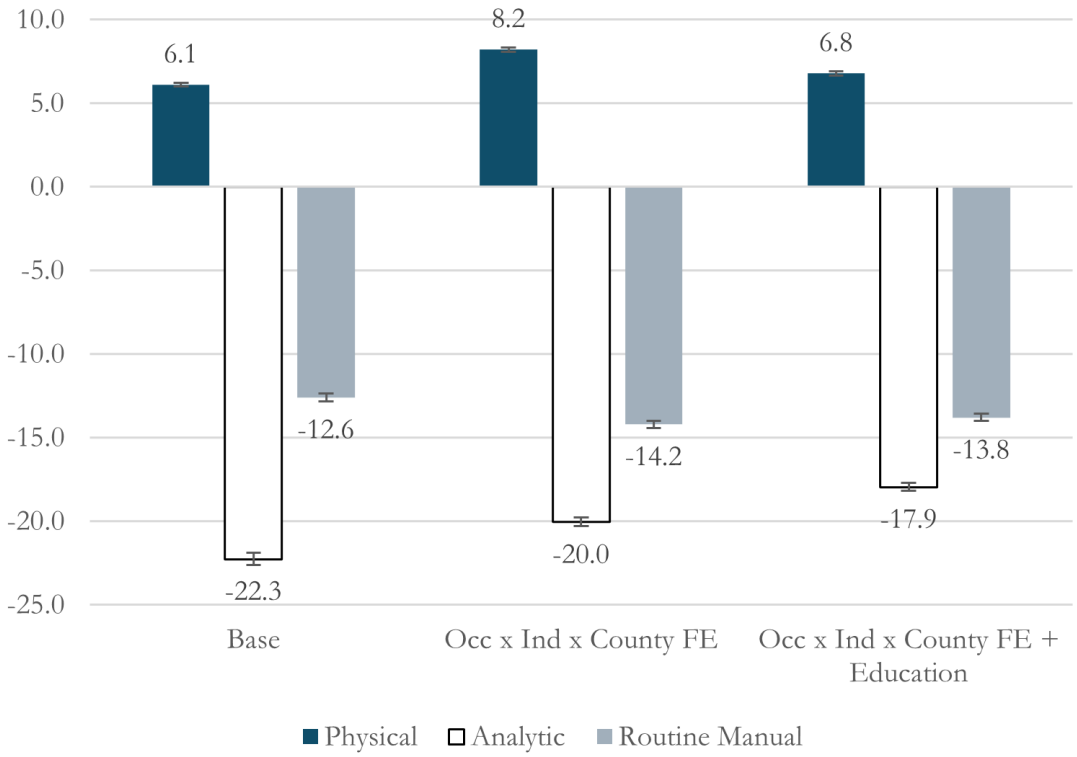
Notes: Underlying data are from the PSID (1980-2010), and the United States Censuses (1900-1940) (Ruggles et al. 2021) with links from the Census Linking Project (Abramitzky et al. 2021) and Ward (2023). Each panel plots the predicted percentile on the dependent variable for those who start at the 75th percentile of the designated task in the first observation period, along with corresponding 95% confidence intervals. This figure replaces the baseline routine manual task with routine task intensity as in Autor and Dorn (2013).

Figure A15: Black-white gaps at the 75th percentile in movement out of routine-manual, conditional on education and location



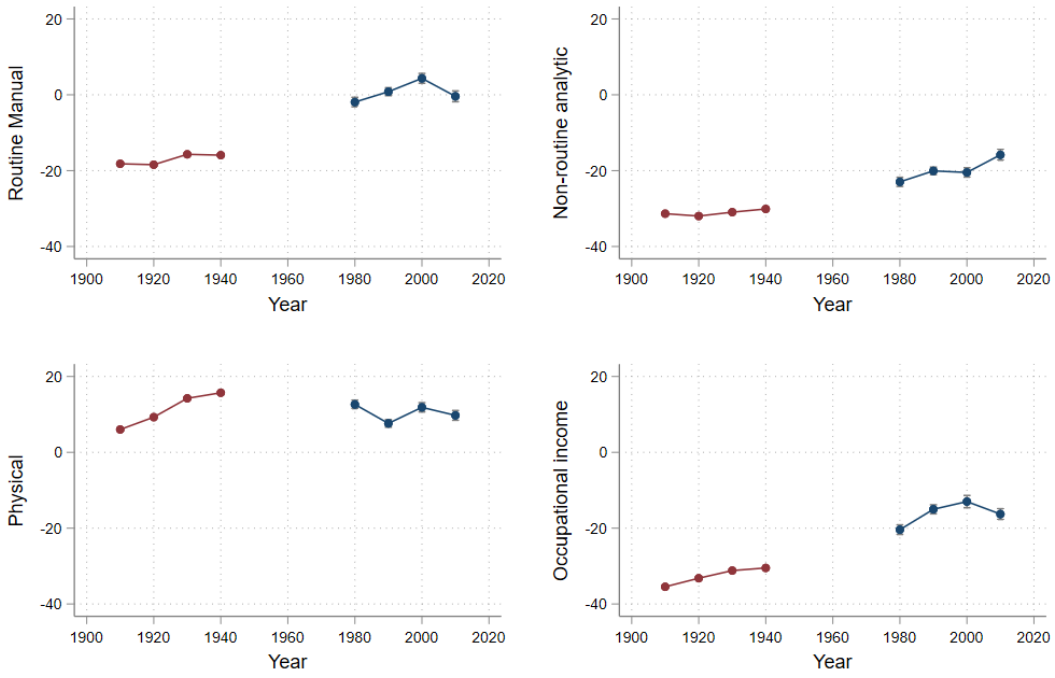
Notes: Underlying data are from the United States Censuses (1930-1940) (Ruggles et al. 2021) with links from the Census Linking Project (Abramitzky et al. 2021) and Ward (2023).The figure shows the Black-white gap for individuals starting at the 75th percentile of routine manual occupations, using historical data (red bars) and the PSID (blue bars), along with corresponding 95% confidence intervals. The base figures include no controls, while the "control" bars control for years of education as indicator variables, and initial state of residence fixed effects. For the historical data, education controls can only be included for the 1930–1940 linked data because education is first observed in 1940.

Figure A16: Black-white intragenerational transitions, additional controls



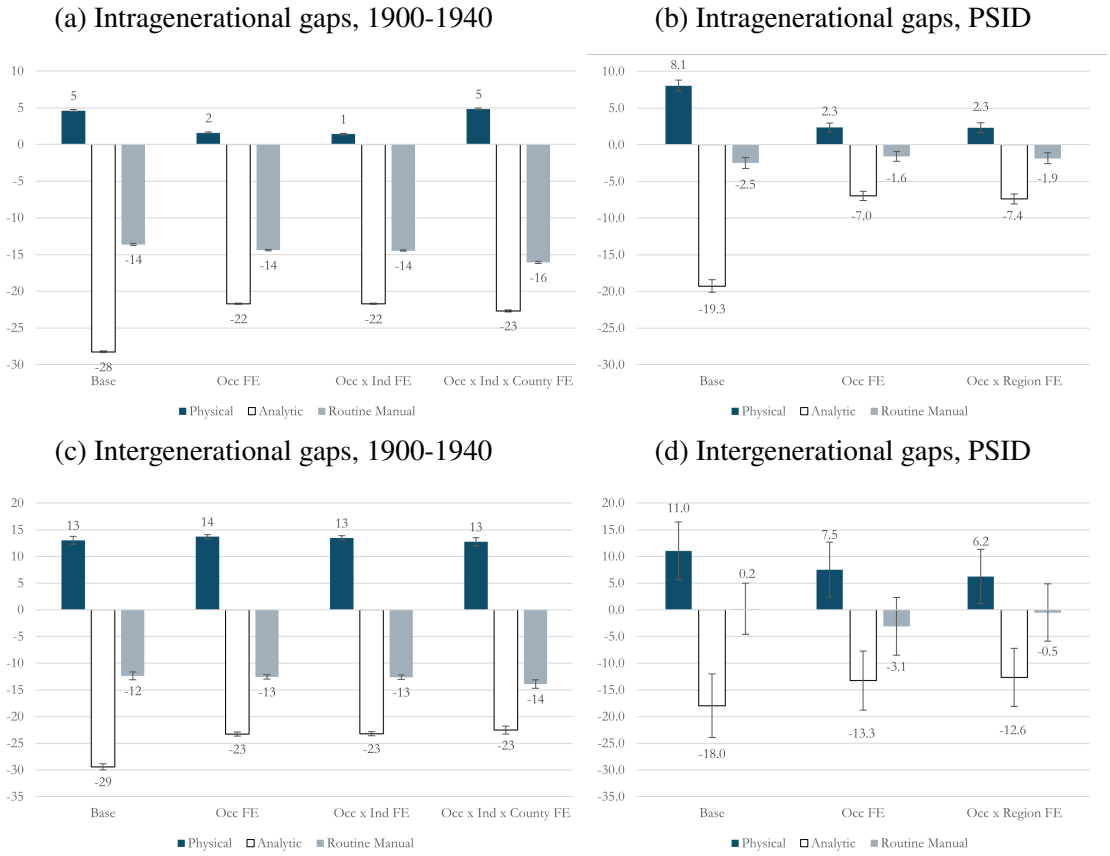
Notes: Underlying data are from the United States Censuses (1930-1940) (Ruggles et al. 2021) with links from the Census Linking Project (Abramitzky et al. 2021) and Ward (2023). This figure presents the Black-white mobility gap for individuals who themselves were initially at the 75th percentile of the task distributions, adding successively more detailed fixed effects measured in time t, controls for 1940 education (the first year in which it is observed, along with corresponding 95% confidence intervals.

Figure A17: Black-white intragenerational steady state gaps



Notes: Underlying data are from the United States Censuses (red) (1900-1940) (Ruggles et al. 2021) and PSID (blue) with links from the Census Linking Project (Abramitzky et al. 2021) and Ward (2023). This figure simulates the Black-white difference in the intersection with the 45 degree line, which plots the steady-state gap (see Figure 6) for each task using our linked data as well as occupational income for comparison.

Figure A18: Transitions out of routine manual, additional controls



Notes: Underlying data are from the PSID (right) and 1900-1940 Censuses (left) (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2021). This figure presents the Black-white mobility gap for individuals who themselves (top) or their fathers (bottom) were initially at the 75th percentile of the routine manual task distribution, adding successively more detailed fixed effects measured in time t, along with corresponding 95% confidence intervals. Year is additionally controlled for in the fixed effects.

Table B1: Mincerian task premia

	(1) 1940	(2) 1950	(3) 1960	(4) 1970	(5) 1980	(6) 1990	(7) 2000	(8) 2010	(9) 2021
A: Routine Manual									
Task Intensity	0.003***	0.001***	0.001***	0.000***	0.000***	-0.000***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.187	0.100	0.178	0.161	0.107	0.157	0.174	0.214	0.157
N	104240	35067	677946	286809	876563	234531	1244995	223567	230749
B: Non-routine Analytic									
Task Intensity	0.008***	0.004***	0.004***	0.004***	0.003***	0.005***	0.006***	0.007***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.263	0.133	0.206	0.191	0.125	0.193	0.212	0.268	0.216
N	104240	35067	677946	286809	876563	234531	1244995	223567	230749
C: Physical									
Task Intensity	-0.004***	-0.002***	-0.002***	-0.003***	-0.002***	-0.004***	-0.005***	-0.005***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.198	0.101	0.181	0.175	0.115	0.178	0.197	0.243	0.185
N	104240	35067	677946	286809	876563	234531	1244995	223567	230749

Notes: This table shows the point estimate from a regression the log weekly wage income on percentile rank of a task, a quadratic in age, and years of education. Data are from the 1940 IPUMS and the 2021 ACS (Ruggles et al. 2021). Sample is 30–45-year-old male wage workers with an occupation. Robust standard errors are in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table B2: Racial differences in task premia

	(1) 1940	(2) 1950	(3) 1960	(4) 1970	(5) 1980	(6) 1990	(7) 2000	(8) 2010	(9) 2021
A: Routine Manual, White Return									
Task Intensity	0.002***	0.001***	0.001***	0.000*	0.000*	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.152	0.075	0.151	0.150	0.105	0.152	0.176	0.213	0.155
N	94210	31606	612427	255786	767465	197821	986137	173633	149259
B: Routine Manual, Black Return									
Task Intensity	0.000	0.001*	0.003***	0.002***	0.001***	0.001***	-0.000	-0.001**	-0.001**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.090	0.055	0.117	0.111	0.073	0.107	0.105	0.140	0.097
N	9574	3308	59874	27270	83020	19460	110459	18698	16691
C: Non-routine Analytic, White Return									
Task Intensity	0.007***	0.004***	0.004***	0.004***	0.003***	0.004***	0.005***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.229	0.104	0.177	0.175	0.120	0.182	0.208	0.261	0.200
N	94210	31606	612427	255786	767465	197821	986137	173633	149259
D: Non-routine Analytic, Black Return									
Task Intensity	0.003***	0.002**	0.002***	0.003***	0.003***	0.004***	0.004***	0.006***	0.006***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.100	0.057	0.112	0.117	0.079	0.136	0.130	0.179	0.143
N	9574	3308	59874	27270	83020	19460	110459	18698	16691
E: Physical, White Return									
Task Intensity	-0.004***	-0.001***	-0.002***	-0.003***	-0.002***	-0.004***	-0.004***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.168	0.078	0.155	0.161	0.112	0.170	0.197	0.238	0.176
N	94210	31606	612427	255786	767465	197821	986137	173633	149259
F: Physical, Black Return									
Task Intensity	0.001*	-0.000	-0.003***	-0.004***	-0.003***	-0.004***	-0.004***	-0.005***	-0.005***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
r2	0.090	0.052	0.113	0.126	0.079	0.130	0.124	0.164	0.119
N	9574	3308	59874	27270	83020	19460	110459	18698	16691

Notes: This table shows the point estimate from a regression the log weekly wage income on percentile rank of a task, a quadratic in age, and years of education, run separately for Black and white men. Data are from the 1940 IPUMS and the 2021 ACS (Ruggles et al. 2021). Sample is 30–45-year-old male wage workers with an occupation. Robust standard errors are in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

Table B3: Black-white mobility gaps across the 20th century: own lifetime

	(1) 1910	(2) 1920	(3) 1930	(4) 1940	(5) 1980	(6) 1990	(7) 2000	(8) 2010
A: Routine Manual								
Mobility Gap	-15.21	-14.91	-12.95	-12.59	-2.205	-3.639	-1.400	-3.178
	(0.157)***	(0.151)***	(0.147)***	(0.118)***	(0.747)**	(0.672)***	(0.840)	(0.923)***
	[1.601]***	[1.400]***	[1.080]***	[0.997]***	[1.002]*	[1.010]***	[1.087]	[1.117]**
White task mean	51.8	51.7	48.9	47.6	48.8	47.8	44.8	44.1
Black task mean	35.0	34.2	32.5	31.9	53.1	52.0	51.1	47.8
R-Squared	0.186	0.187	0.179	0.188	0.362	0.312	0.331	0.253
Obs	1938849	2668262	3578595	4567601	9844	16959	11616	10947
B: Non-routine Analytic								
Mobility Gap	-25.15	-25.53	-24.66	-22.25	-14.35	-9.855	-8.650	-8.946
	(0.223)***	(0.226)***	(0.210)***	(0.179)***	(1.944)***	(1.109)***	(1.156)***	(1.147)***
	[2.915]***	[2.735]***	[2.601]***	[2.362]***	[3.625]***	[1.663]***	[1.384]***	[1.588]***
White task mean	57.3	57.8	57.1	54.8	63.4	64.7	67.3	65.4
Black task mean	21.0	21.6	21.9	22.0	33.1	39.2	44.9	47.7
R-Squared	0.223	0.236	0.239	0.253	0.509	0.463	0.452	0.387
Obs	1938849	2668262	3578595	4567601	9844	16959	11616	10947
C: Physical								
Mobility Gap	0.652	2.090	5.350	6.109	3.617	1.366	2.565	3.346
	(0.104)***	(0.0860)***	(0.0728)***	(0.0587)***	(0.623)***	(0.509)**	(0.714)***	(0.748)***
	[2.116]	[2.078]	[1.350]***	[1.786]***	[0.997]***	[1.095]	[0.960]**	[0.837]***
White task mean	54.8	53.2	51.3	50.8	40.3	39.3	35.5	35.6
Black task mean	66.4	66.7	67.4	67.8	58.0	52.1	48.5	46.0
R-Squared	0.219	0.250	0.261	0.284	0.448	0.415	0.422	0.374
Obs	1938849	2668262	3578595	4567601	9844	16959	11616	10947
D: Occupational Score								
Mobility Gap	-20.83	-19.95	-19.49	-17.63	-18.74	-9.025	-4.961	-9.567
	(0.204)***	(0.198)***	(0.172)***	(0.154)***	(1.561)***	(1.096)***	(1.350)***	(1.338)***
	[1.543]***	[1.501]***	[1.670]***	[1.558]***	[3.203]***	[1.708]***	[1.895]**	[1.529]***
R-Squared	0.325	0.357	0.367	0.382	0.324	0.302	0.337	0.317
Obs	1983834	2744465	3694429	4710271	9760	16637	11333	10739

Notes: This table reports the the Black-white mobility gap for those initially at the 75th percentile of the task distribution along with robust standard errors (in parenthesis) and standard errors clustered by initial occupation [in square brackets]. Underlying data are from the PSID (1980-2010) and US Censuses (1900-1940) (Ruggles et al. 2021). Links from the Census Linking Project (Abramitzky et al. 2021). All measures are percentile ranked. * p<0.10, ** p<0.05, *** p<0.01.

Table B4: Black-white mobility gaps across the 20th century: movement out of routine-manual

	White		Black	
	(1) Historical	(2) Modern	(3) Historical	(4) Modern
A: Routine Manual				
Predicted task rank	62.750***	65.094***	49.459***	62.247***
	(0.011)	(0.207)	(0.078)	(0.409)
r2	0.165	0.319	0.097	0.185
N	10408113	30018	406345	9504
B: Non-routine Analytic				
Predicted task rank	58.147***	52.280***	30.010***	33.572***
	(0.010)	(0.259)	(0.065)	(0.463)
r2	0.012	0.051	0.019	0.041
N	10408113	30018	406345	9504
C: Physical				
Predicted task rank	55.460***	59.369***	61.315***	67.052***
	(0.011)	(0.218)	(0.076)	(0.394)
r2	0.023	0.181	0.010	0.119
N	10408113	30018	406345	9504
D: Occupational Score				
Predicted task rank	54.234***	55.840***	24.088***	29.051***
	(0.010)	(0.226)	(0.073)	(0.372)
r2	0.006	0.040	0.001	0.025
N	10540807	29851	410166	9490

Notes: This table reports the predicted percentile on the dependent variable for those who start at the 75th percentile of routine-manual in the first Census or an earlier PSID wave, along with robust standard errors (in parenthesis). Underlying data are from the PSID (1980-2010) and US Censuses (1900-1940) (Ruggles et al. 2021). Links from the Census Linking Project (Abramitzky et al. 2021). All measures are percentile ranked. * p<0.10, ** p<0.05, *** p<0.01.

Table B5: Black-white intergenerational gaps in task mobility: intergenerational mobility gaps at the 75th percentile

	(1) 1920	(2) 1930	(3) 1940	(4) 1960	(5) 1970	(6) 1990	(7) 2000	(8) 2010
A: Routine Manual								
Mobility gap	-14.35	-12.93	-11.77	-11.21	-7.735	4.646	-4.680	0.275
	(1.121)***	(0.733)***	(0.485)***	(1.823)***	(1.353)***	(4.686)	(5.109)	(2.915)
	[1.295]***	[1.075]***	[1.004]***	[1.938]***	[1.112]***	[3.878]	[3.377]	[3.061]
White task mean	51.2	48.7	47.3	47.8	46.8	45.0	44.0	39.9
Black task mean	34.4	32.5	32.2	35.9	40.2	53.7	47.1	43.6
R-Squared	0.058	0.050	0.037	0.022	0.012	0.002	0.028	0.013
Obs	189701	471789	1380072	13832	20850	562	706	1215
B: Non-routine Analytic								
Mobility gap	-24.56	-25.98	-23.91	-25.59	-15.69	-3.610	-5.038	-15.32
	(1.453)***	(0.850)***	(0.597)***	(2.534)***	(1.890)***	(5.041)	(7.963)	(5.314)**
	[1.658]***	[2.395]***	[2.377]***	[4.155]***	[2.941]***	[5.588]	[7.188]	[4.485]***
White task mean	58.1	56.6	54.0	60.9	61.9	65.8	67.8	70.9
Black task mean	21.2	21.2	22.1	28.1	40.6	43.8	46.0	56.2
R-Squared	0.135	0.134	0.112	0.097	0.069	0.133	0.080	0.072
Obs	189701	471789	1380072	13832	20850	562	706	1215
C: Physical								
Mobility gap	9.686	13.37	14.41	13.39	8.094	11.89	2.634	1.969
	(0.601)***	(0.364)***	(0.247)***	(1.023)***	(0.855)***	(4.463)**	(4.601)	(3.737)
	[1.365]***	[1.526]***	[1.419]***	[1.560]***	[2.083]***	[4.471]**	[3.942]	[3.949]
White task mean	52.4	50.4	49.9	43.7	42.3	34.2	35.6	29.8
Black task mean	67.0	67.3	67.2	62.1	53.3	49.9	50.8	36.1
R-Squared	0.077	0.097	0.090	0.098	0.067	0.087	0.058	0.067
Obs	189701	471789	1380072	13832	20850	562	706	1215
D: Occupational Score								
Mobility gap	-19.17	-21.13	-19.61	-25.84	-17.74	-7.117	-10.00	-6.320
	(0.961)***	(0.618)***	(0.459)***	(1.702)***	(1.434)***	(5.510)	(9.236)	(5.897)
	[2.953]***	[3.113]***	[2.491]***	[1.798]***	[1.509]***	[5.641]	[8.619]	[4.873]
R-Squared	0.183	0.185	0.169	0.114	0.064	0.078	0.031	0.062
Obs	194573	485940	1426256	14320	21505	556	690	464

Notes: This table reports the Black-white difference in expected rank at the conditioning on having a father at the 75th percentile of that task, along with robust standard errors (in parenthesis) and standard errors clustered by initial occupation [in square brackets]. Underlying data are from the PSID (1980-2010), OCG (1960-1970), and US Censuses (1900-1940) (Ruggles et al. 2021). Links from the Census Linking Project (Abramitzky et al. 2021). All measures are percentile ranked. * p<0.10, ** p<0.05, *** p<0.01.

Table B6: Black-white intergenerational gaps in task mobility: steady-state race gaps

	(1) 1920	(2) 1930	(3) 1940	(4) 1960	(5) 1970	(6) 1990	(7) 2000	(8) 2010
A: Routine Manual								
Steady state gap	-15.887***	-15.346***	-14.017***	-11.591***	-5.453***	1.669	-4.730	0.381
	(0.395)	(0.239)	(0.181)	(0.921)	(0.811)	(3.675)	(2.948)	(2.225)
R-Squared	0.058	0.050	0.037	0.022	0.012	0.002	0.028	0.013
Obs	189701	471789	1380072	13832	20850	562	706	1215
B: Non-routine Analytic								
Steady state gap	-29.560***	-31.292***	-28.833***	-29.291***	-18.263***	-13.639***	-7.681	-13.162***
	(0.322)	(0.180)	(0.152)	(0.784)	(0.870)	(3.330)	(4.807)	(3.428)
R-Squared	0.135	0.134	0.112	0.097	0.069	0.133	0.080	0.072
Obs	189701	471789	1380072	13832	20850	562	706	1215
C: Physical								
Steady state gap	14.503***	19.518***	20.355***	18.710***	11.985***	12.625***	6.179	5.683*
	(0.496)	(0.314)	(0.215)	(0.932)	(0.725)	(3.724)	(3.741)	(2.864)
R-Squared	0.077	0.097	0.090	0.098	0.067	0.087	0.058	0.067
Obs	189701	471789	1380072	13832	20850	562	706	1215
D: Occupational Score								
Steady state gap	-24.213***	-25.846***	-24.296***	-26.692***	-17.390***	-13.129**	-10.733*	-12.891**
	(0.338)	(0.208)	(0.169)	(0.779)	(0.733)	(4.280)	(4.708)	(4.169)
R-Squared	0.183	0.185	0.169	0.114	0.064	0.078	0.031	0.062
Obs	194573	485940	1426256	14320	21505	556	690	464

Notes: This table reports the Black-white difference in the intersection with the 45 degree line, which gaps the steady-state gap (see Figure 6), along with robust standard errors (in parenthesis). Underlying data are from the PSID (1980-2010), OCG (1960-1970), and US Censuses (1900-1940) (Ruggles et al. 2021). Links from the Census Linking Project (Abramitzky et al. 2021). All measures are percentile ranked. * p<0.10, ** p<0.05, *** p<0.01.

Table B7: Effects of local labor market factors on Black-white task mobility gaps: intragenerational

	Historical (1900-1940 Census)				Modern (PSID)		
	(1) Base	(2) + Occ + Yr FE	(3) + Ind FE	(4) + County FE	(5) Base	(6) + Occ + Yr FE	(7) + Region FE
A: Routine Manual							
Mobility Gap	-13.624***	-14.404***	-14.465***	-16.073***	-2.487***	-1.600***	-1.862***
	(0.070)	(0.049)	(0.049)	(0.070)	(0.379)	(0.339)	(0.379)
R-Squared	0.185	0.219	0.228	0.314	0.306	0.372	0.410
Obs	12753307	12753306	12750286	11599698	54529	54460	53871
B: Non-routine Analytic							
Mobility Gap	-24.093***	-22.735***	-22.323***	-22.705***	-10.010***	-9.339***	-9.588***
	(0.103)	(0.061)	(0.061)	(0.080)	(0.575)	(0.398)	(0.425)
R-Squared	0.241	0.268	0.277	0.355	0.439	0.490	0.524
Obs	12753307	12753306	12750286	11599698	54529	54460	53871
C: Physical							
Mobility Gap	4.263***	4.811***	4.368***	6.181***	2.671***	2.698***	2.727***
	(0.038)	(0.029)	(0.029)	(0.043)	(0.306)	(0.289)	(0.324)
R-Squared	0.260	0.297	0.310	0.391	0.407	0.456	0.489
Obs	12753307	12753306	12750286	11599698	54529	54460	53871

Notes: This table reports the the Black-white mobility gap for those initially at the 75th percentile of the task distribution with additional fixed effects, as noted, along with robust standard errors (in parenthesis). Underlying data are from the US Censuses (1900-1940) (Ruggles et al. 2021) and PSID. Links from the Census Linking Project (Abramitzky et al. 2021). All measures are percentile ranked. * p<0.10, ** p<0.05, *** p<0.01.

Table B8: Effects of local labor market factors on Black-white task mobility gaps: intergenerational

	Historical (1900-1940 Census)				Modern (PSID)		
	(1) Base	(2) + Occ + Yr FE	(3) + Ind FE	(4) + County FE	(5) Base	(6) + Occ + Yr FE	(7) + Region FE
A: Routine Manual							
Mobility Gap	-12.362***	-12.781***	-12.814***	-14.033***	0.185	-3.120	-0.524
	(0.383)	(0.218)	(0.221)	(0.414)	(2.447)	(2.760)	(2.740)
R-Squared	0.042	0.045	0.050	0.196	0.010	0.208	0.219
Obs	2041562	1925166	1922752	1683528	2486	2347	2376
B: Non-routine Analytic							
Mobility Gap	-24.519***	-26.329***	-26.033***	-25.713***	-9.524**	-6.160	-10.759**
	(0.465)	(0.214)	(0.217)	(0.443)	(3.581)	(4.033)	(4.050)
R-Squared	0.119	0.149	0.157	0.285	0.093	0.296	0.306
Obs	2041562	1925166	1922752	1683528	2486	2347	2376
C: Physical							
Mobility Gap	13.702***	13.179***	12.864***	11.862***	5.902*	7.331**	3.594
	(0.194)	(0.118)	(0.120)	(0.216)	(2.452)	(2.347)	(2.381)
R-Squared	0.090	0.118	0.128	0.265	0.069	0.282	0.288
Obs	2041562	1925166	1922752	1683528	2486	2347	2376

Notes: This table reports the the Black-white mobility gap for those whose fathers were initially at the 75th percentile of the task distribution with additional fixed effects, as noted, along with robust standard errors (in parenthesis). Underlying data are from the US Censuses (1900-1940) (Ruggles et al. 2021) and PSID. Links from the Census Linking Project (Abramitzky et al. 2021). All measures are percentile ranked. * p<0.10, ** p<0.05, *** p<0.01.

C. Details on the construction of task content

The task data used throughout the paper come from a 1956 United States Employment Service publication, *Estimates of Worker Traits for 4,000 Jobs*. They are based on the *Dictionary of Occupational Titles* from 1939 and 1949, which are descriptions of what each job entailed written by employment experts who observed people performing these jobs in the field. The Dictionaries described about 12,000 jobs, and 4,000 of those were published, with more formal coding for tasks attached, in the 1956 publication, with the goal that this information be used to match people to jobs in employment offices around the country. The 1949 Dictionary updated the descriptions for only a subset of jobs. The 4,000 jobs in DOT were matched to Census occ1950 and ind1950 codes manually, using the occstring variable—this means that multiple DOTs were averaged and collapsed into the much smaller set of Census occupation-industries, with weights applied based on the frequency with which each occstring appeared. Appendix A of Gray (2013) describes the process in more detail, with examples.

We follow the existing literature in thinking of tasks as a feature of a job, and the variables that we use are reasonable composites of the base variables—e.g. routine-manual and non-routine analytic, which are similar to the main variables used elsewhere. We followed Autor et al. (2006) and Autor et al. (2008) in using three broad task categories which included one routine measure. Some base variables were rated as dummies, informing us if that characteristic was a defining element of a job, while most are ratings of the level of task required within a job, usually splitting jobs into quintiles of the task distribution.

For this paper, we further collapsed the task data by occ1950 code using 18-55 year olds in the full-count 1940 Census. We then merged these occupational task measures to the 1950 Census and constructed percentile-ranked measures.[30]

We present some of our results instead using the 1977 DOT ratings, in this Appendix. This DOT is the one most commonly used in the modern literature and we used publicly available data matched to Census occ1990 and occ1950 codes. The main difference between the 1956 and 1977 DOTs is that GED was one variable representing an average of ratings for reasoning, mathematical and language development in the earlier edition, while the 1977 version has different variables for each of those. Again, only a subset of the jobs were recoded in the 1977 and then 1991 versions of the DOT.

Table C1. Definition of Training Time Variables

Variable	DOT Definition	Example?
Training	Specific vocational training Training time 1. Short demonstration - 30 days 2. 30 days to 3 months 3. 3-6 months 4. 6 months-year 5. 1-2 years 6. 2-4 years 7. 4-10 years 8. 10+ years	1. bean piler, awning spreader, 2. Census taker, hostess, soap presser 3. Jackhammer operator, boarding-machine operator, script reader 4. air-valve repairment, lye treater, patrolman 5. Abrasive grader, fish hatchery man, floral designer 6. Diver, flyman, nurseryman 7. Clerical technician, fur finisher, copy reader 8. Die checker, electrical engineer, manager 9. Executive chef, president of university
GED	General educational development. Rated on scale from 1-7 for language, mathematical, and reasoning development.	See Appendix Figure X

Notes: From Appendix A ("Manual for Rating Training Time") from *Estimates of Worker Traits for 4,000 Jobs* (1956).

Table C2. Definition of aptitude variables

Variable	DOT Definition	Example?
Verbal	Ability to understand meanings of words and ideas associated with them, and to use them effectively. To comprehend language, to understand relationship between words and to understand meanings of whole sentences and paragraphs. To present information clearly.	Level 1: editor, newspaper Level 2: radio announcer Level 3: salesperson Level 4: none given Level 5: none given
Numerical	Ability to perform arithmetic operations quickly and accurately.	Level 1: mechanical engineer Level 2: bookkeeping machine operator Level 3: carpenter Level 4: counter Level 5: none given
Spatial	Ability to comprehend forms in space and understand relationships of plane and solid objects.	Level 1: dentist Level 2: machinist Level 3: carpenter Level 4: tobacco wrapper Level 5: none given
Form Perception	Ability to perceive pertinent details in objects or in pictorial or graphic material. To make visual comparisons and discriminations and see slight differences in shapes and shadings of figures and widths and lengths of lines	Level 1: none given Level 2: stenographer Level 3: paperhanger Level 4: furniture assembler Level 5: none given
Clerical Perception	Ability to perceive pertinent details in objects or in pictorial or graphic material. To observe differences in copy, to proofread words and numerals	Level 1: proofreader Level 2: stenographer Level 3: cashier-wrapper Level 4: machinist Level 5: none given
Motor Coordination	Ability to coordinate eyes and hands or fingers rapidly and accurately in making precise movements with speed. Ability to make a movement response accurately and quickly.	Level 1: none given Level 2: key-punch operator Level 3: machinist Level 4: fruit cutter Level 5: none given
Finger Dexterity	Ability to move the fingers, and manipulate small objects with the fingers, rapidly or accurately.	Level 1: surgeon Level 2: instrument maker Level 3: weaver Level 4: bagger Level 5: none given

Table C2. Definition of aptitude variables (continued)

Manual Dexterity	Ability to move the hands easily and skillfully. To work with the hands in placing and turning motions.	Level 1: none given Level 2: packer Level 3: loom fixer Level 4: rag sorter Level 5: none given
Eye-hand-foot coordination	Ability to move the hand and foot coordinately with each other in accordance with visual stimuli.	Level 1: baseball player Level 2: structural steel worker Level 3: longshoreman Level 4: paper cutter Level 5: none given
Color discrimination	Ability to perceive or recognize similarities or differences in colors, or in shades or other values of the same color.	Level 1: color matcher Level 2: interior decorator Level 3: fruit grader Level 4: dye weigher Level 5: none given

Notes: From Appendix B ("Manual for rating aptitudes") from *Estimates of Worker Traits for 4,000 Jobs* (1956). Rated on scale from 1 to 5. Level 1: top 10 percent, level 2: next 10 to 33 percent. Level 3: middle third (33-66 percent). Level 4: 66-90 percent. Level 5: bottom 10 percent.

Table C3. Definitions for rating temperaments variables

Variable	DOT Definition
Repetitive	Situations involving repetitive or short cycle operations carried out according to set procedures or sequences
Specific Instruction	Situations involving doing things only under specific instruction, allowing little or no room for independent action or judgment in working our job problems
Direction, control, and planning	Situations involving the direction, control, and planning of an entire activity or the activities of others
Dealing with people	Situations involving the necessity of dealing with people in actual job duties beyond giving and receiving instruction
Judgement	Situations involving the evaluation (arriving at generalizations, judgments or decisions) of information against sensory or judgmental criteria
Measurable	Situations involving the evaluation of information against measurable or verifiable criteria
Feelings	Situations involving the interpretation of feelings, ideas or facts in terms of personal viewpoint
Set Limits	Situations involving the precise attainment of set limits, tolerances, or standards

Notes: From Appendix C ("Manual for rating temperaments") from *Estimates of Worker Traits for 4,000 Jobs* (1956). The variables are rated as either Yes/No.

Table C4. Definitions of physical task variables

Variable	DOT Definition	Example?
Strength	Lifting, carrying, pushing or pulling. Sedentary work: lifting 10 pounds maximum, involves sitting. Light work: lifting 20 pounds maximum with frequent lifting and carrying of objects weighing up to 10 pounds. Could also indicate walking/standing to a significant degree Medium work: lifting 50 pounds maximum with frequent lifting and carrying of objects weighing up to 25 pounds Heavy Work: lifting 100 pounds maximum with frequent lifting and carrying of objects weighing up to 50 pounds Very Heavy work: lifting objects in excess of 100 pounds with frequent lifting and carrying of objects weighing up to 50 pounds	Sedentary: Stenographer Light work: Elevator operator Medium work: Tire repairman Heavy: Pipe fitter Very heavy: Rigger helper
Climbing	Climbing: Ascending or descending ladders, stairs, scaffolding, ramps, poles, ropes and the like Balancing: Maintaining body equilibrium to prevent falling when walking	Water, dining car, mark caller, lineman, acrobatic dancer
Stooping	Stooping: bending the body downward and forward by bending the spine at the waist. Kneeling: bending the legs at the knees to come to rest on the knee or knees. Crouching: Bending the body downward and forward by bending the legs and spine. Crawling: moving about on the hands or hands and feet	Weeder, loader and unloader, charwoman
Reaching	Reaching: extending the hands and arms in any direction Handling: Seizing, holding, grasping, turning or otherwise working with hand or hands (not fingering) Fingering: picking, pinching, or otherwise working with fingers (not whole hand or arm) Feeling: Perceiving such attributions of objects as size, shape, temperature or texture, by means of receptors in the skin.	Addresser, porter, reporter, tailor

Table C4. Definitions of physical task variables (continued)

Talk Hear	Talking: expressing or exchanging ideas by means of spoken words. Hearing: perceiving the nature of sounds by the ear.	Morse operator, information operator, barker
Seeing	Ability to perceive the nature of objects by the eye. More important aspects are acuity, muscle balance, depth perception, field of vision, accommodation and color vision	Airplane pilot, boarding machine operator, bus driver, machine cutter.

Notes: From Appendix E ("Manual for rating physical capacities and working conditions") from *Estimates of Worker Traits for 4,000 Jobs* (1956). Variables are rated as yes/no.

Table C5. Definition of working conditions variables

Variable	DOT Definition	Example?
In Out	Work inside or outside. Inside/Outside is to be rated if the worker spends approximately 75 percent or more of his time inside/outside.	None given
Cold	Extremes of cold plus temperature changes: Cold: Temperatures sufficiently low to cause marked bodily discomfort, unless the worker is provided with exceptional protection Temperature changes: variations in temperature which are sufficiently marked and abrupt to cause marked bodily reactions	Ice box man, storage man, beef cutter.
Heat	Extremes of heat plus temperature changes: Heat: Temperatures sufficiently low to cause marked bodily discomfort, unless the worker is provided with exceptional protection Temperature changes: variations in temperature which are sufficiently marked and abrupt to cause marked bodily reactions	Cook, furnace man, motion picture projectionist
Wet	Wet and Humid Wet: Contact with water or other liquids Humid: Atmospheric condition with moisture content sufficiently high to cause marked bodily discomfort	Hand dishwasher, hog sticker, shirt-collar-and-cuff-press operator

Noise	Sufficient noise, either constant or intermittent, to caused marked distraction or possible injury to the sense of hearing, or to cause bodily harm if endured day after day (¿80 decibels)	Farm spinner, machine driller for quarry
Hazard	Industrial hazard, such as proximity to moving mechanical parts, electrical shock, working on scaffolding and high places, exposure to burns, etc.	Fireman, lineman, blaster
Fumes	Fumes, Odors, Toxic conditions, Dust or Poor Ventilation Fumes: smoky or vaporous exhalations, usually odorous, thrown off as the result of combustion or chemical reaction Odors: Noxious smells, either toxic or nontoxic Toxic: exposure to toxic dust, fumes, gases, vapors, mists, or liquids which cause general or localized disabling conditions as a result of inhalation or action on the skin Dust: Air filled with small particles of any kind, such as textile dust, flour, wood, leather, feathers, etc., and inorganic dust, including silica and asbestos, which make the workplace unpleasant or are the source of occupational diseases Poor ventilation: insufficient movement of air causing a feeling of suffocation	Grain stacker, garbage man, lead kettleman,

Notes: From Appendix E ("Manual for rating physical capacities and working conditions") from *Estimates of Worker Traits for 4,000 Jobs* (1956). Variables are rated as yes/no.

Table C6. Constructed measures

Nasty	cold+heat+wet+noise+hazard+fumes+in_out
Physical	**climbing+stooping+reaching+talkhear+seeing+strength**
White collar	clerical+numerical+verbal
Body	strength+climbing+stooping+reaching
Routine-Manual	**Findex+motor+formp+manual**
Non-routine Interactive	dcp+depl
Non-routine Analytic	**ged+numerical+measurable**
Routine Cognitive	setlimits+color+repetitive
Manual Broad	manual motor eyehf findex strength formp color spatial
Communication	**clerical numerical verbal dcp depl ged**

D. Details on linked data

We measure workers' mobility in task content across censuses with linked data in the early 20th century. This section describes the sample construction and weighting process.

D.1 Intragenerational data

First, we downloaded the census links available from the Census Linking Project (Abramitzky et al., 2012). We use ten-year links between 1900-1910, 1910-1920, 1920-1930, and 1930-1940. We keep Black and white males whose race matches across censuses. Our sample comprises 28-55 year olds in the second census.

There are many different linking methods available in the Census Linking Project, but we use links that are "Exact" and "Conservative." "Exact" links are created by matching on exact first name and last name strings, as opposed to cleaning strings with a phonetic algorithm like the NYSIIS phonetic code (New York Immunization Information System phonetic code). Bailey et al. (2020) recommend using exact strings in order to avoid false positives. "Conservative" links drop any individual with the same first name and last name combination within plus or minus two years of birth. This restriction reduces the probability of matching to the wrong man.

The benefit of a conservative linking method is that false positives are reduced. However, the cost is a reduced linking rate and an unrepresentative sample. The backward linking rate from the second census is between 14.6 and 21.7 percent. Failing to link could be due to name misspellings, common names, or age heaping. To address selection into the linked sample, we use the inverse probability weighting procedure suggested by Bailey et al. (2020). To maintain consistency with the intergenerational data from Ward (2023), we:

1. Pool the linked sample with the full-count census of males in the second census. For example, with the 1900-1910 links, we pool the linked individuals in 1910 with the 1910 full-count census. Therefore, the next step will weight the data to be representative of those who do not die or out-migrate by the next census.

2. We estimate a probit to predict who is in the linked sample. The probit uses the following variables:

    - Black indicator variable
    - Age (10-year bins) and its interaction with the Black variable
    - Occupation category (white-collar, semi-skilled, farmer, low-skilled) and its interaction with the Black variable
    - Region of residence (North, South, West or Midwest) and its interaction with the Black variable
    - Whether one lives in a different state from state of birth

3. Based on the probit coefficient, we calculate the probability of being linked, $\hat{p}$. Figure D1 plots the densities for the predicted probabilities across the linked and unlinked group, and shows that there is strong overlap across groups.

4. The weights used for the analysis are calculated as $\left(\frac{1-\hat{p}}{\hat{p}})\right)\left(\frac{q}{1-q}\right)$, where q is the share of the population that is linked.

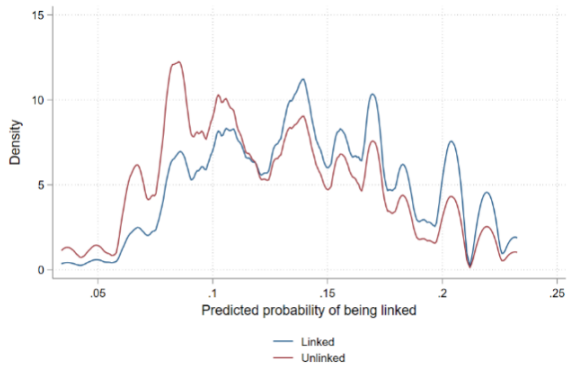
Ultimately, the data contain 15,264,852 linked men.

D.2 Intergenerational data

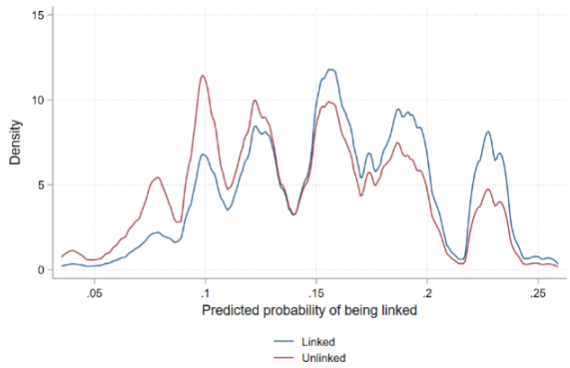
The intergenerational data are from Ward (2023), which follows the same process as above but for the father-son dataset. Since the data are intergenerational instead of intragenerational, there are a few important differences. First, the data are of 0-14 year old males observed with 25-55 year old fathers in the first census. Second, the data links either 20, 30, or 40 years later to observe the child in adulthood. We keep children who are between 25 and 55 years of age in adulthood. Third, we link fathers to a second census ten years earlier or later to obtain a second occupation observation. This procedures helps to reduce measurement error when trying to accurately measure the occupational task content of fathers. Fourth, weights are calculated based on the son's adult observation. Fifth, only censuses between 1900 and 1940 are used to create these data. See the Online Appendix of Ward (2023) for details on representativeness of the intergenerational sample.

Figure D1: Kernel densities for linking probability for the intragenerational data

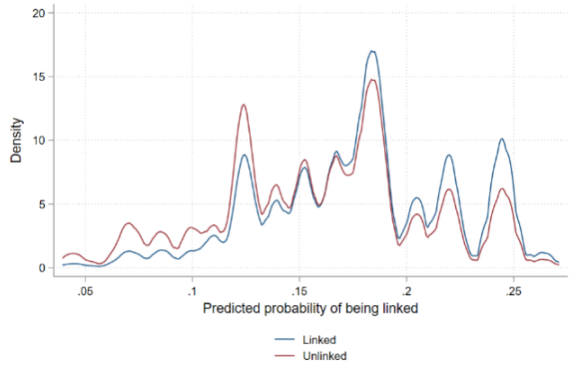
(a) 1900-1910 Census



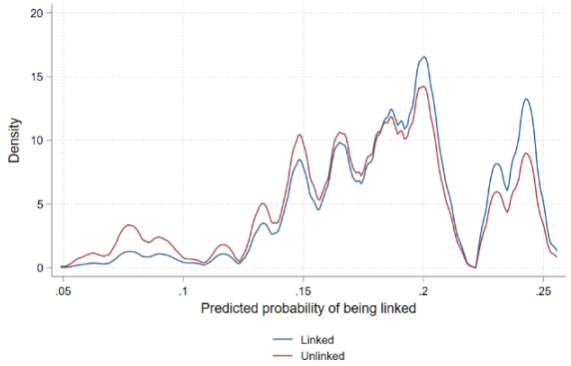
(b) 1910-1920 Census



(c) 1920-1930 Census



(d) 1930-1940 Census



Notes: These figures plot the densities of the predicted probabilities p across the groups successfully linked and unsuccessfully linked. The plots show strong overlap in the probabilities, which suggests that selection into the sample on unrepresentative characteristics is not strong.

Table D1: Representativeness of the linked samples (1900-1910, 1910-1920)

		Linked (1900-1910)			Linked (1910-1920)	
	Population	Unweighted	Weighted	Population	Unweighted	Weighted
Black	0.091	0.044	0.093	0.090	0.039	0.092
	(0.288)	(0.205)	(0.291)	(0.286)	(0.194)	(0.289)
Age	39.507	40.061	39.721	39.851	39.874	39.961
	(7.886)	(7.981)	(7.913)	(7.812)	(7.900)	(7.851)
Northeast	0.300	0.275	0.293	0.296	0.269	0.291
	(0.458)	(0.447)	(0.455)	(0.457)	(0.444)	(0.454)
Midwest	0.333	0.402	0.333	0.332	0.394	0.331
	(0.471)	(0.490)	(0.471)	(0.471)	(0.489)	(0.470)
South	0.269	0.230	0.279	0.270	0.224	0.279
	(0.444)	(0.421)	(0.448)	(0.444)	(0.417)	(0.448)
West	0.097	0.093	0.095	0.101	0.112	0.100
	(0.296)	(0.291)	(0.294)	(0.302)	(0.315)	(0.300)
Migrant	0.482	0.602	0.487	0.495	0.613	0.497
	(0.500)	(0.489)	(0.500)	(0.500)	(0.487)	(0.500)
White Collar	0.199	0.244	0.203	0.208	0.256	0.212
	(0.399)	(0.430)	(0.402)	(0.406)	(0.436)	(0.408)
Farmer	0.229	0.285	0.233	0.206	0.250	0.208
	(0.420)	(0.451)	(0.423)	(0.404)	(0.433)	(0.406)
Unskilled	0.237	0.164	0.231	0.213	0.148	0.208
	(0.425)	(0.370)	(0.421)	(0.409)	(0.355)	(0.406)
Skilled	0.273	0.250	0.272	0.305	0.283	0.304
	(0.446)	(0.433)	(0.445)	(0.460)	(0.451)	(0.460)
Observations	16,367,381	2,385,715	2,385,715	19,396,220	3,150,538	3,150,538

Notes: The table shows the descriptive statistics of the 1900-1910 and 1910-1920 linked data. The representativeness is based on the second census. The weighted columns are the descriptive statistics after weighting the data as described in this appendix.

Table D2: Representativeness of the linked samples (1920-1930, 1930-1940)

		Linked (1920-1930)			Linked (1930-1940)	
	Population	Unweighted	Weighted	Population	Unweighted	Weighted
Black	0.090	0.035	0.091	0.088	0.035	0.088
	(0.286)	(0.184)	(0.288)	(0.283)	(0.184)	(0.283)
Age	40.229	40.212	40.286	40.485	40.456	40.494
	(7.832)	(7.872)	(7.866)	(7.989)	(7.969)	(7.988)
Northeast	0.294	0.269	0.290	0.288	0.266	0.287
	(0.456)	(0.444)	(0.454)	(0.453)	(0.442)	(0.453)
Midwest	0.326	0.394	0.326	0.312	0.382	0.312
	(0.469)	(0.489)	(0.469)	(0.463)	(0.486)	(0.463)
South	0.269	0.211	0.274	0.285	0.217	0.287
	(0.443)	(0.408)	(0.446)	(0.452)	(0.412)	(0.452)
West	0.110	0.126	0.110	0.114	0.135	0.114
	(0.313)	(0.332)	(0.312)	(0.318)	(0.342)	(0.318)
Migrant	0.514	0.613	0.514	0.583	0.630	0.582
	(0.500)	(0.487)	(0.500)	(0.493)	(0.483)	(0.493)
White Collar	0.253	0.300	0.256	0.271	0.305	0.273
	(0.435)	(0.458)	(0.436)	(0.445)	(0.461)	(0.445)
Farmer	0.160	0.183	0.160	0.122	0.136	0.121
	(0.366)	(0.387)	(0.366)	(0.327)	(0.342)	(0.326)
Unskilled	0.215	0.157	0.213	0.219	0.176	0.218
	(0.411)	(0.363)	(0.409)	(0.413)	(0.381)	(0.413)
Skilled	0.310	0.304	0.310	0.332	0.342	0.332
	(0.463)	(0.460)	(0.462)	(0.471)	(0.474)	(0.471)
Observations	22,667,075	4,312,305	4,312,305	25,040,632	5,416,294	5,416,294

Notes: The table shows the descriptive statistics of the 1920-1930 and 1930-1940 linked data. The representativeness is based on the second census. The weighted columns are the descriptive statistics after weighting the data as described in this appendix.