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Rowena Gray
Siobhan M. O'Keefe
Sarah Quincy
Zachary Ward

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ABSTRACT

We present new evidence on the long-run trend 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 from 1960 onwards. Longitudinal data suggests that transitions to new task content were racially biased: Black men moved to jobs with lower rewarded task content than white men, conditional on initial task content, though gaps decreased after World War II. Routine-intensive Black workers were less likely to move up into non-routine analytic work compared to white workers in both historical and modern periods. The results suggest that task-displacement shocks, such as automating routine-manual work, widen Black-white inequality

Rowena Gray
Department of Economics
University of California Merced
5200 N. Lake Road
Merced, CA 95343
rgray6@ucmerced.edu

Siobhan M. O'Keefe
Department of Economics
Davidson College
Davidson, NC 28036
siokeefe@davidson.edu

Sarah Quincy
Department of Economics
Vanderbilt University
2301 Vanderbilt Place
Nashville, TN 37235
and NBER
sarah.quincy@vanderbilt.edu

Zachary Ward
Department of Economics
Baylor University
One Bear Place
Waco, TX 76798
and NBER
zach.a.ward@gmail.com

1 Introduction

The trajectory of Black labor market outcomes relative to white Americans has been well-documented across the second half of the twentieth century. Wages displayed strong convergence in the 1940-1980 period, followed by a notable stagnation or even divergence after 1980 (Juhn et al., 1991; Jaynes, 1990; Bayer and Charles, 2018). The pre-World War II era has received less attention due to limited wage data availability, but was known for a high degree of racial occupation segregation and wage gaps (Collins and Wanamaker, 2022; Margo, 2016; Myrdal, 2017; Sundstrom, 1994). Using a task-based approach, we show that the task composition of occupations plays an important role in perpetuating Black-white labor market disparities.

We identify the task concentrations of Black men relative to white men to provide new insights into why Black progress stalled at various periods over the past 120 years. The task-based approach is a powerful framework for explaining trends in wage inequality (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2022), but, until recently, it is rarely linked to racial inequality (Dicandia, 2022 ; Hurst et al., forthcoming). In this paper, we use a new long-run task dataset that maps task intensities into occupations over the last 120 years. This allows us to measure the relative exposure of Black and white men to task demand shocks in a consistent way over the last century. Moreover, we can identify racial differences in task premia, as Black and white workers may be paid differently for the same tasks. Finally, we use longitudinal data to measure racial differences in task transitions, exploring whether workers exposed to the same demand shock transition differently into higher- or lower-paid work. This approach goes beyond previous cross-sectional research that assumes Black and white workers equally adapt to labor demand shocks. Overall, our approach provides a richer understanding of Black-white inequality over the past 120 years and complements prior work that focuses on other factors such as discrimination (Aizer et al., 2022), schooling (Carruthers and Wanamaker, 2017a), or institutional changes to 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 descriptions of task content from 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 link individuals across Censuses and with their fathers which allows us to explore transitions for workers over their lifecycle and across generations. We find differences in these transitions to be important in explaining racial task gaps.

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.[2] 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 two increases and declines over the past 120 years; the "hollowing out" pattern identified by (Autor et al., 2003) for the post-1960 period has a historical analogue before World War II. These findings are similar within each census region and are not driven by the shift out of agriculture, which suggests that working in cognitively, not physically, intensive tasks was broadly predictive of higher earnings.

Second, we document that racial differences in task content are persistent. White men in 1900 were more likely to be in modern work than Black men in 1950, and this gulf remains today. The gaps in 1900 and 1940 were almost identical, as Black men concentrated in physical tasks, but less so in routine-manual and non-routine cognitive tasks. Then,

[2] These findings are consistent with other research which examines 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.

between 1940 and 1980, 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. Since 1980, progress has stalled again, resembling the early 20th century trend. These patterns hold when controlling for education or when dropping agricultural workers, which we take as evidence that Black workers were more subject to long-run declines in demand and less exposed to increases in demand for non-routine analytic tasks.

Third, we illustrate that there has been convergence in the labor market returns to each task by race. In 1940, tasks yielded very different wage premia across Black and white workers. For instance, we estimate a smaller premium for non-routine analytic tasks for Black workers compared to white workers in 1940, perhaps reflecting discrimination in these jobs (Hurst et al., forthcoming). However, these racial differences in task premia converged strongly between 1940 and 1980 such that today there is a nearly perfect correlation between Black and white task premia. This result suggests that Black and white workers had different incentives to sort into occupations in 1940, but these incentives aligned by 1980 and cannot explain today's racial wage gap. Instead, long-run changes in relative demand for tasks continue to affect racial income convergence through changes in the quantities of each task.

We finish by estimating racial differences in workers' task transitions over time. The above analysis suggests that task quantities play an important role in perpetuating differences in the work performed by Black and white men. To do so, we introduce the concept of task persistence. We adopt the approach used in the intergenerational mobility literature by regressing the current task content percentile rank on a prior percentile rank and an indicator variable for being Black (Collins and Wanamaker, 2022; Jácome et al., 2021). We create this measure when tracking men across the life cycle, where we compare task ranks ten years apart; and across generations, where we compare fathers' and sons' task content. For the early 20th century, we use linked data across the 1900-1940 complete-count censuses; for the modern era, we use the Panel Study of Income Dynamics (PSID) for 1968-2019. We additionally use data from the 1962 and 1973 Occupational Changes in a Generation (OCG) studies to estimate racial differences in intergenerational transitions in the mid-20th century. We then compare workers' persistence in the same task to their transitions into other tasks over time to study how task displacement varies by race and task over time.

This longitudinal approach provides new insights into why overall racial convergence in labor market outcomes is incomplete. Conditional on initial task content, Black men are consistently more likely to end up in occupations that require intensive use of physical tasks, and less likely to stay in non-routine analytic work 10 years later. Though these transition differentials narrowed after 1940, we find that early differences still matter for labor market disparities due to the existence of intergenerational racial task gaps. Intergenerational mobility differences across race display a broadly similar pattern as those within the life cycle but, in some cases, are close to zero in the modern period. Even conditional on entry into similar work, racial differences in persistence in high versus low-paying tasks remain sizeable both within and across generations. We also show that for a given initial routine-manual intensity, Black workers are more likely to transition to physically-intensive jobs than analytical jobs, relative to white workers.

Racial differences in task transitions may arise from differences in occupational or industry sorting, skills, or location in the United States. While we do not directly test the impact of a specific technological shock on Black-white transitions, we can control for the same variations used by other researchers to estimate the impact of such shocks. In our rich historical data from before World War II, we account for technological shocks with an extensive set of fixed effects, including the interaction of detailed occupation codes, industry codes and county of residence. This approach allows us to control for such factors as the spread of electricity across counties (Gaggl et al., 2021), the impact of the tractor in agriculture (French, 2024), and other labor-saving machines like the automatic stitching or switching machines (Cockriel, 2024; Feigenbaum and Gross, 2024). We find large differences in Black-white transitions both within and across generations, even after accounting for these fixed effects. This result suggests that technological shocks impacted Black and white workers differently, which usually isn't accounted for in models of the labor market impact 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 account for changing measures based on different editions of the DOT between 1939 and 1991. However, there is evidence that we are accurately capturing trends in the early 20th Century since there is stability in many job descriptions.[3] A second limitation is that, due to limited wage data prior to 1940, we are unable to explicitly link changes in task measures to changes in wage inequality in all years so we cannot fully compare our early results to the research on modern automation and hollowing out (Autor et al., 2003; Acemoglu and Restrepo, 2022). We do find compositional changes in line with that literature.

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 electrification, automated telephone operation, and the more general move from hand to machine production (Atack et al., 2019; Feigenbaum and Gross, 2024; Gray, 2013). We contribute not just a more comprehensive depiction of task employment over the past 120 years, but also measure whether the rate of task changes evolved over time, yielding a new understanding of the timing of the rise of modern 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 (e.g. 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 et al.,

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

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-Leon, 2022; 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 in 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, but tasks help to uncover the implications of this beyond the contemporaneous wage differentials– that Black workers remained in lower paid, less complex tasks and jobs for much longer than whites. The evolution to modern work began only for white workers in 1900, with Black workers shifting later, around 1950.

Task data has been used to analyze racial gaps since 1960, either emphasizing different task premia across Black and white workers (Hurst et al., forthcoming) or differences in employment shares across tasks (Dicandia, 2022), providing intuition behind current racial differences in automation exposure (Lerch, forthcoming; Mason, 2022; Aizer et al., 2022). Gould (2021) has linked manufacturing decline to a broad set of economic and social outcomes that have been more negative for Black men relative to white men, and Acemoglu and Restrepo (2022) agree that the impact of technological change varies greatly across demographic groups. By following workers' intensity of low-, medium-, and high-return tasks over time, we present new information on long-run racial task gap trends before the automation period and use those to inform the racial income gap debate which has previously lacked a task perspective. Specifically, we emphasize that Black workers remain more exposed to task displacement shocks due to heightened probabilities of being in routine-manual and physical jobs in the first place.

Another key contribution is to examine how Black and white tasks differ not just in the cross-section, but also in longitudinal data. Our use of longitudinal data 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 et al., 2024). We contribute new evidence measuring differences by race, previously unexplored. Not only do we extend this literature by comparing historical linked data to modern data, we also estimate across-generation mobility. All these additions are related 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 et al., 2021; Ward, 2023). We show that Black and white workers do not transition in a similar way following a displacement, suggesting that there remain barriers in the labor market. Our findings suggest that the racial wage gap could be reduced by about 20% today were Black workers to have the same task content as white workers.

2 Data

2.1 Task Definitions

Our paper measures the long-run evolution of occupation-based task measures. Descriptions of tasks required in an occupation were created during the Great Depression as a tool to address long-term unemployment. We use data 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 (e.g., verbal skill, motor coordination, finger dexterity), temperament (e.g., work situations involving repetition, isolation, or dealing with people), and physical capabilities (e.g., 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. [5] These measures allow us to measure the shift away from traditional tasks such as physical strength and factory-style work (often viewed as substitutes for capital), towards more cognitive-skill intensive work, typically considered capital complementary in the modern period, as technology has improved. They allow us to compare to other research on task changes in the modern period. For instance, Autor et al. (2003) highlight the rise and fall of routine-manual jobs and the increased importance of analytic tasks beginning in the 1970s.

The full definitions of all underlying variables are given in Appendix B; here we explain how our composite measures were constructed. Routineness 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 on a factory floor or production line type 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

[4]Another example is the clerical variable which measures, on a scale of one to five, the amount of clerical competency required to perform an occupation. 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, lower than an occupation such as proofreader where clerical accuracy is even more paramount. In contrast, an example of a job in which clerical accuracy is unimportant is a machinist.

[5]A fourth composite measure, communication, was constructed as an alternate representation of modern work, as described in Michaels et al. (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 et al. (2018) on urbanization's role in the growth of interactive tasks.

handlers are all physically intensive occupations by this measure.

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).[6] 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.[7]

To describe modern task content, we follow the modern-day literature and use information from the 1977 DOT (Autor et al., 2003; Autor and Price, 2013).[8] 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 composite task measures with 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.[9] 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

[6]The sample is limited to 18-55 year-olds with an occupation.

[7]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.

[8]The update to the DOT measures, O*NET, has been used elsewhere (e.g., 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.

[9]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 percentiles from the 84th to 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).

that rely on text analysis of job descriptions (Atalay et al., 2020; Michaels et al., 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 within-industry technological and other changes.

2.2 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, 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 individuals of prime age (18-55) who listed an occupation. 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, although our results are robust to not making this choice.

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 individuals 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 18-55-year-old males in the 1900-1930 US censuses, and then link them ten years later. For intergenerational data, we link 0-14-year-old sons 20, 30, or 40 years later to the 1920-1940 US Censuses.[10] The data are weighted for representativeness using inverse probability weights (Bailey et al., 2020). Full details on linking, weighting and representativeness are given in Appendix C.

2.3 PSID data

We use longitudinal data from the PSID to compare with linked historical data. 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.[11]

[10]These are the same data as in (Ward, 2023). Ward (2023) takes 0-14-year-old children 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). The data is also weighted to be representative of the underlying population using inverse proportional weights.

[11]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

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 to reduce measurement error, but this method only works 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 individuals, rather than the absolute level of mobility.

In order to investigate task persistence in the period between the historical census and the PSID, we turn to the 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 16 years old, 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 (ages 18-55, black or white, with an occupation) are consistent with our other analyses. The intergenerational results in Figures 2 and 7 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.

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.

3 120 Years of Task Trends

3.1 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 summary task measures: routine-manual, physical labor, and non-routine analytic.

Over the course of the 20th century, the economy shifted towards occupations that were less physical, and the physical task measure halved in intensity. At the same time, non-routine analytic tasks 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 et al., 2003; Michaels et al., 2018; Goldin and Katz, 2009; Deming, 2017).

We show that routine-manual work experienced three distinct eras of task changes. First, there was a rise and fall between 1900 and 1940; then a two-decade rise after World War II, and a decline since the 1960s. Early in the 20th century, routine-manual work first rose slowly, as steam-powered machinery helped to replace tasks performed by hand (Atack et al., 2019, 2022).[12] During the 1920-40 period, as many expressed concern that mass unemployment in part reflected industrial mechanization, we find a fall in routine-manual labor for the average worker (Jerome, 1934). After this early period of hollowing out, we see a sustained rise in

[12] We note that the increase is not large relative to the changes in other tasks; it may be that a stronger increase in routine-manual occupations occurred earlier in the 19th century when steam first started to power machinery and operatives began replacing artisans (Goldin and Sokoloff, 1984; Atack et al., 2008).

routine-manual intensity during the postwar period before the modern period of hollowing out began (Autor et al., 2003). The fall between 1920 and 1940 was about 4 points, which contrasts with the much larger 9-point drop in the index from 51 to 42, 1970-2021.

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. For instance, the late 20th century story of the rise and long-term fall of routine jobs is visible, which partially reflects automation from computerization and robots (Autor et al., 2003; Acemoglu and Restrepo, 2019). We also find that non-routine analytic tasks continued to expand (Michaels et al., 2018). These results are robust to using only the 1977 version of the DOT data already familiar in the literature, as shown in the Appendix. These differences in workers' employment from 1900 to 1940, 1940 to 1970, and 1970 to now likely reflect innovation-based shifts in labor demand over the long run rather than quirks of our data definitions.

These trends are robust to dropping agriculture and are similar across regions (Figures 1b and A3, respectively). We see this also in the non-monotonic trends in routine-manual tasks, despite the fairly monotonic movement out of agriculture and towards manufacturing and then services. We go further in Figure A4 to show our basic task trends accounting for shifts in broad industry category.[13] We found that about two thirds of the century-wide trends in physical and nonroutine 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 (Gaggl et al., 2021; Autor and Dorn, 2013), but it is certainly not the only determinant that we have uncovered in this paper. We also show in Section 4 below, consistent with the research of, for example, Bhagia and Bryson (2023), that cross-industry shifts are less important in explaining the relative performance of Black

[13] We categorize the data into 12 different industry categories based on the *ind*1950 variable from IPUMS.

workers compared to white workers, the focus of the latter half of the paper.

3.2 Workers' Task Persistence

These aggregate changes in task content come from pooled cross-sectional data, which makes it unclear how often workers switched into different tasks. An economy with rapid changes in task demand likely displays a high amount of "task mobility", which captures how the task content in one's occupation persists across time. Using longitudinal data, we compare the rank-rank correlation of task content over workers' own lifetimes and across generations to benchmark this concept from the early 20th century to now. We complement longitudinal modern labor data from the PSID and OCG with linked census data from the early 20th century and estimate the following equation:

$$Rank(Task_{i,t}) = \beta_0 + \beta_1 Rank(Task_{i,t-10}) + \epsilon_{i,t} \tag{1}$$

This is a common specification in the intergenerational mobility literature, modified for task content ranks instead of income ranks (e.g., Chetty et al. (2014)). If task mobility was low, then $\hat{\beta}_1$ is estimated to be near one; if task mobility was high, then $\hat{\beta}_1$ is near zero. Since a higher $\hat{\beta}_1$ indicates that task content was similar across censuses, we sometimes refer to estimates of $\hat{\beta}_1$ as "task persistence".

Figure 2a plots task persistence within the lifecycle for the three tasks, as well as for occupational income. The results suggest that changing task intensity over the lifecycle was common. The correlation in task intensity across a decade was often between 0.40 and 0.65.[14] This suggests that approximately half of task gaps between two individuals persisted to the next decade. In general, we find that task persistence was slightly higher in the PSID (1980-2010) relative to the historical census data. However, one should keep in mind that there is likely more error in historical data due to uncertain linking and messy occupational data. It

[14]Figure A5 shows that task stability increased with age. Even for our oldest cohorts of workers in the first period, 40-45 year olds, the correlation with their task measure 10 years later was still low.

may also be possible that task mobility has been stable over the 20th century. Regardless of the data or methods, we can rule out large shifts in task mobility when the economy was undergoing the "hollowing out" periods between 1920 and 1940 and post 1980.

A father's task content appears to weakly predict a son's task content, as shown in Figure 2b. Overall father-son associations are around 0.20.[15]. Task mobility was particularly high for routine-manual tasks, which may reflect the hollowing out of these tasks, which led to different tasks for the subsequent generation. These results suggest that intergenerational task mobility has been roughly constant over the last 120 years but varies substantially by task.

3.3 Task Returns Over Time

While the overall task content of American labor has shifted remarkably over the last 120 years, it is unclear whether the return to task content has also shifted, due in part to the increasing educational attainment of the population (Goldin and Katz, 2009). To examine this question, we estimate 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 30-45-year-old wage workers:[16]

$$log(WeeklyWage_i) = \beta_0 + \beta_1 Rank\left(Task_i\right) + \beta_2 YearsEd_i + \beta_3 A_i + \beta_4 A_i^2 + \varepsilon_i \qquad (2)$$

We estimate the regression for each cross section between 1940 and 2021.[17] Note that the wage premia do not account for business or farm income due to data definitions. We

[15] Previous work has shown that measurement error can meaningfully bias estimates of intergenerational mobility (Ward, 2023). If we use an IV method to correct for this measurement error, father's task content can still be used to predict a son's task content, and the association increases to about 0.40 (Figure A6).

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

[17] We find that these results are largely unchanged in a sibling fixed effects approach which controls for household-level unobservables using linked historical censuses and the PSID microdata for 1969–2015.

then plot the ranking of these task premia over time in Figure 3a.

First, Figure 3a 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 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. These task premia did not widen again until after 1980 when physical tasks are both performed and paid less and non-routine analytic tasks have risen in both quantity and return.

Though routine manual work has remained the middle return task over time, its relative remuneration has fallen consistently from 1940 to now. There is no evidence of a post-Great Compression reversal. Instead, during the postwar rise in routine-manual task intensity, its relative wages *fell*. Over time, routine-manual tasks were no longer associated with high incomes, denoted by a positive coefficient in this approach. The modern hollowing out period, then, has continued a longer-run pattern of routine-manual incomes falling while reversing the convergence in high and low return task premia from the 1940s.

Although we focus in this paper on 3 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 3b 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 returns indicates that task quantities likely play a particularly important role in shaping income disparities over time.

We plot a 45-degree line to clarify which tasks' returns have changed over time. For example, routine-manual is to the right of the line, illustrating it was higher paid in 1940 than in 2021. We see particularly steep declines in the relative returns to tasks like *repetitive* and *climbing*, 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 returns and intensities contribute to trends in racial inequality in labor market outcomes.

4 Tasks' Role in Racial Labor Market Gaps

4.1 Black-White Task Content Disparities

We have shown the change in the quantity and price of tasks for the overall economy, but this masks substantial differences by race. Figure 4 plots differences in task intensity between Black and white workers.[18] 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, we also plot the difference in occupational income in every cross-section.

There is no evidence that the first major task displacement episode in our data induced any sort of convergence across race in labor market outcomes. 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.[19] As a result of this marked racial divergence in task trends, the

[18] See Figure A7 for the levels of Black and white task percentiles.

[19] 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 A8a). However, the timing of the decline in Black physical task intensity corresponds to shifts in both Black labor supply and Southern labor demand induced by increases

typical pre-World War II Black worker was a farm laborer or wood sawyer, substantially more brawn-intensive than the average worker in the US economy.

As Black workers remained in physically intensive jobs, white workers were far more exposed to the rise and fall in routine-manual work before 1940. Consequently, the pre-1940 period of technologically-driven demand increases for non-routine analytic tasks was experienced largely by white workers. White workers were thus in occupations such as carpenter, salesman, and cabinetmaker, while Black workers remained 30 percentiles lower in the non-routine analytic distribution, in jobs such as farm laborer, shoemaker, and newsboy. The first era of task transformation in the 20th century, then, was concentrated among white workers, and Black workers did not experience this first transition into modern work.

In contrast, a period of rapid convergence after World War II 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 had 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).

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 aggregated share of these innovation-complementary jobs increased (e.g.

in Black workers' geographic mobility and technological advances in agriculture (Derenoncourt, 2022; Collins and Wanamaker, 2014; Ward, 2023; Hornbeck and Naidu, 2014). Additionally, our physical task measure quantifies whether the job includes reaching or stooping, which were important tasks for Southern farm laborers in the 1939 DOT. Thus, the introduction of the mechanical cotton picker in 1949 and subsequent adoption during the 1950s helped to reduce farm labor and physical work for those remaining in agriculture.

Autor et al. (2024)), Black workers did increase their intensity in non-routine analytic tasks, but did not fully converge to white workers' intensity.

Certainly some of the convergence observed in Figure 4 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 III et al., 1991; Aneja and Avenancio-Leon, 2022). 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; Hurst et al., forthcoming; Ferrara, 2022). We note, however, that controlling for state of residence, age, and human capital does little to close the Black-white gaps on their own over time.[20] To the extent that modern innovations increase the substitutability of human physical 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 et al., forthcoming; Lerch, forthcoming).

4.2 Relative Task Returns By Race

We investigate here whether the gulf in task quantities by race over time identified above was exacerbated by differences in 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.[21]

We re-estimate Equation 2 separately by race and plot the results in Figure 5. Now the

[20] 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 A8b 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 1940-1980 do not close by much. Further, gaps remain for non-routine analytic and physical jobs today when controlling for education.

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

task premia reflect whether specializing in a task was associated with a higher wage within-race. In 1940, for instance, physical work had a positive premium for Black men but not for white men. Physically demanding jobs led to higher wages within the Black population, reflecting the highly segregated labor market at the end of the first era of hollowing out.

Some striking differences remained in returns by race after World War II despite a rapid narrowing in task quantity gaps. Between 1950 and 1980, Black wages were higher for routine-manual work than they were for white workers. 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 wages. On the other hand, Black workers had a lower premium for non-routine analytic work, perhaps because discrimination limited large wage gains in occupations with these tasks. These racial return disparities indicate that Black and white men had different pecuniary incentives to sort into tasks during both the mid-century rise in routine-manual labor demand and the century-long rise in non-routine analytic demand, all other labor market frictions held constant.

Over time, the gulf between Black and white task returns has been bridged. In the bottom right of Figure 5, 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; even if racial differences in task quantities were erased, there would still be an income gap between Black and white workers. After 1950 we see rapid increases in this correlation, especially in the civil rights era, with near total convergence occurring by 2000. White and Black workers today have similar income-based incentives to sort into the same tasks ex ante, making their actual task outcomes especially important for understanding the persistence of racial income gaps. This trend in racial task premia can partly explain rising within-race inequality. For example, Jaynes (1990) discussed how the recent decades had witnessed growing numbers of Black men who struggled in the labor market, alongside a growing cadre of highly educated Black male workers who were doing better than ever, and as we show that meant performing ever more similar tasks as white men.

4.3 Decomposing the Racial Wage Gap

Here we provide some suggestive evidence on how our results relate to the racial wage gap, from 1940 onwards. The paper identified two candidate explanations, in that both task content and task compensation differed by race. Using the same sample as was used to construct task wages, we conducted a Oaxaca-style decomposition to evaluate the contributions of these two components to average racial wage gaps.[22] The thought experiment here is to say how much of the racial wage gap would be removed if we assign Black workers the same task content as white workers (endowment effect); or how much of the wage gap can be explained by differences in task compensation by race (coefficient effect).

The results are presented in Figure 6. We show that differences in task content played an important role in the racial wage gap before 1970, with up to a 50% reduction predicted if Black men had been doing similar tasks as white men. The pattern for task content coincides with an era of stalled progress on Black-white task convergence, in line with the eras of progress that we identified earlier: of Black-white convergence from 1940 to 1980 and then stagnation in the past four decades. Although smaller than in the beginning of the twentieth century, racial disparieties in task intensity persist. Today, if Black workers had the same task content as white workers, the racial wage gap would be 20 percent lower. In the most recent period, differences in compensation play a more substantial role. Even though task premia are converging over this time period (Figure 5, lower right panel), differences in task premia continue to explain a large portion of the now smaller wage gap.

[22] See, for example, Jann (2008) for a nice discussion of Oaxaca decompositions.

5 The Black-White Task Persistence Gap

5.1 Trends in Racial Task Persistence Gaps

Next, we turn back to the longitudinal data to understand how task mobility affects these racial gaps. This permits us to test whether the sizeable differences in task intensity in the cross-section are largely a factor of entry barriers or if other frictions hinder task convergence once workers are in the labor market. Racially biased income transitions have been documented elsewhere (Akee et al., 2019; Collins and Wanamaker, 2022; Chetty et al., 2020; Daly et al., 2020). But there is only limited evidence for biases in task transitions– Golan et al. (2024) provide some recent evidence that Black workers *begin* their working lives in jobs requiring less complex tasks, and this compounds over time such that it can have a large impact on racial inequality over the life cycle. Here we provide information on task transitions over a longer run, and we focus on the degree to which white and Black men experience similar trajectories in job experiences overall, abstracting from differences in labor market entry conditions (e.g. education, location, and incarceration).[23]

To measure such mobility gaps, we modify Equation 1 to include an indicator variable for one's race being reported as Black. Each point on a plot represents the gap between Black and white task persistence where the second observation occurs in time t with the associated 95 percent confidence interval. A positive number indicates Black males were more likely to be in an occupation intensive in the task, conditional on the level of intensity in that task a decade prior.

We find that the 20th century began with large racial differences in task mobility (see Figure 7a).[24] By 1940 gaps had widened in ways consistent with white men exiting low-paid

[23]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). For the PSID, we regress an indicator for claiming no occupation on task content from ten years prior. We find that there is a racial difference, where Black males were 1.2 to 1.9 percentage points more likely to not claim an occupation conditional on initial task content, further lowering their ability to move up the task ladder.

[24]Research such as Collins (2000) has been able to show the start of increased mobility for Black Americans from WWII onwards, although, 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,

tasks more than Black men and Black men leaving high-paid tasks more frequently. In the historical hollowing out period, Black men were more likely to end up in a physical task job, but less likely to remain in a routine-manual job than white men in similar work previously. The largest disparities before World War II were in non-routine analytic work such that Black men fell 20 ranks below white men in the same task rank in the prior census. For instance, this would be equivalent of Black workers leaving a watchman job (38th percentile in non-routine analytic) for farm laborer work (18th percentile), while white men remained in the former job. This is consistent with the large occupational income gaps also displayed in Figure 7a, but provides a task framework for interpreting these results.

Between 1940, our last historical observation, and 1980, our first PSID observation, we find substantial declines in all mobility gaps.[25] During this forty-year window, we find that the Black-white differences in our two higher-return tasks fell. The non-routine analytic return persistence measure halved, while the routine manual equivalent became indistinguishable from zero. Without additional longitudinal data, however, we cannot rule out that this is a trend which began in 1940.

Like the racial income gap, this convergence has stalled in recent years. Despite the similarity of Black and white returns for non-routine analytic work today, Black men's intensities of these tasks still fell between survey waves by 10 ranks more than those of white men. A similar narrowing of the physical task 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 progress on racial differences in mobility for physically-demanding jobs. Despite reductions in other labor market disparities, Black men remain 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).

upon transitioning back to civilian production.

[25] We cannot use the 1950 100% sample because the income data are not yet reliable, according to IPUMS.

5.2 The Transition out of Routine-Manual Work By Race

By mapping tasks to longitudinal occupational data, we can also estimate the effects of declines in routine-manual work on workers' long-run labor market outcomes. We focus on this case study because of the well-documented role of computerization in the demise of routine work. Here, we investigate differential experiences by race in the face of the demise of routine-manual work, which has declined twice in the past century as technology has evolved. Overall, the cross-sectional data shows that Black-white gaps in routine-manual content have disappeared (Figure 4) along with mobility gaps in the longitudinal data (Figure 7a). Here we instead focus on what workers do when leaving routine-manual work and how those transitions varied by workers' reported race in both the historical and modern declines of routine-manual tasks.

To measure racial differences in the movement out of routine-manual work, we estimate the predicted task percentile of an individual starting at the 75th percentile of the routine-manual task distribution in the previous census or an earlier wave of the PSID.[26] 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 middle of the skill ladder. Both groups experience a fall in routine manual content over the decade but the similarities stop there. White workers often move up the skill ladder when transitioning out of routine manual work, but Black workers are more likely to move down. No matter the time period, white routine workers are far more likely to move into non-routine analytic work than Black routine workers. Instead of transitioning into non-routine analytic work like white workers, Black routine workers are more likely to enter jobs that are more physically intensive. Gaps in most of these transition measures have narrowed

[26] 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.

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. Together, these differences in task transitions explain why Black routine workers transition to jobs with meaningfully lower occupational scores than similarly routine white workers in both time periods.

The appendix exhibits similar figures for starting in non-routine analytic and physically intensive work which reveal a similar pattern over time (Figure A9). In each period and task, white men move up (or fail to move down) the skill ladder more frequently and Black men move down (or fail to move up) the skill ladder. We take this as evidence that task transitions compound the racial divides in task persistence illustrated in the previous subsection. In both periods of hollowing out, 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, unlike white men. Despite some progress towards convergence, task persistence and displacement continue to contribute to racial disparities in labor market experience.

5.3 Intergenerational Gaps in Task Mobility

We take a longer-run approach to task transitions by examining the potential transmission of task content across generations. To do so, we replace the outcome variable in Section 5.1, workers' task ranks in $t + 10$, with the son's task rank. Again, a positive number indicates that Black sons' task ranks are higher than white sons' task ranks when controlling for their fathers' labor market experiences.

Intergenerational task mobility differences by race 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 were far more likely to be in physical work if their fathers were, 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 World War II, we observe some, but not complete, convergence. We do not estimate the same magnitude of cross-generational gaps as before World War II, although later estimates are noisy due to a limited PSID sample size. Beginning with sons' observations in 1960, we document task mobility differences trending towards zero for all of our three tasks. Most of the convergence in intergenerational task mobility occurred in the 1960s and 1970s, periods associated with both reductions in labor market barriers and convergence in labor market returns by race.[27] In the decades immediately following World War II, all of the mobility gaps fell in magnitude by roughly ten points, constituting almost all of the progress made in leveling the intergenerational difference in tasks over the past 120 years. 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.[28]

Finally, the appendix displays intergenerational task transition results, and again finds evidence of partial convergence, especially in the 1960s and 1970s (Figure A11). In all three periods, Black sons have remained more likely to move down the skill ladder if their fathers did routine-manual work while white sons continue to move up to non-routine analytic work. We view these results as suggestive of technological change yielding higher white concentration in non-routine analytic work and higher Black concentration in physical work over the long-run.

5.4 Explanations for the Task Persistence Gap

The above analysis illustrates that Black males have consistently been less likely to work in, and remain in, modern jobs compared to white males, instead entering and remaining in low-return tasks. Certainly, long-run differences in education levels may explain this result. If Black workers attain lower levels of education than white workers, then one would expect Black workers to concentrate in physical tasks and be less concentrated in non-routine analytic work. As Black-white educational gaps have narrowed over time, so have

[27] See, for instance, related work by Donohue III et al. (1991).

[28] 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 A10.

the cross-sectional task gaps. However, when controlling for binary education measures, as in Figure A8b, large differences in tasks by race remain, suggesting additional explanations are necessary.

Task persistence varies between physical, routine, and analytical tasks, with the smallest differences occurring in the middle-return task, routine manual work. Task-based theories of labor demand provide some intuition for why workers' probability of remaining in a job varies non-monotonically with skill. The relationship between capital complementarity and skill can be non-monotonic, leading to polarization of the skill distribution as technology makes some jobs more substitutable with machinery (Acemoglu and Autor, 2011). In these models, worker heterogeneity "hollows out" the skill distribution as machines automate middle-skill tasks. In the context of the racial income gap, these theories predict that technology can widen racial labor market disparities through occupational sorting, which shapes one's capital complementarity, as in Lerch (forthcoming). However, it is not entirely clear why race plays a role in task *transitions* from the same task in this framework, as workers' starting points are by definition the same.

The task transition findings in this paper suggest that labor demand shifts also interact with race. Discrimination likely plays a role. For instance, both historical and modern research emphasize white workers' overt intolerance for Black co-workers or supervisors as explanations for both Black workers' exclusion from job promotion and sorting into more physically intensive work, even within the same firm (Dewey, 1952; Sundstrom, 1994; Maloney, 1995; Foote et al., 2003; Charles and Guryan, 2008). Other research points to a more subtle combination of the rising importance of soft and interpersonal skills in the labor market with continued discomfort for cross-racial interactions as a reason for continued differences in task concentration across race and gender and for resultant pay inequities (Borghans et al., 2014; Fan et al., 2017; Hurst et al., forthcoming).

Other work suggests that there may be racial differences in workers' job transitions more generally, as the Black male unemployment rate has been higher than the white male unemployment rate since the 1930s (Bound and Freeman, 1992; Sundstrom, 1992; Fairlie and Sundstrom, 1997). More recently, Daly et al. (2020) showed that Black workers indeed experience separations at a higher rate than white workers, with longer spells of unemployment, and that these transitions feed into the racial wage gap. If racial disparities in unemployment are sufficiently large to explain racial disparities in task persistence, then we would expect Black workers' task persistence to be farthest behind white workers in the task with the strongest decline in employment, physical work. However, we find large Black-white mobility gaps for analytical work, which was growing in demand, suggesting that unemployment is not driving our results.

Moreover, Black and white workers may not be exposed to the same labor demand shocks due to differences in location. Especially early in our sample, Black workers were disproportionately concentrated in the rural South, which was not as technologically advanced as the rest of the United States (Wright et al., 1986). Though Figure A8a shows that these results are robust to dropping farming, and Figure A8b controls for individuals' state, local labor market shocks may be important drivers of the results in this paper.

The historical data are sufficiently powered and detailed to permit us to test whether local labor market or occupational sorting effects help explain our task persistence gaps (which is not true of the PSID data). 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:

$$y_{iojc,t+10} = \beta_0 + \beta_1 Black_i + \beta_2 y_{i,t} + \gamma_{ojc,t} + \varepsilon_{iojc,t+10} \tag{3}$$

where the fixed effects are based on the interaction of occupation o, industry j and county c indicators. We also control for year of observation. 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 $OCC1950$ and year causes the Black coefficient on physical tasks to fall, while keeping the coefficients on analytic and routine-manual jobs more 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 $IND1950$, 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.

Finally, we interact year, occupation, industry, and county, absorbing variation in both geographic and occupational sorting. Others have used variation by occupation/industry/county to estimate the impact of technology on labor market outcomes, such as the spread of electricity (Gaggl et al., 2021), automated switching machines for telephone operatives (Feigenbaum and Gross, 2024), the tractor for agricultural workers (French, 2024), and stitching machines for shoemakers (Cockriel, 2024). Even with this demanding specification, the Black-white gap in task content remains close to the baseline, particularly within one generation. Starting with the intragenerational mobility results in Figure 9a, the physical gap remains positive and is 6.0, only 0.2 percentage points lower than the baseline, while the routine manual coefficient is larger by 4.4 percentage points and the non-routine analytic measure is 2.3 percentage points larger than the baseline. This implies that even within narrowly defined occupation-industry-county groups, similar Black and white workers experienced very different labor market transitions.

Similarly, father-based fixed effects only slightly attenuate Black-white gaps in transitions in the historical period (Figure 9b). This contrasts with work on the intergenerational mobility of the children of immigrants, which finds that almost all of the mobility premium for the children of immigrants relative to US-born children can be explained by immigrants moving to fast-growing locations (Abramitzky et al., 2021). Instead, our results align with modern work on Black-white mobility gaps. Chetty et al. (2020) show that including controls for parental income and census block shrinks the Black-white income mobility gap, but does not eliminate it. Similarly, we find that using precise information on a father's labor market outcome decreases the Black-white gap in physical tasks by about 38%, but it does not eliminate it. The mobility gaps for the other tasks are even less affected: the gap for analytical gaps only shrinks by about 11% and actually increases by 20% for routine manual tasks.

These results suggest that even within narrowly defined job and location categories, Black and white workers had very different task transitions before World War II. These racial disparities depend on the task being considered, as Black workers remained in physically intensive jobs and exited non-routine analytically intensive jobs at much higher rates than white workers. The historical evidence discussed above provides intuition for the barriers Black workers faced in the labor market. These results suggest that research should account for this racial heterogeneity when using task-based models to estimate the impact on labor market inequality.

6 Conclusion

In this paper, we harmonize task measures over the last 120 years 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 positions to Black workers. In turn, Black workers followed the same trends, albeit a full half-century later.

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. These task barriers existed historically and persist even today. Our findings 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.

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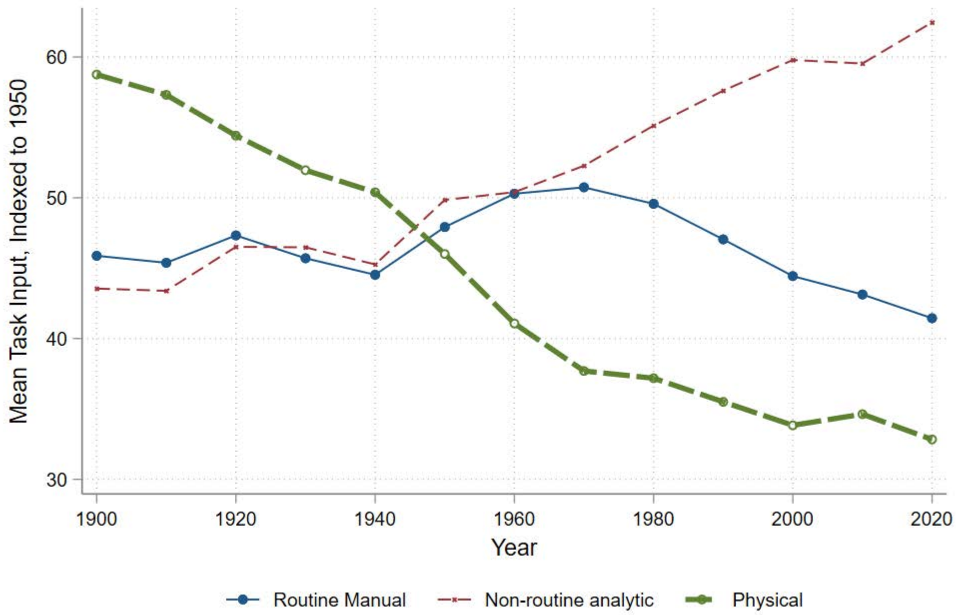
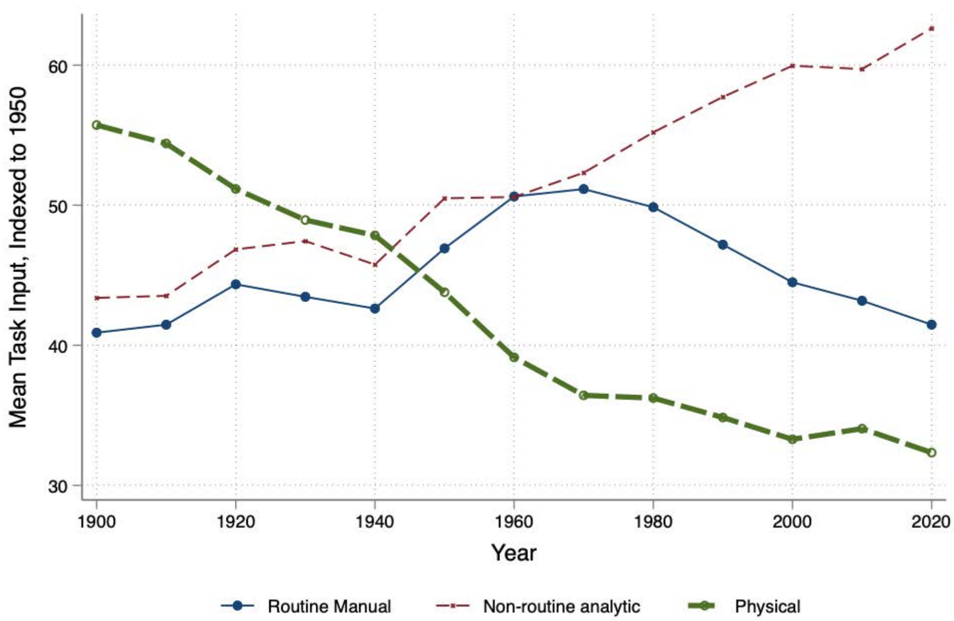
7 Figures

Figure 1: National trends in task content

(a) Level of task content, all industries



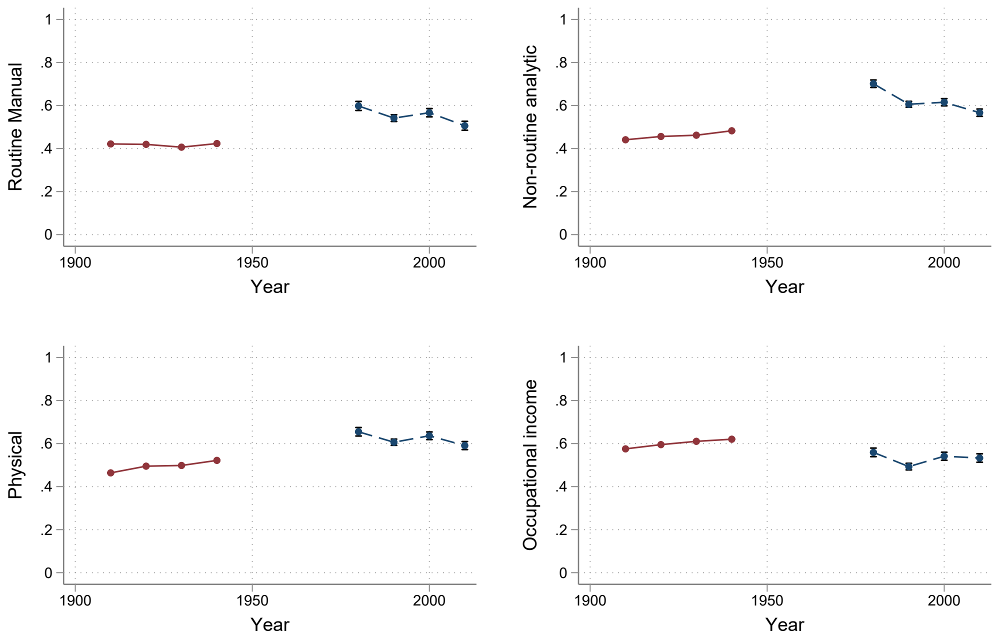
(b) Level of task content, excluding agriculture



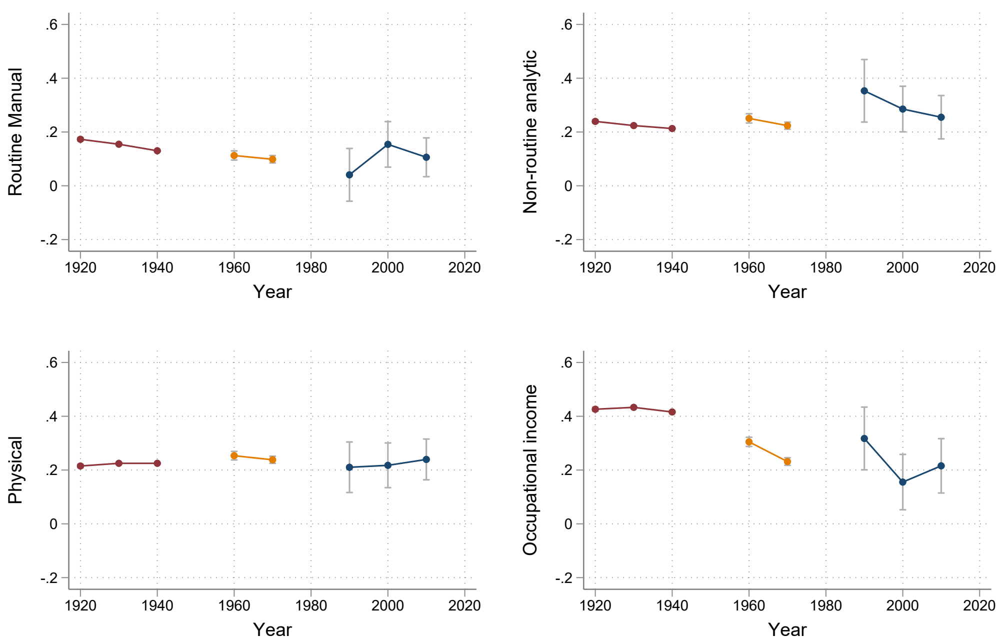
Notes: Data are from the 1900-2000 censuses, and the 2010 and 2021 ACS (Ruggles et al., 2023). Sample is 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table B6 for task definitions. Panel B drops farmers and farm laborers.

Figure 2: Task persistence, then and now

(a) Within one generation



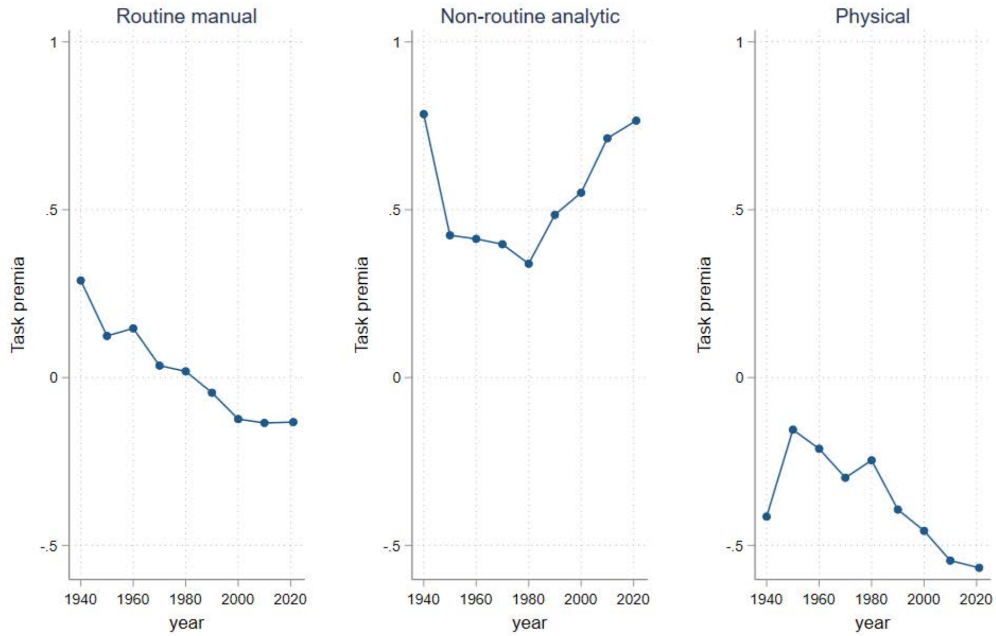
(b) Across generations from father to son



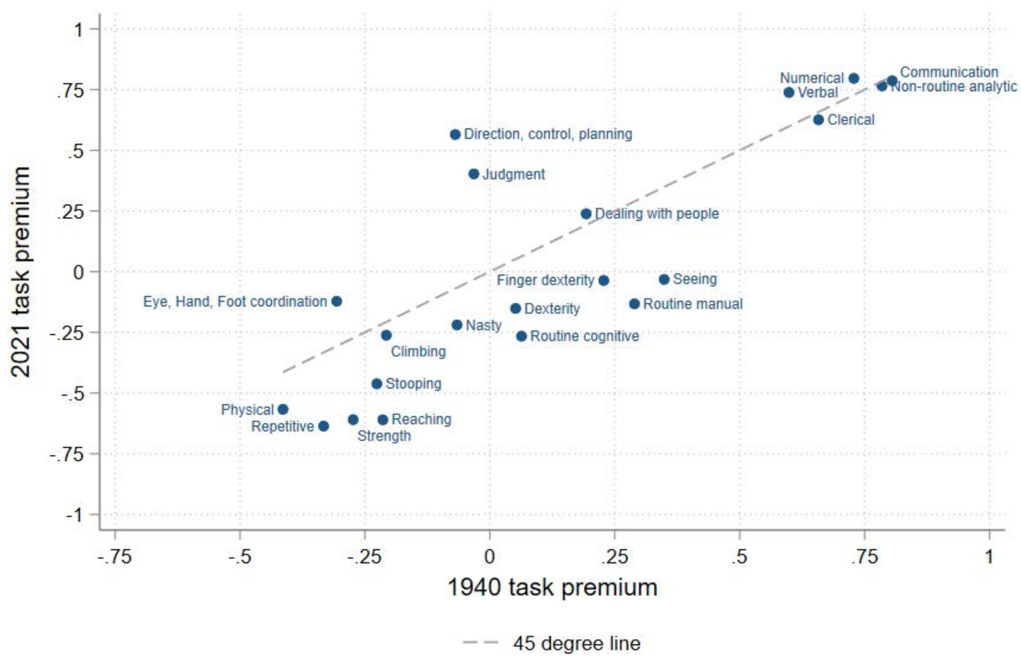
Notes: Underlying data are from the PSID (blue), OCG (orange), and 1900-1940 Censuses (red), (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2021) in Panel A and Ward (2023) in Panel B. Panel A shows the point estimate from a regression of the outcome in census t+10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

Figure 3: Task premia over time

(a) Mincerian task premia

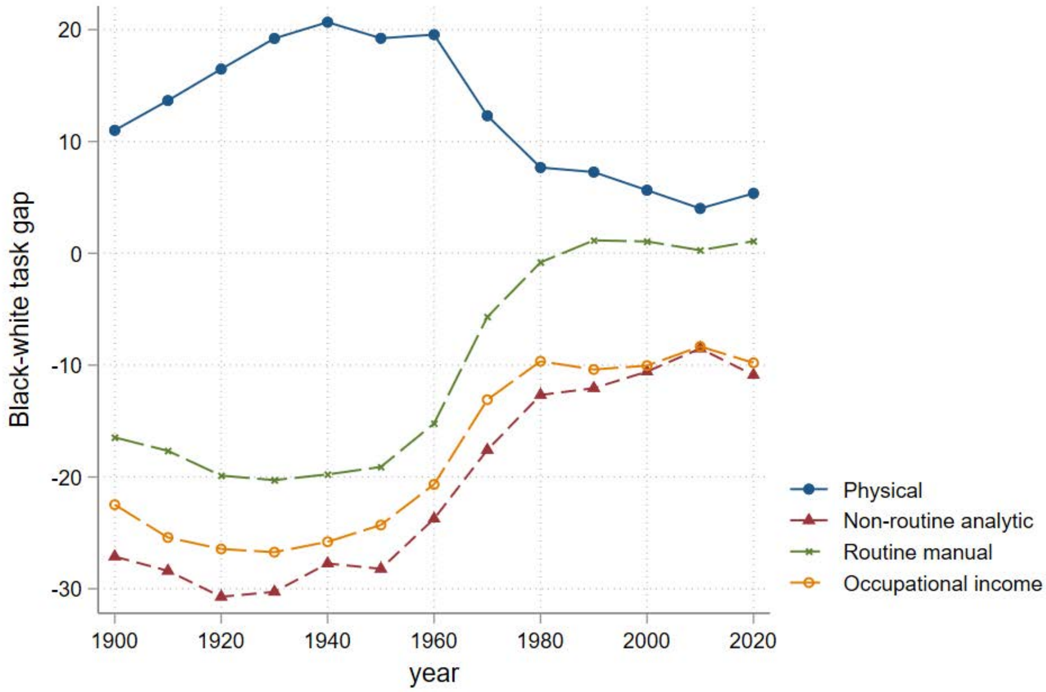


(b) Stability of task premia 1940 and 2021



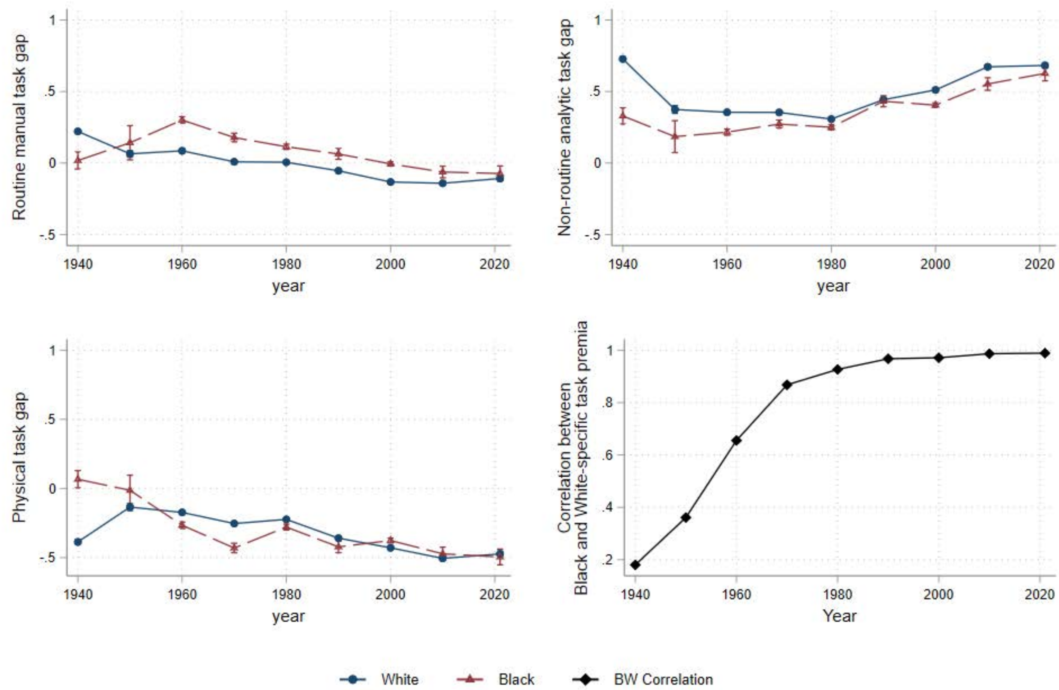
Notes: Data are from the 1940 IPUMS and the 2021 ACS (Ruggles et al. 2021). Sample is 30-45-year-old male wage workers with an occupation. Task premia are estimated by regressing the log of weekly wage income on percentile rank of task, a quadratic in age, and years of education. See Tables B1-B6 for definitions.

Figure 4: Black-white differences in tasks over time



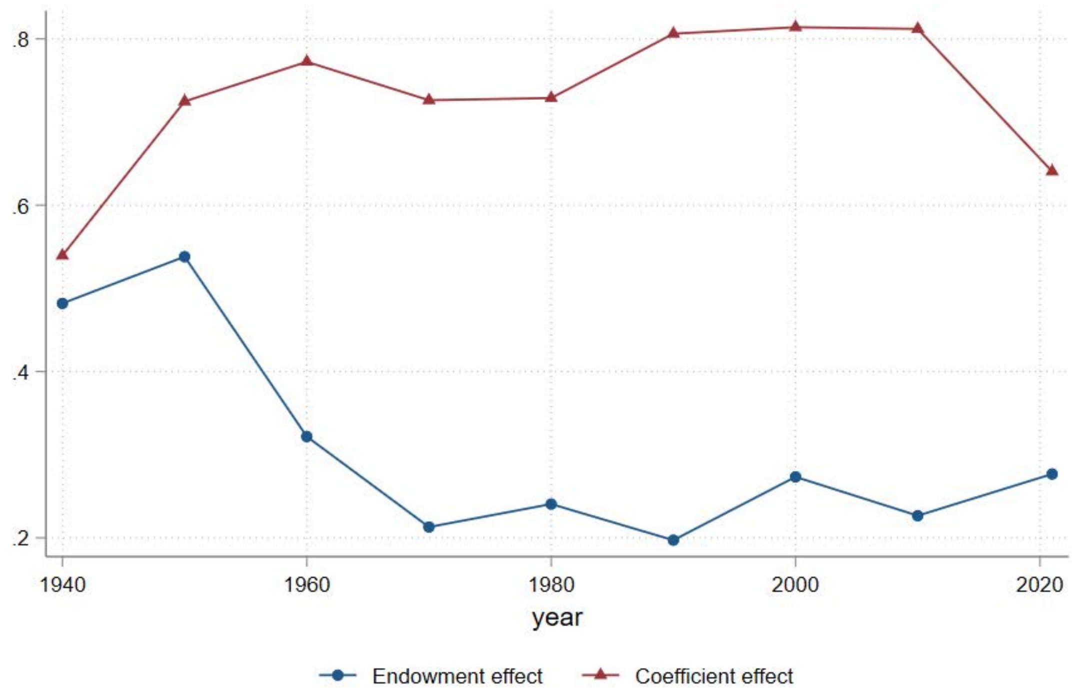
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table B6 for task definitions.

Figure 5: Racial differences in task premia



Notes: Data are from the 1940-2000 Censuses, 2010 ACS 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 separately by reported race. See Tables B1-B6 for definitions.

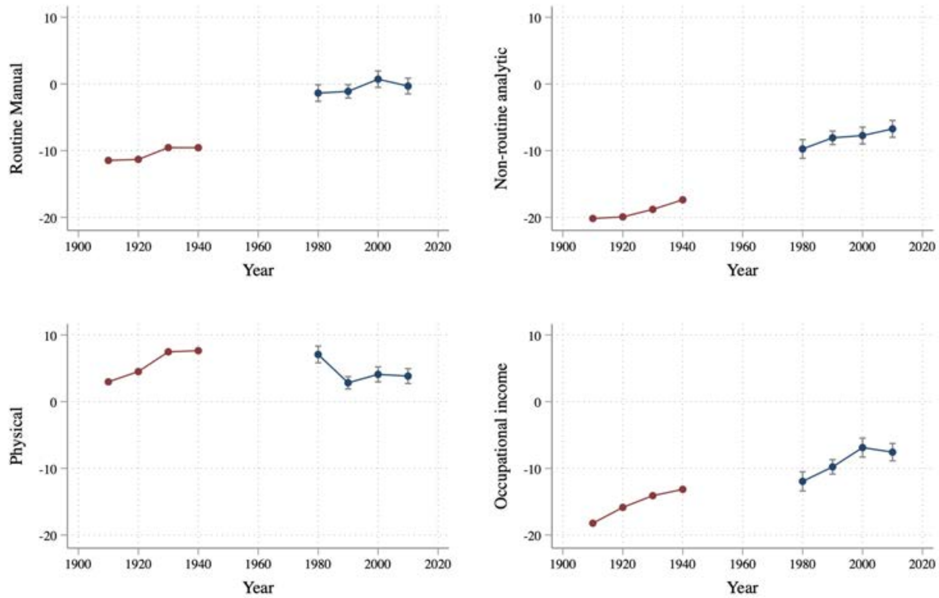
Figure 6: Tasks and the Black-white wage gap



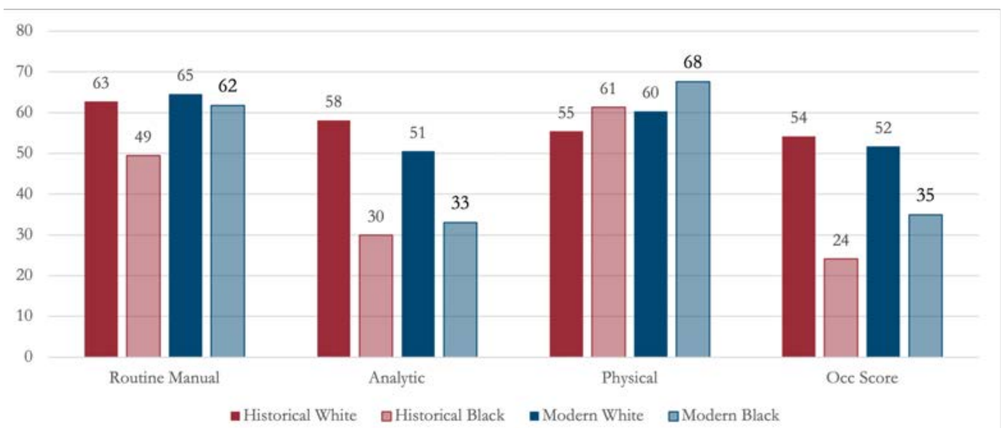
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Data are of 30-45-year-old men with an occupation. The endowment effect represents the portion of the Black-white wage gap that can be attributed to the differences in tasks performed by Black and white workers. The coefficient effect is the portion of the Black-white wage gap attributed to differences in the task prices for Black and white workers. Numbers will not sum to 1 due to interactions between the two effects. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950.

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

(a) Own lifetime

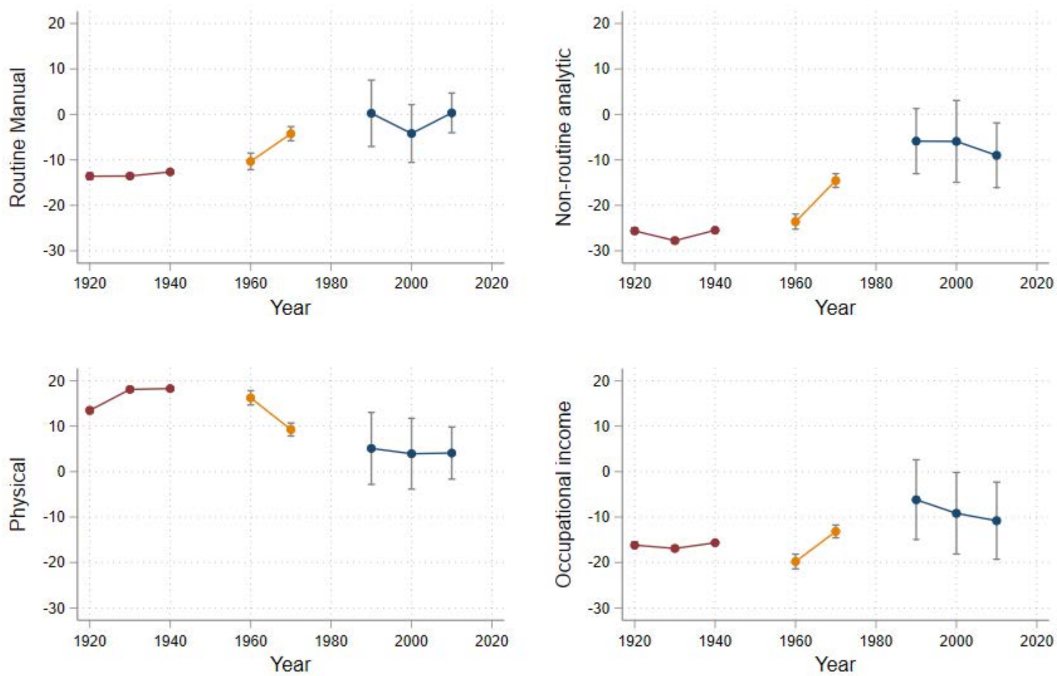


(b) Movement out of Routine-Manual



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 point estimate on the Black indicator from a regression of the son's outcome on the father's and a Black indicator. 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.

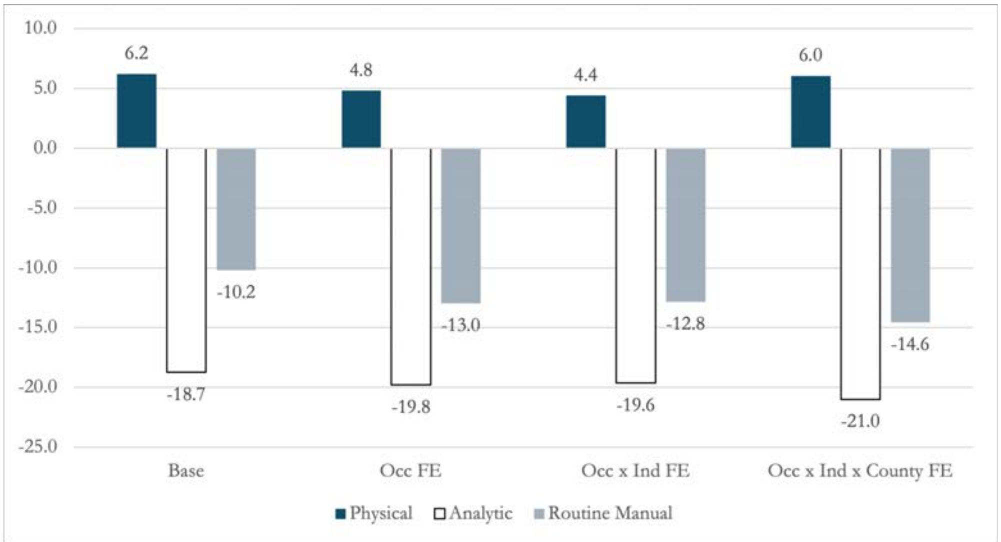
Figure 8: Black-white intergenerational gaps in task mobility



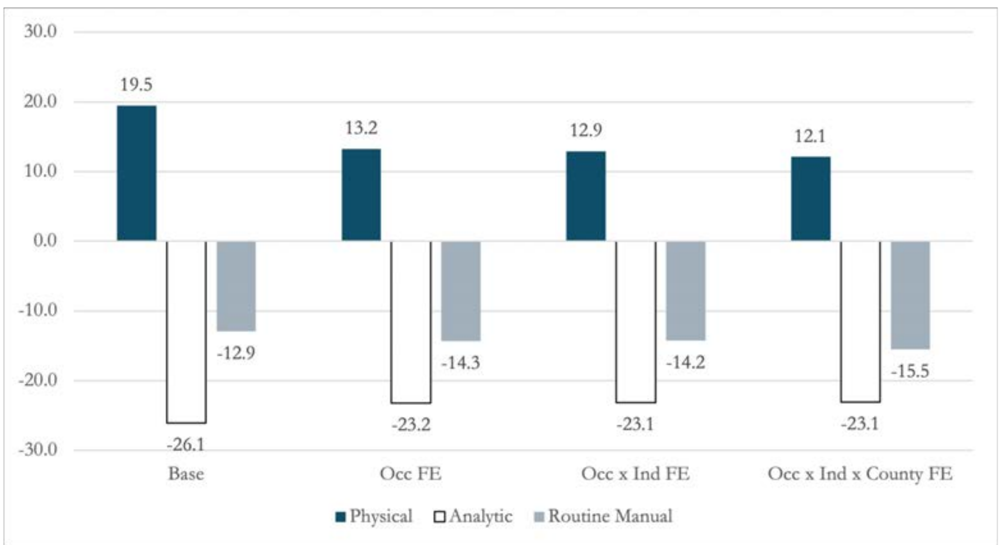
Notes: Underlying data are from the PSID (blue), OCG (orange), 1900-1940 Censuses (red) (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2021). The figure shows the point estimate from a Black indicator variable from a regression of the son's task on the father's task and a Black indicator. All measures are percentile ranked. Occupational income is a 0-100 percentile ranked measure that imputes income by occupation.

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

(a) Black-white intragenerational gaps in task mobility



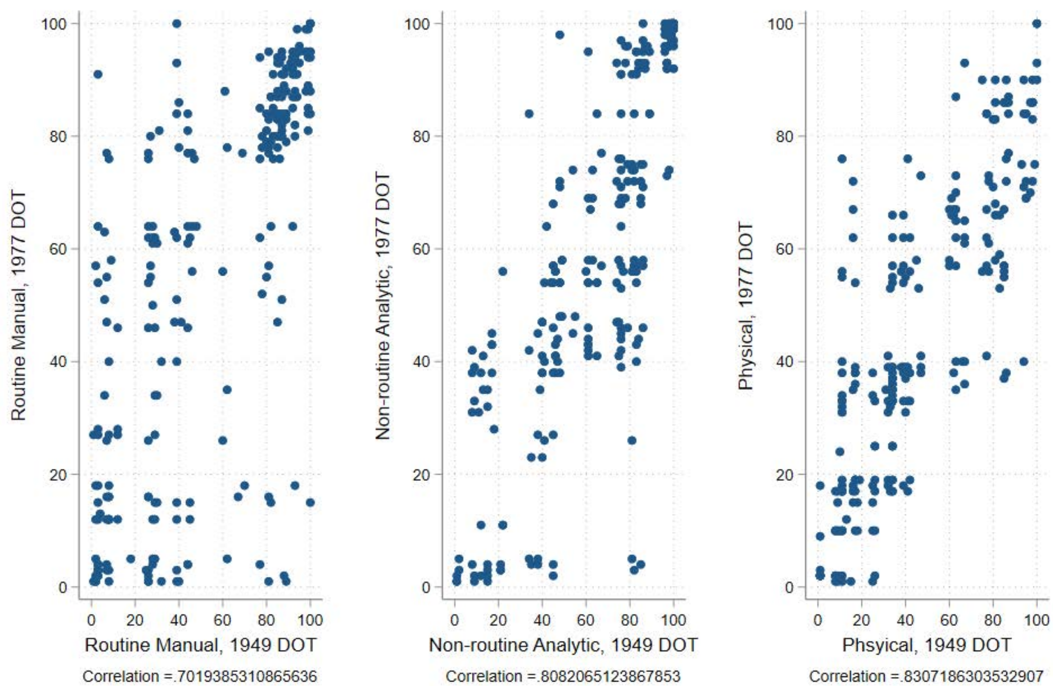
(b) Black-white intergenerational gaps in task mobility



Notes: Underlying data are from the 1900-1940 Censuses (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2021). The figure shows the point estimate from a Black indicator variable from a regression of the worker's task in time $t + 10$ on their task intensity in time t, adding successively more detailed fixed effects measured in time t. Year is additionally control for in the fixed effects.

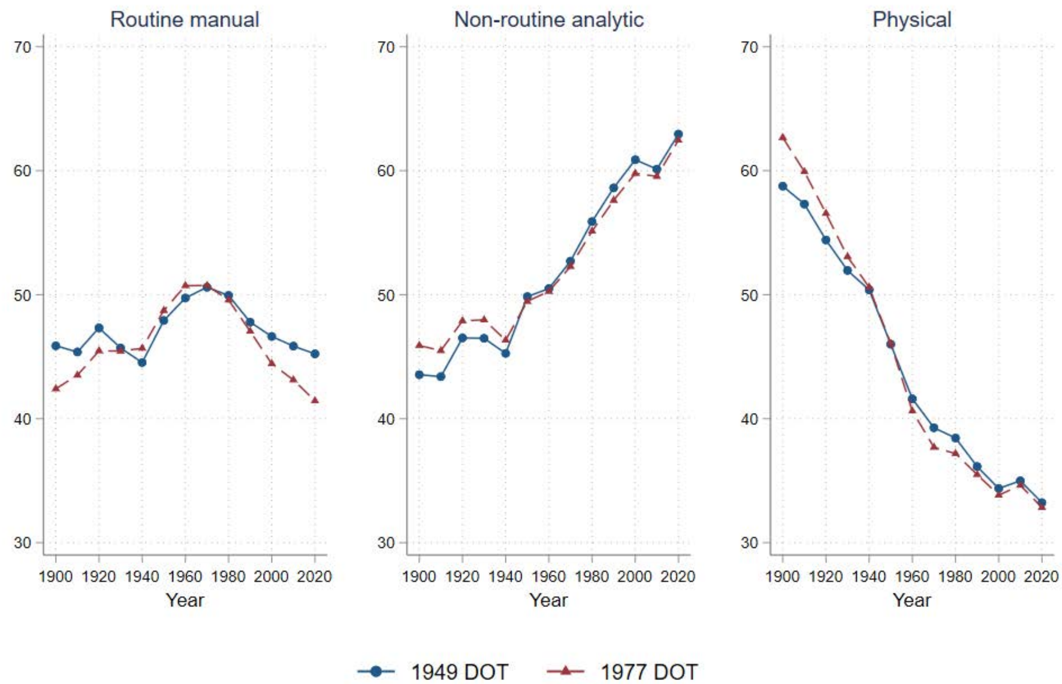
A Additional Figures

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



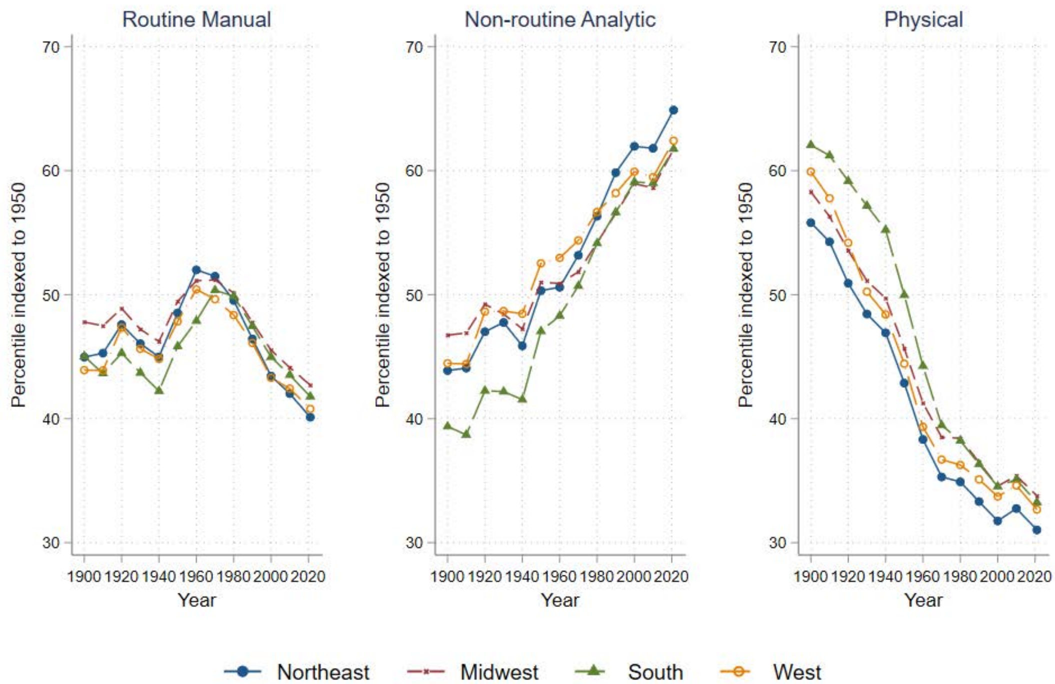
Notes: The unit of observation is an occupation (occ1950 code). This figure plots the percentile ranking of each occupation in 1949 against its percentile rank in 1977.

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



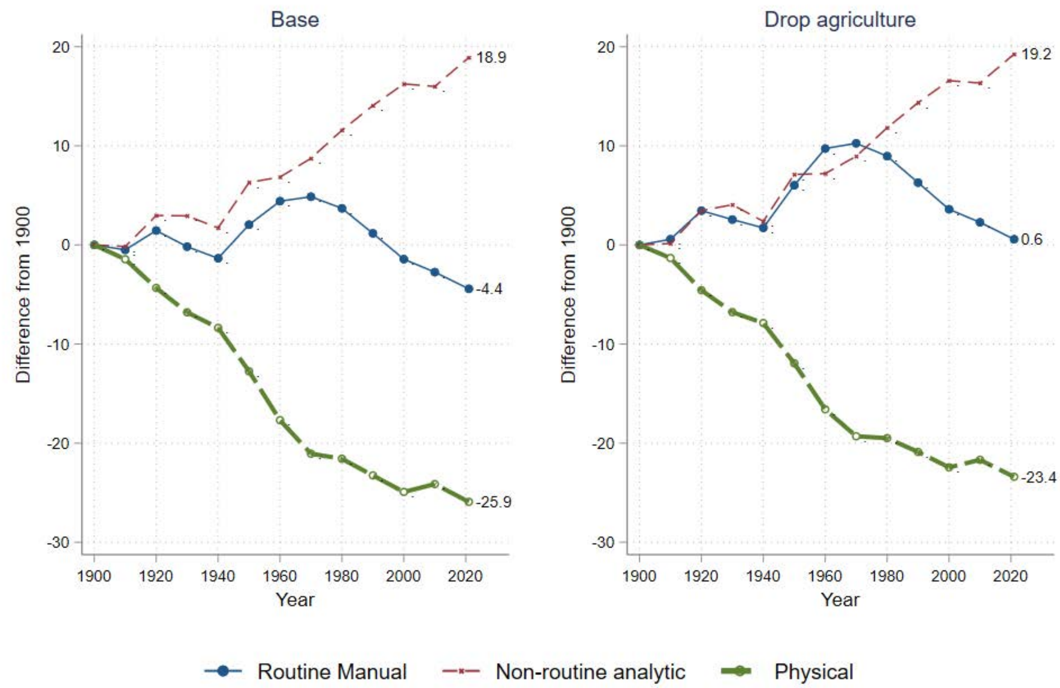
Notes: This figure compares the trend in routine-manual and non-routine analytic when using the task intensity measures based on the 1949 Dictionary of Occupational Titles, versus the task content based on the 1977 Dictionary of Occupational Titles.

Figure A3: Task measures by census region



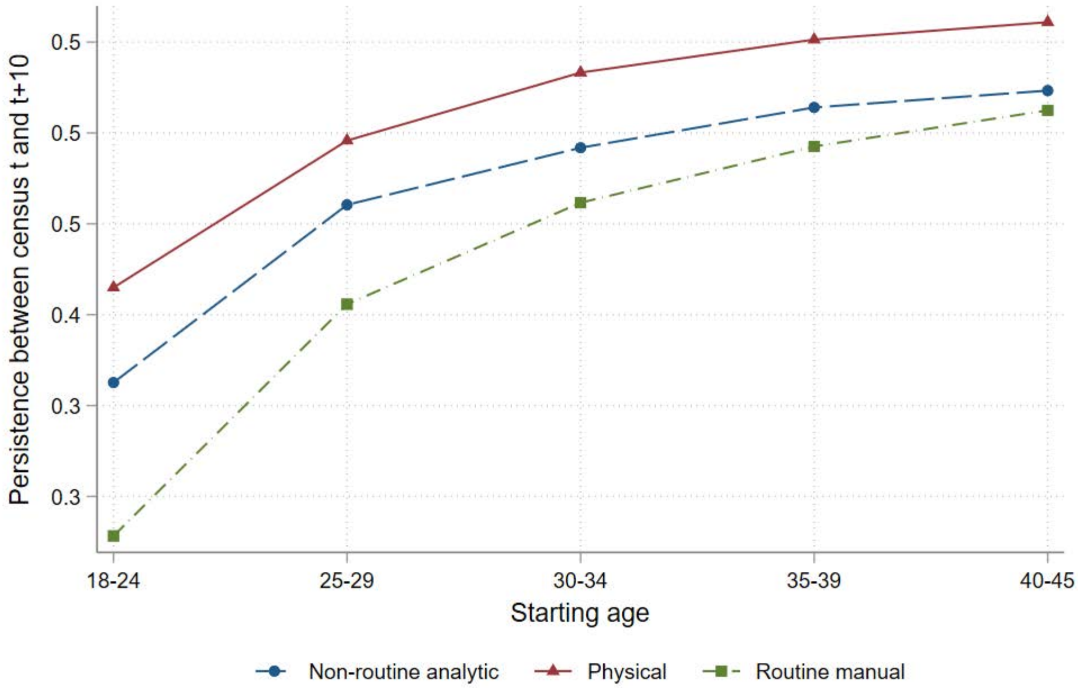
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table B6 for task definitions.

Figure A4: National trend in task content, adding industry fixed effects



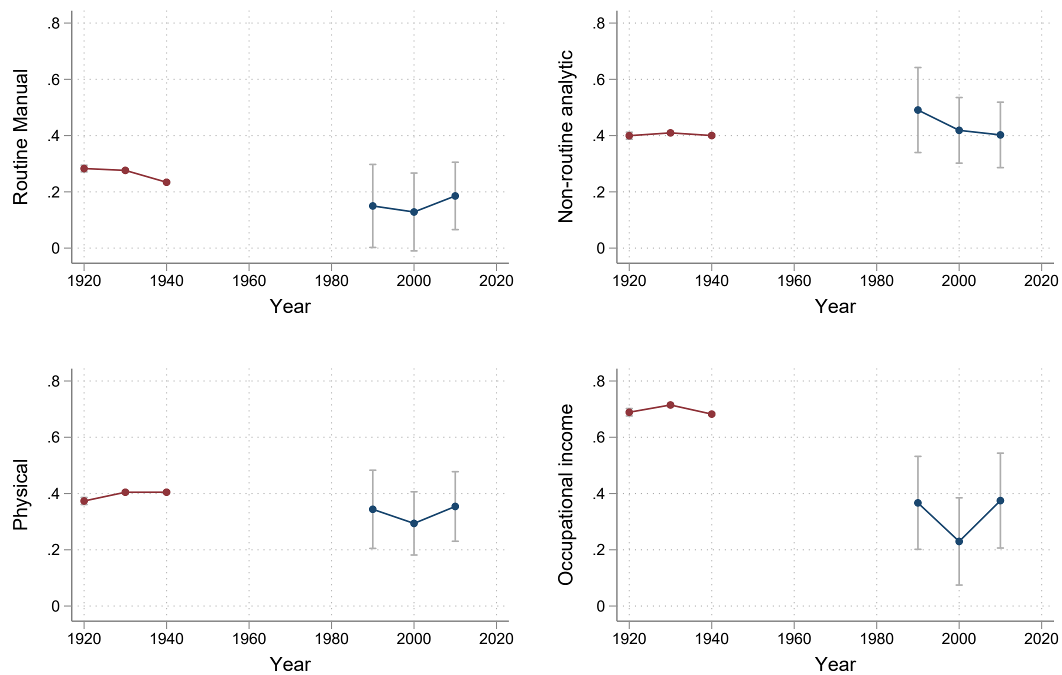
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al., 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table B6 for task definitions. Industry fixed effects defined as first digit of IND1950.

Figure A5: Persistence of task content throughout the life cycle



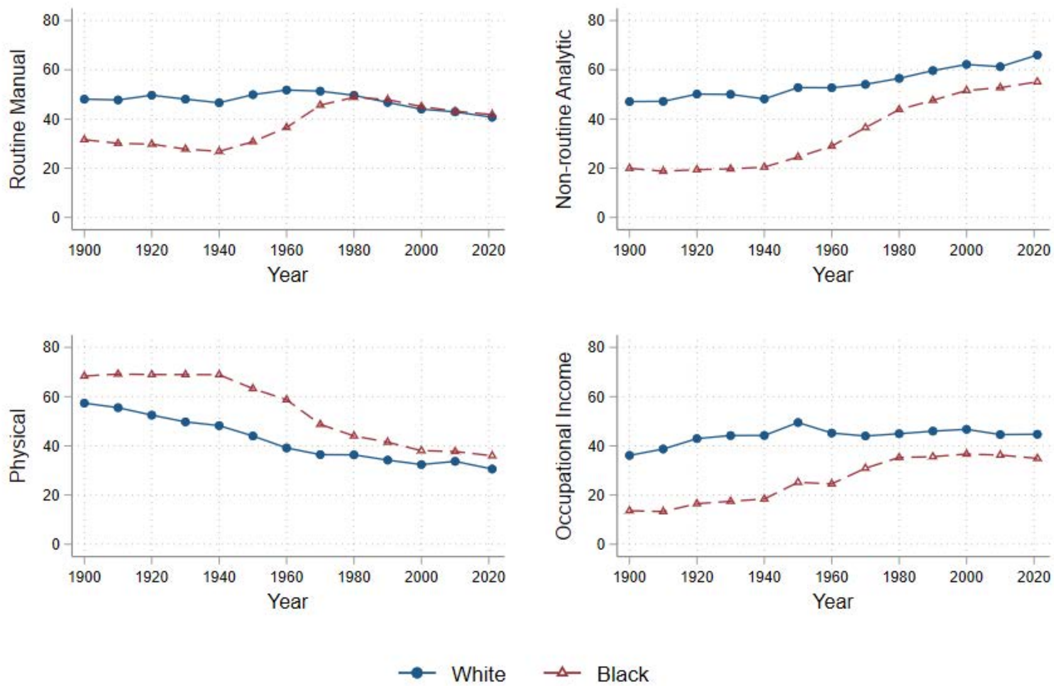
Notes: Data are from the 1900-1940 censuses (Ruggles et al. 2021). Each point plots a separate regression of the task content in time t+10 on the task content in census t by age and task. The main point of the figure is that the occupational task content was more persistent across a 10-year period throughout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

Figure A6: Persistence 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 observation.

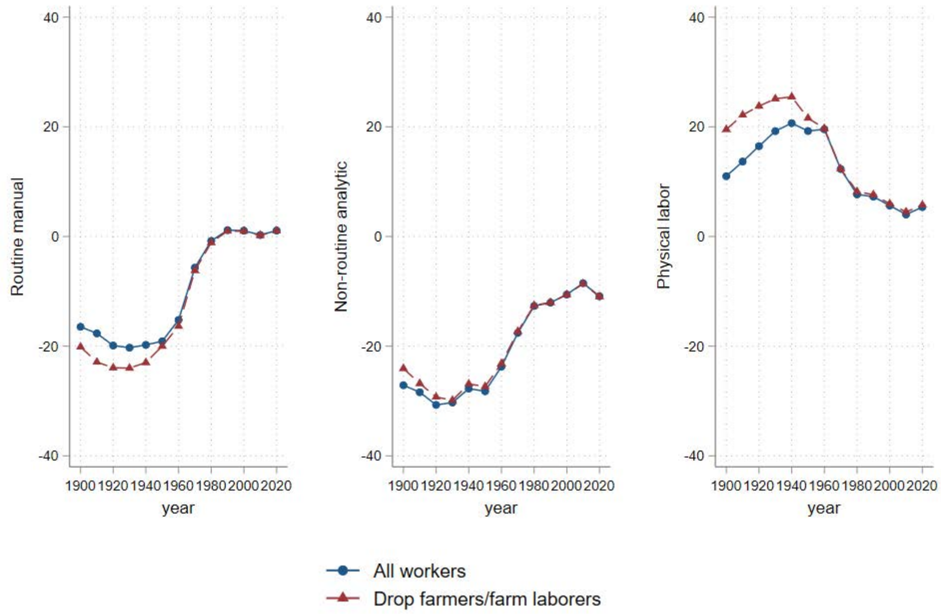
Figure A7: Black-white trends in levels



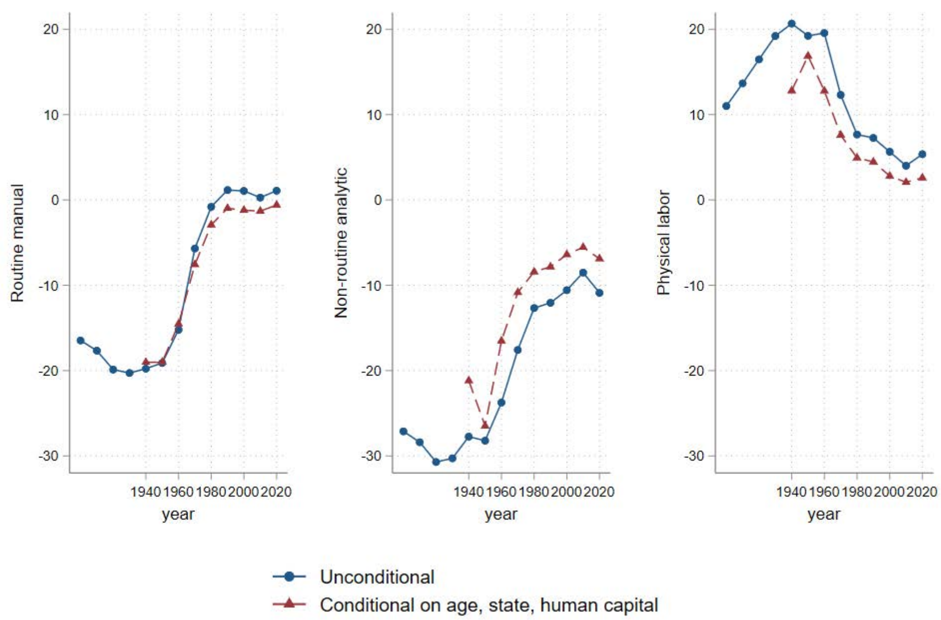
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table B6 for task definitions.

Figure A8: Black-white trends accounting for observable differences

(a) With and without agricultural workers



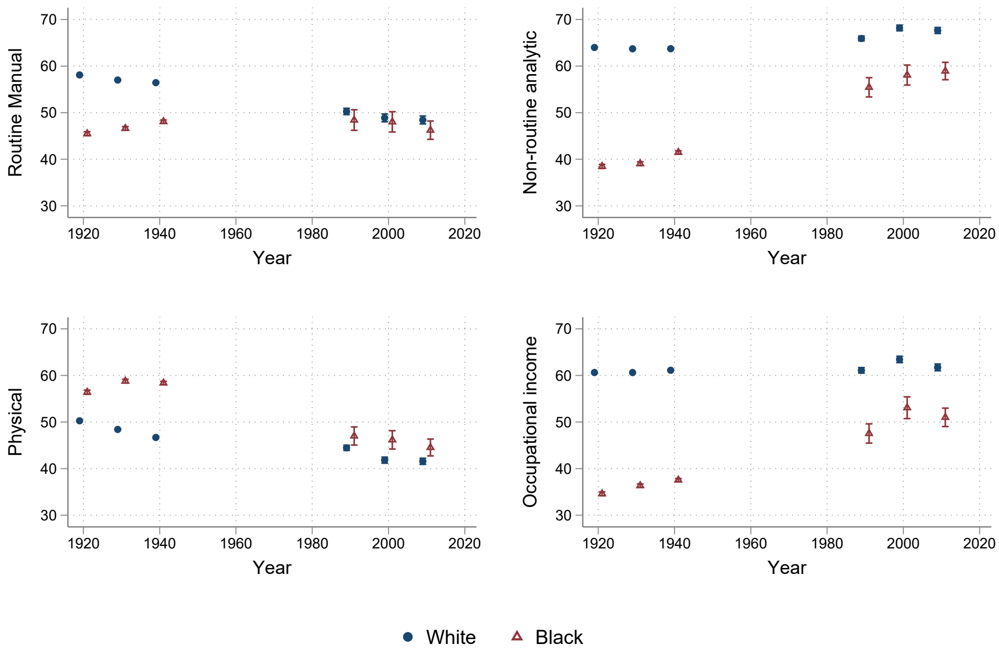
(b) Conditional on observables



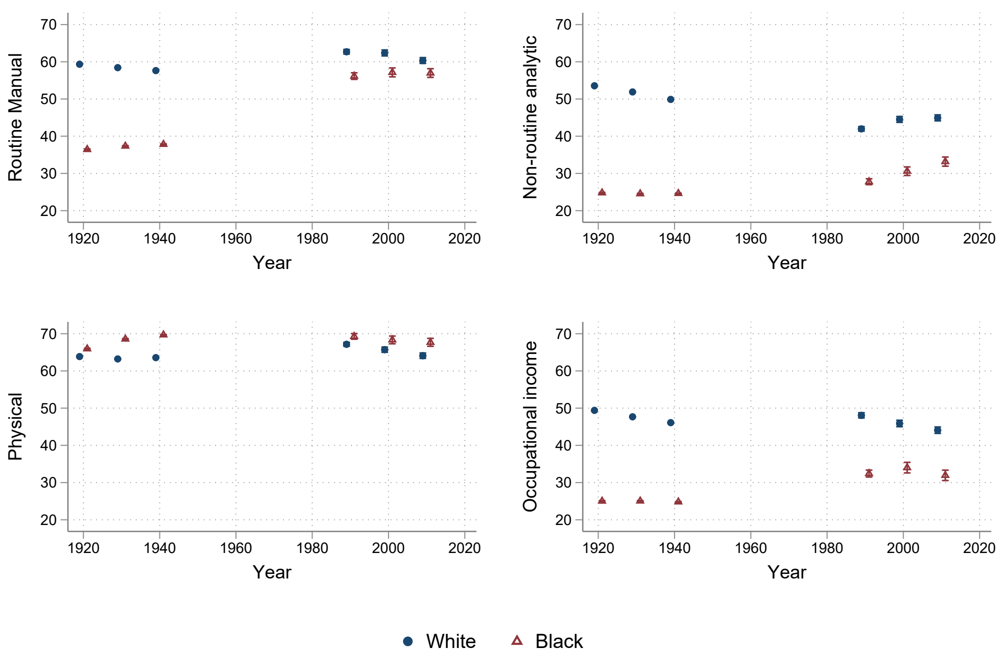
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2021 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. See Table B6 for task definitions.

Figure A9: Black-white mobility gaps across the 20^{th} century, additional tasks

(a) Movement out of Non-Routine Analytic

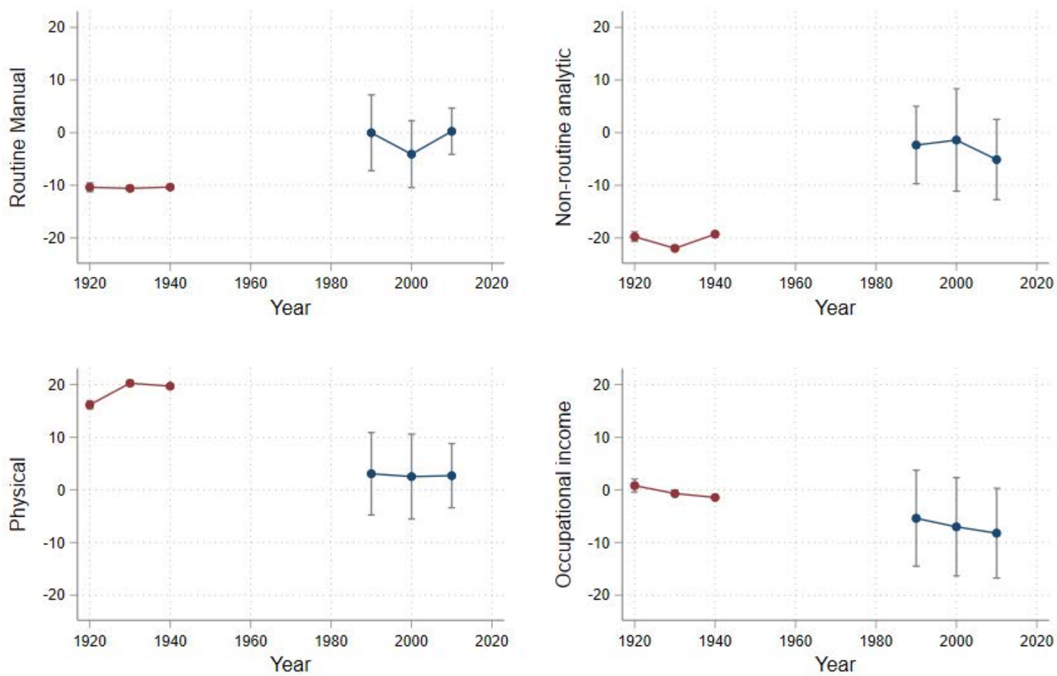


(b) Movement out of Physical



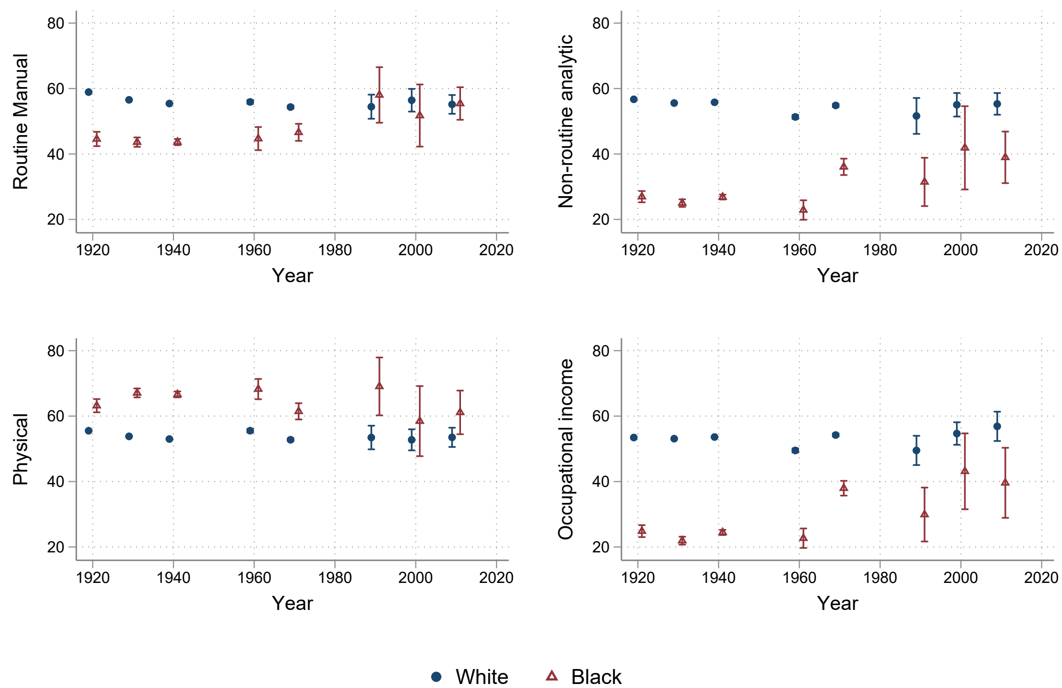
Notes: Underlying data are from the PSID (1980-2010), and the United States Censuses (1900-1940) (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2021) in Panel A and Ward (2023) in Panel B. Each panel plots the predicted percentile on the dependent variable for those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

Figure A10: 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 observation to address potential measurement error, per Ward (2023).

Figure A11: 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 on the dependent variable for those who father's were observed at the 75th percentile of the routine manual task.

Table A1: Correlation of task measures

	Occ. income	Physical	Routine Manual	Nonroutine Analytic
Occ. income	1			
Physical	-0.362	1		
Routine Manual	0.117	0.114	1	
Nonroutine Analytic	0.696	-0.445	0.300	1

Notes: The table shows the pairwise correlation in task measures and occupational income in the 1950 Census.

B 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. 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.[29]

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.

[29] The results are qualitatively unchanged if we use the 1940 or 1950 Census to percentile rank the task measures.

Table B1. 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 B2. 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 B2. 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 B3. 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 B4. 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 B4. 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 B5. 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 B6. 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**

C Details on linked data

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

C.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 also reduces the probability of matching to a wrong individual.

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 individuals 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 C1 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 individuals.

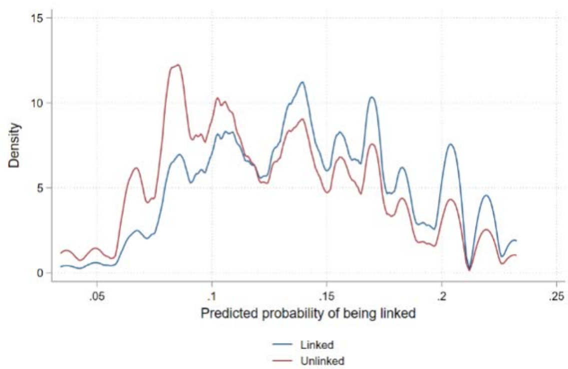
C.2 Intergenerational data

The intergenerational data are from Ward (2023), which follows the same process as above but for intergenerational data. Since the data are intergenerational instead of intragenerational, there are a few important differences. First, the data are of 0-14 year olds 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. The reason why is to reduce measurement error when trying to accurately measure the occupational task content of an individual. Fourth, weights are calculated based on the son's adult observation. Fifth, only censuses between 1900 and 1940 are used to create these data.

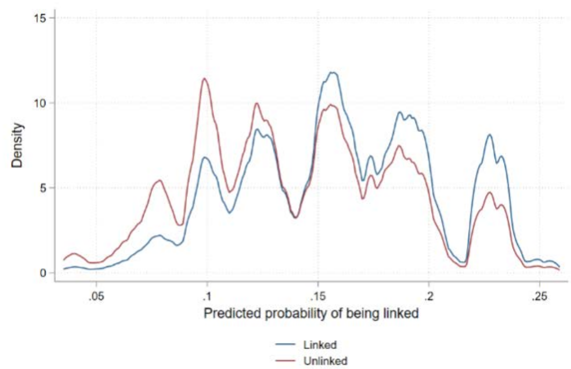
See the Online Appendix of Ward (2023) for details on representativeness of the intergenerational sample.

Figure C1: Kernel densities for linking probability for the intragenerational data

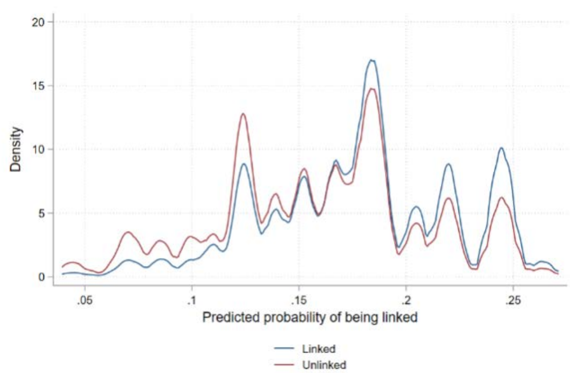
(a) 1900-1910 Census



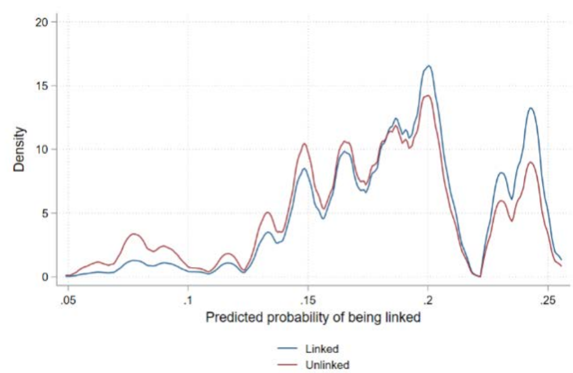
(b) 1910-1920 Census



(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 C1: Representativeness of the linked samples (1900-1910, 1910-1920)

	Population	Linked (1900-1910) Unweighted	Linked (1900-1910) Weighted	Population	Linked (1910-1920) Unweighted	Linked (1910-1920) 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 C2: Representativeness of the linked samples (1920-1930, 1930-1940)

	Population	Linked (1920-1930) Unweighted	Linked (1920-1930) Weighted	Population	Linked (1930-1940) Unweighted	Linked (1930-1940) 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.