Task Inequality and Racial Mobility over the Long Twentieth Century
Rowena Gray, Siobhan O'Keefe, Sarah Quincy, and Zachary Ward

Abstract
We provide a long-term analysis of the evolution of occupational task content using digitized data based on the 1939, 1949 and 1977 *Dictionary of Occupational Titles*. Beginning in the early 20th century reveals that the evolution towards modern work was not monotonic over time nor with respect to race or gender. The shift away from physical and routine tasks and towards cognitive and analytical skill began well before the advent of computers. Black-white gaps varied by task but mostly were large and widening before converging dramatically after 1960. Linked historical censuses suggest that there was substantial mobility in task content both throughout the life cycle and across generations early in the 20th century. These task transitions were racially biased, which suggests that technologically driven task displacement had different impacts by race in the early 20th century.

JEL: N31, N32, J24, J62
Keywords: Job tasks; Occupational mobility; Inequality; Racial wage gaps

Introduction

Polarization of the occupation distribution has been extensively documented for the United States after 1980, with computerization and automation shown to be the main drivers of the trend (Autor et al. 2003, Acemoglu and Restrepo 2019). This task displacement is an important explanation for trends in recent inequality, as well as for income gaps by gender and race (Acemoglu and Restrepo 2021, Black and Oener-Spitz 2010). However, it is unclear whether the relationships observed in recent decades are a new phenomenon or are simply the most recent iteration of a pattern observed throughout American history.

In this paper, we examine the evolution of job tasks in the early 20th century, a period with some of the fastest rates of technological change and structural transformation in American history (Field 2003, Gordon 2010, Gaggl et al. 2021). Similar to today, historical commentators expressed concerns about technological displacement of labor (Jerome 1934) and income and wealth inequality reached high levels (Saez and Zucman 2018, Lindert and Williamson 2016). If technological change led to significant shifts in the relative demand for labor, we expect to observe these displacements clearly in historical data, unobstructed by a developed welfare state or industrial policy innovations.

We use census data combined with information on occupational task content from the *Dictionary of Occupational Titles* (1939 and 1949, hereafter DOT) to construct task trends before World War II. We then merge this series with information from later DOTs to plot task trends over the long twentieth century. We focus on four key tasks that describe the nature of work—routine manual, physical, non-routine analytical, and communication. This allows us to look at how the transformation of American jobs occurred amidst successive general-purpose technologies, from electricity to computers to robots. A long view is especially important since the diffusion of new technology and adoption of their complements can take decades (Griliches 1957).

We further examine the newly constructed trends before World War II with rich longitudinal data on millions of individuals, which allow us to uncover task transitions both over the lifecycle and across generations. Therefore, we can provide new estimates of the fluidity of the labor market in terms of task transitions, which partially captures the extent of technologically-driven task displacement in the economy; moreover, we can measure whether task transitions are different by race.

With this new long-run dataset, combining census information with occupation-level task measures, we document several important trends over the past 120 years. Since the DOT includes task ratings for agriculture, our main results account for the structural shift out of farming. However, most trends are similar if we focus on the non-agricultural sector.

First, there was a secular trend towards more analytic and cognitive tasks between 1900 and 2020, a pattern which existed well before the advent of computers. While analytic and cognitive tasks increased over time, physical tasks (based on strength or body movement) decreased in the long run, which reflects a long-run transition from brawn to brain. However, trends were not always monotonic. Between 1920 and 1940, routine manual task shares decreased. This decline is similar to the modern-day decrease in routine manual that "hollowed out" jobs in the middle of the wage distribution (Autor et al. 2003). However, the early 20th century decrease was shallower and ultimately reverted after World War II. This pause in aggregate task trends between 1920 and 1940 has not previously been captured in long-run series, which has instead relied on broad occupation categories rather than detailed task measures by occupation (Katz and Margo 2014).[1] While task content has been changing over time, we find similar labor market returns to these tasks between 1940 and 2019, before and after the modern episode of skill-biased technological change.

Second, there was substantial mobility across time and across generations in occupational task content in the early 20th century. Measures of intra and intergenerational "task mobility," or the association of occupational task content rank across time, suggest that the early 20th century labor market was fluid as workers and families transitioned from occupation to occupation with different task content.[2] There was more movement into and out of routine manual jobs, but less mobility in the least rewarded (physical) or highest rewarded tasks (non-routine analytic). This fluidity may reflect rapid technological change that altered the nature of work or workers' tendency to move locations In spite of this high task mobility, individuals still ended up in similar parts of the occupational income distribution.

Third, racial gaps in occupational task content were wide in the early 20th century and did not exhibit much convergence until after 1960. Black workers were more likely to perform physical labor tasks in the early 20th century, but less likely to perform routine manual, non-routine analytic or communication tasks. Some of these gaps *widened* between 1900 and 1960, which is

[1] Katz and Margo (2014) do find a "hollowing out" of the skill distribution within the manufacturing sector in the 19th and early 20th centuries due to the replacement of artisanal jobs. However, these forces within the manufacturing sector were counteracted by the growth of manufacturing (away from agriculture). In the overall economy, the share of middle-skill jobs held steady.

[2] Part of the fluidity is due to measurement error in the occupational data (Ward 2021), but we show that the result holds in intergenerational data based on methods that account for measurement error.

surprising in light of estimates of income and wage convergence (Margo 2016, Juhn et al. 1991). It was not until after 1940, and particularly after 1960, that racial gaps in task content started to narrow. After this period of rapid convergence, Black-white task gaps have been roughly steady in the past couple of decades, similar to the wage gap. Using linked data, we show that early 20th century task mobility varied by race. Conditional on initial task content, Black males were more likely to remain in jobs with physical tasks, on average the lowest paying task in 1940, and less likely to stay in jobs with non-routine analytic tasks, which were usually high paying. A similar gap existed across generations.

Fourth, gender gaps in task content have changed over time, and in many cases, have flipped. In 1900, females with reported occupations were less likely to perform communication, routine manual, and non-routine analytic tasks. Today, these gaps have switched, in line with trends in educational attainment (Goldin et al. 2006). However, females have always been less likely to perform physical tasks than males, with zero convergence of this gap over time.

The above results were generated using existing DOT measures from 1977, used in Autor et al. 2003, combined with a detailed dataset of 4,000 job ratings coded from job descriptions in the earliest DOTs (United States Employment Service 1956, Gray 2013). Since our ratings are based on contemporary analysts' task assessments, our approach contrasts with others who rely on text analysis of job descriptions (Atalay et al. 2020, Michaels et al. 2019, Kogan et al. 2021). We then crosswalk these ratings to census occupational codes and percentile rank each occupation based on their physical, routine manual, non-routine analytic, and communication tasks, each indexed to the 1950 census.

There are a few limitations to our approach. Primarily, within-occupation changes trend in task content are based on changes of the occupational distribution rather than within task shifts are mostly unobserved throughout the 20th century. While within-occupation changes in tasks have certainly been identified (Atalay et al. 2020), there is evidence that we are accurately capturing trends since job descriptions in the 1939 DOT are similar to those in 1918 (Gray 2013, Swan 1918). Nevertheless, most of our analysis is based on between-occupational shifts in task content. To the extent that task content is similar across race and gender within occupation, task gaps across race and gender groups may contain less error. Second, due to limited wage data prior to 1940, we are unable to explicitly connect the changes to task distribution to changes in wage inequality in the same manner as the modern-day connection between the automation of routine tasks and inequality (Autor et al. 2003, Acemoglu and Restrepo 2021).

Our study contributes to the literature on specific technological shocks in the early 20th century, such as from electricity or automated telephone operation, as well as the more general move from hand to machine production (Atack et al. 2019, Feigenbaum and Gross 2020, Gray 2013). These studies of particular periods or technologies are insightful, but the broader long-run trend in tasks remains largely unknown. A related paper on long-run trends is Katz and Margo (2014), who examine changes to the occupation distributions between 1850 and 2010 based on broad occupational categories. We build upon this approach by using detailed task data by occupation, which uncovers a pause in some of the task trends between 1920 and 1940, a nuance not captured in previous research. Michaels et al. (2019) is most related to our paper in that they chart out the long-run trend of interactive tasks between 1880 and 2000. We document a similar rise in communication-based tasks based on measures from the earlier DOT. We broaden the focus from interaction and communication tasks to reflect the larger task literature. We also use linked micro-data to uncover task transitions throughout the lifecycle and across generations, and document how task content varies by gender and race.

Our novel results on the racial gap in task content complement the literature on the long-run racial income gap (Bayer and Charles 2018, Collins and Wanamaker 2022, Margo 2016). Prior work on the pre-World War II era focused on wage, education or income differences across groups, but has not documented differences in tasks or task mobility. Others have recently explored Black-white differences in average task content since the 1960s, arguing that they help to explain the trend in the Black-white wage gap since 1960 (Dicandia 2022, Golan et al. 2019, Hurst et al. 2021). Our data shows that, for those with occupations, the Black-white gap in routine manual, non-routine analytic and communication tasks was largest in the early 20th century and stagnated for decades before experiencing substantial convergence after 1960. In contrast to research showing that the Great Migration of Blacks out of the South in the early 20th century helped to close Black-white economic gaps (Boustan 2015, Collins and Wanamaker 2014), we show in linked data that migration was associated with increased Black-white task gaps. Therefore, while Black migrants ended up in higher wage jobs, the tasks they performed were more physical and less non-routine analytic. This in turn may have slowed the group's progress towards modern work, associated with better-rewarded cognitive skills, in the longer run.

In general, we find that intragenerational and intergenerational mobility was racially biased, such that Black males ended up lower in the non-routine analytic distribution than white males who started in the same place. Only recently have historical intergenerational mobility studies on income included Black men (Collins and Wanamaker 2017 and Ward 2021). Our paper contributes to the knowledge of mobility of minority groups in an earlier period than was previously possible, focusing on job tasks which are a fairly consistent measure over time. Our finding that Black workers experienced convergence in job tasks starting slowly in 1940 but most dramatically after the Civil Rights Movement is complemented by new estimates of intergenerational income mobility from Jacome et al. 2021 which suggest that relative mobility increased from the 1910-20s to the 1940-50s birth cohorts.

While we largely focus on racial differences in task content, which is driven by the ability to link males across censuses and the limited discussion of race in the existing tasks literature, we also summarize the evolution of gender gaps. The historical literature has focused mainly on the timing of the increase in female labor force participation rather than detailed measures of task content across groups (Goldin and Olivetti 2013, Goldin 2006). While an older sociology literature explored differences in tasks by gender (Manley 1995), the modern economics tasks literature has expanded to document trends over recent decades and to relate these to reductions in the gender pay gap (Black and Spitz-Oener 2010). We contribute to the literature by documenting female tasks conditional on being employed across last 120 years, complementing the occupational analysis in work such as Bellou and Cardia (2016) and Boustan and Collins (2014). By using this longer-run perspective, we show that a key bellwether of the gender pay gap over the 20th century is the non-routine analytic task gap. In periods where this task differential narrowed, so did the gender wage gap. However, as female employment diverged from male employment in these tasks, as after 1980, the gender pay gap has stalled.

In the remainder of the paper we describe the construction of our comprehensive dataset on workplace tasks over more than a century; we then present the broad trends in the intensity and value of our four key tasks; and we define our concept of task mobility, documenting mobility trends for different cohorts of workers' lifecycles and at the intergenerational level between fathers and sons. We conclude with a discussion about what these measures of task mobility add to our understanding of the changing racial wage gap over the long twentieth century.

Data Sources

Task Data

Task data has existed almost from the advent of employment assistance agencies, to deal with the difficulties of long-term unemployment from the Great Depression onwards. To describe tasks in the first half of the 20^{th} century, we utilize the original version of the *Dictionary of Occupational Titles* (DOT) data, (US Employment Service, 1956) which was based on task ratings of 4,000 jobs observed by employment experts from about 1939 to 1949 (US Employment Service, 1949), as presented in Gray (2013) and where more detail on the broader dataset can be found. The data measures the intensity of usage of certain tasks, such as strength and clerical skill, and also uses dichotomous variables that detail whether certain tasks are a key feature of a job, such as being repetitive or involving dealing with people or directing and planning a project from start to finish. For example, the *strength* variable describes, on a scale of one to five where five includes the heaviest occupations, the level of physical strength needed in an occupation. The *clerical* variable measures, on a scale of one to five, the amount of clerical competency required to perform an occupation, where one is the value given to occupations where clerical accuracy is most important. 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 very unimportant is a machinist.

We highlight the trends in four tasks that reflect the literature's focus on task content and technological change: routine manual; non-routine analytic; communication; and physical. This allows us to speak to the discussion of the long-run switch out of traditional tasks such as physical strength and from early 20^{th} century factory style work which had become highly routine, towards modern work tasks that have made jobs more cognitive-skill intensive. We proxy this mostly with the non-routine analytic task measure, following Autor et al. (2003). Communication tasks are thought to have risen with economic development, urbanization and agglomeration, while social skills have been identified as a key growth area since 2000 (Michaels et al. 2019, Deming 2017). So, while there is some overlap in the communication and non-routine analytic measures that we use here, we wanted to explore the long-run trends in both proxies for modern tasks for completeness.

The full definitions of all underlying variables are given in Appendix B; here we explain how our composite measures were constructed. Routineness is the average of finger dexterity, motor, manual 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. 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. Communication averages numerical, clerical, and verbal tasks, as well as the education-level variable and indicators for whether a job involves dealing with people and directing and planning projects. Finally, physical takes the average of how much strength is required in a job and requirements for climbing, reaching, and stooping.

Importantly, 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. Farmers were ranked at the 67-70th percentile in physical and routine manual tasks, as well as for non-routine analytic. They were closer to the median level for communication task content (57th percentile). 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.

The task measures were matched to the census data using the same procedure as outlined in Gray (2013). Because the tasks are measured on different ordinal scales, they were percentile ranked based on their position in in the 1950 Census -- this means that any changes in the task variables are changes from the 1950 baseline.[3]

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).[4] 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 (Atalay et al. 2020). We are able to create the same 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 (Appendix Figure A3). 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.

With these four tasks, we are capturing information relevant to the main narratives in the economics tasks literature. We speak to the discussion of the long-run switch out of traditional tasks such as physical strength and from early 20th century factory style work which had become highly routine, towards modern work tasks that have made jobs more cognitive-skill intensive. We proxy this mostly with the non-routine analytic task measure, following Autor et al. (2003). Communication tasks are thought to have risen with economic development, urbanization and agglomeration, while social skills have been identified as a key growth area since 2000 (Michaels et al. 2019, Deming 2017). So, while there is some overlap in the communication and non-routine

[3] 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.
[4] The update to the DOT measures, O*NET, has been used elsewhere (e.g., Peri and Sparber 2009). However, Autor (2013) notes that the O*NET measures are more complex than DOT measures such that it is difficult to merge measures over time.

analytic measures that we use here, we explore the long-run trends in both proxies for modern tasks for completeness.

Census Data

After creating task content measures at the occupational level (*occ1950),* we merge them to cross-sectional data between 1900 and 2019.[5] We use the full-count censuses between 1900 and 1940, 5 percent or 1 percent samples from 1950 to 2000, and the 2010 and 2019 American Community Survey (ACS). We aim to measure 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.

In addition to the cross-sectional census data, we measure how occupational task content varies across the lifecycle and across generations. To estimate task mobility throughout a lifecycle, we use early 20th century linked data that track an individual across ten years (pooling 1900-1910, 1910-1920, 1920-1930, and 1930-1940). For intergenerational associations, we use data from Ward (2021), which pools linked data that tracks sons from childhood to adulthood from the same early 20th century censuses.[6] The links are created by the Census Linking Project (Abramitzky et al. 2020), which are then merged into full-count data from IPUMS (Ruggles et al. 2020). 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.

Main Trends

Figure 1 shows the broad trends in the four main summary task measures, looking at data for all workers in each census year—communication, routine manual, physical labor, and non-routine analytic.

Over the course of the 20th century, the physical labor component of employment has steadily halved in intensity. The other tasks did not have similar monotonic changes over the course of the past 120 years. From 1900 to 1920, the three other tasks rose almost in parallel to replace physical labor. These trends paused during the Great Depression, but strong growth in non-physical labor intensities continued during and immediately after World War II.

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 with later versions of the *DOT*. 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 both communication and non-routine analytic tasks continued to expand

[5] Specifically, we map the 1956 task measures to the *occ1950* census codes and then merge these to individual worker information.

[6] Ward (2021) takes 0-14-year-old children in the 1900-1920 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. The linking algorithm is based on Abramitzky et al. (2012). 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.

(Deming 2017, Michaels et al. 2019). These results are robust to using only the 1977 version of the DOT data already familiar in the literature.

[Figure 1 about here]

Similar to the late 20th century, the early 20th century also had a reversal of routine manual jobs. However, the magnitude of this shift was small: the routine manual index increased from 46 to 48 between 1900 and 1920, and then dropped from 48 to 45 between 1920 and 1940. This contrasts with a 9-point drop from 51 to 42 between 1970 and 2020. The early reversal of routine-manual occupations appears to have occurred economy-wide, since the routine manual index fell for every census region, as well as when limiting the sample to males, US-born workers, or non-agricultural workers. The economy-wide fall in routineness between the world wars fits with the findings of Gray (2013) on the manufacturing sector because our measure includes various proxies for dexterity, which was the main hollowed out task identified in that paper.

In addition to the slowdown in routine task content between 1920 and 1940, the upward trend of communication and non-routine analytical work also stalled. The slowdown in movement off the farm during the Great Depression may also account for why the national trend including all sectors displays greater rollbacks in the modern task intensities than the non-agricultural employment trends. This result is consistent with a slowdown in urbanization and a return to farms as employment opportunities dried up in cities (Boustan et al. 2014, Boone and Wilse-Samson 2021). Katz and Margo (2014) also find that the increase in the share of white-collar jobs slowed down between 1930 and 1940; however, they do not find a reversal of the pre-trend. The slowdown during the Great Depression is similar to the stalling of communication and non-routine analytic task content during the Great Recession in 2010. These results suggest that large macroeconomic shocks halt task transitions in the aggregate economy, even while large technological shifts may be taking place within certain sectors that are still changing the nature of work (Gray 2013, Jaimovich and Siu 2020).

These aggregate task changes mask variation across race, where Black-white gaps were large in the early 20th century and converged at different rates over time. These results are in Figure 2. At the start of our sample in 1900, Black workers held jobs that were more physically demanding than white workers. However, Black workers held occupations with fewer routine manual, non-routine analytic and communication tasks.

[Figure 2 about here]

White workers transitioned toward jobs with fewer physical tasks immediately and continuously since 1900, while Black workers only saw these shifts after 1940. It was not until 1960 that the physical content for Black workers jobs matched the physical content for white workers in 1900. There remains a positive gap in 2019 as Black workers are still more likely to work in jobs with greater physical demands. White workers also slowly increased their communication and non-routine analytic tasks from 1900 to the present day, opening up a large racial gap in these tasks by 1960. Black workers' rapid gains during the Civil Rights era from 1960 to 1980 erased much of that gap.

In contrast to white workers' relatively steady share in routine jobs, Black workers' routineness increased dramatically towards the white rate after 1960. This was a period of racial wage convergence, partially due to the second Great Migration out of the South. After 1980 both white and Black workers had declines in routineness when task displacement due to automation and computerization was highest (Autor and Salomons 2018). The decline in routineness is also consistent with a decline in well-paid factory jobs for Black workers, jobs that they had only recently gained full access to (Gould et al. 2021, Lazonick et al. 2021).

As a result of these differences in modern task acquisitions, Black-white gaps *widened* in the first half of the 20th century. Between 1900 and 1960, the Black-white gap in all the task measures increased by about 8 points (Appendix Figure A5). Controlling for state of residence, age, or basic human capital does little to close these gaps, leaving open the question of whether other observables can explain this phenomenon.[7]

One explanation for widening gaps before 1960 is the higher Black concentrations in agriculture. If one drops farmers and farm laborers, then Black-white task differentials widened by less in the early 20th century (1-4 points compared to 8 points) (Appendix Figure A5). However, this widening of the task gap is still surprising since income convergence has been documented elsewhere (Margo 2016). Most of the income gains for Black workers during this earlier period came from migration (Collins and Wanamaker 2014); however, it appears that migration did not lead to more complex task content. Migrants out of the South and out of agriculture saw wage gains from each of those choices, but Blacks remained limited to the lowest rungs of the Northern manufacturing job ladder, which locked them out of the best routine-intensive factory floor work, and kept them increasingly far from better-paid nonroutine analytic work of any kind. We will later return to the relationship between internal migration and task transitions in our analysis using linked data.

We also find evidence of differences in task composition in response to shorter-run macroeconomic trends, complementing earlier work on racial differences in sectoral composition during the Great Depression (Margo 1993, Sundstrom 1992). Black workers' physical task intensity remained constant from 1930 to 1940, even as white workers continued to exit physical-oriented work. Appendix Figure A1 shows that even when conditioning on age, literacy, and state of residence, routine manual task intensity gaps widened from 1930 to 1940. In contrast, Black workers' non-routine analytic share actually rose relative to white workers, interrupting a period of divergence. These results contrast with the longer-run trends, indicating that the overall impacts of task transitions over workers' lifetimes should be examined in a longitudinal framework, as we do below.

While the direction of Black-white task gaps remained stable since 1900, male-female gaps have mostly flipped in sign. As displayed in Figure 2, men were more likely to perform routine manual and non-routine analytic tasks in 1900, but 120 years later, men were less likely to be in these occupations. The rise in women's routine manual work occurred earlier, surpassing men after 1920. In fact, male routine manual task intensities have steadily declined over the long twentieth

[7] Basic human capital is measured with literacy in pre-1940 data and with whether one has more than 4 years of education in later data. While there is more information about education in later censuses, we aim to keep the specification consistent over time.

century, transitioning largely to non-routine analytic and communication intensive work. Despite this reallocation toward both these tasks for male workers, an acceleration in female non-routine analytic task intensity post-World War II led to higher female specialization than male after 1980, even as the gender wage gap has stalled (Goldin 2006).

Disaggregating labor market trends by tasks reveals that the timing of the transition to modern work was uneven across race and gender divides. Increasing access to education and labor market attachment since 1960 have probably driven women's faster accumulation of modern, complex skills. As women's education attainment has surpassed men, they have been able to make long-term investments in their skills and enter the labor market at a time when those skills have highest value, as we will show in the following section.

Task returns over time

While the task content of work has shifted remarkably over the last 120 years, it is unclear whether the return to task content has also shifted. Is the premium for performing physical jobs the same over time, or do these transitions in the economy cause changes to task returns? To examine this question, we estimate the returns to summary task measures using the 1940 Census, the earliest date where this exercise is possible, and the 2019 ACS cross-sections. We move beyond the composite measures of routine manual, non-routine analytic, communication and physical, and estimate the premium for each task component in our dataset. Specifically, we regress the percentile rank of wage income on the percentile rank of task intensity, a quadratic in age, and years of educational attainment for male 30-45-year-old wage workers.

$$Rank(WageIncome_i) = \beta_0 + \beta_1 Rank(task_i) + \beta_2 educ_i + \beta_3 A_i + \beta_4 A_i^2 + \varepsilon_i \ (1)$$

We estimate the regression for each year.[8] We then plot the ranking of these task premia across the full range of task measures that we have available in Figure 3A. Finally, note that these results are only for wage workers, and thus do not include business or farm income.

[Figure 3 about here]

First, task premia in 1940 were positively associated with those in 2019, which reflects a remarkable stability over time. Today, we know that occupations with more communication tasks and non-routine analytic tasks tend to have higher compensation (Peri and Sparber 2009, Deming 2017). On the other hand, routine manual and physical strength tasks are more lowly compensated. This pattern from 2019 also held in 1940. Going from a 0 to 100 percentile communication task is associated with a 27 percentile increase in labor income in 1940; it was associated with a 25 percentile increase in 2019. Similarly, a 100-unit increase in physical task was associated with a decrease of 30 ranks in the income distribution in 1940; in 2019, it was 20 ranks.

The figure also plots the 45-degree line, which shows that the task premia have converged since 1940. That is, the premia for lowly rewarded tasks was less negative in 2019 than it was in

[8] We demonstrate that these results are largely unchanged in a sibling fixed effect approach which controls for household-level unobservables using linked historical censuses and the Panel Study of Income Dynamics (PSID) microdata for 1969--2015. These results, as well as the absolute task returns, are found in Appendix A.

1940; similarly, the premium for highly rewarded tasks in 2019 is less than it was in 1940. The plot makes it easy to see which task returns have changed between 1940 and 2019, as they are located off the 45-degree line.

While there are similar task return rankings over time, there are some reversals of fortune between 1940 and 2019, which are more clearly shown in Figure 3B after ranking the premia. Non-routine work is ranked lower than communication in 1940 due to the earlier period's higher compensation for clerical and verbal work. Similarly, routine cognitive work was ranked higher than routine manual work in 1940 but not 2019 due to the decline in remuneration for repetitive-oriented tasks in the modern period. Although we focus in this paper on the four task summary measures, the changes in returns for individual tasks, such as *reaching* and *direction*, indicate that there are important shifts in the underlying tasks as well.

Combining these results with the task employment measures above, we illustrate that white workers were more likely to be in highly compensated tasks in 1940. The Black-white convergence in task intensities after 1940, therefore, likely contributed to the decline in the racial wage gap. The story is less clear for the gender wage gap—men worked in both the lowest-compensation fields in 1940, intensive in physical labor, but not the next-lowest, routine manual. These return rankings were constructed using only men, which also neglects the potential for within age-education-occupation discrimination based on gender and/or race. However, these results indicate that increased entry for minority groups has occurred largely in higher compensation tasks. Changing task compositions, then, may play a substantial role in the evolution of the racial labor market opportunity gap, and we examine this possibility in more detail in the next section.

Task mobility

An enduring concern about technological change is that it displaces tasks and increases wage inequality (e.g., Autor et al. 2003, Acemoglu and Restrepo 2021, Graetz 2020, Jerome 1934). An economy with high task displacement likely displays a high amount of "task mobility", which captures how the task content in one's occupation persists across time. However, high task mobility may also reflect that workers could easily switch between jobs, which would mute negative welfare impacts from innovation. In this section, we turn to linked data in the early 20th century to estimate how task content persisted not only within one male worker over time, but also from father to son. We compare task mobility estimates to more traditional estimates of social mobility based on occupational income.

Looking first at intragenerational changes, we measure task mobility via the rank-rank association across censuses:

$$Rank\left(Task_{i,t}\right) = \beta_0 + \beta_1 Rank(Task_{i,t-10}) + \varepsilon_{i,t} \qquad (2)$$

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." Before presenting results, note that measurement error in historical occupational data attenuates estimates (Ward 2021). To provide context for the magnitude of the task persistence estimates, we compare them to the persistence of the percentile rank of occupational income, which has been used elsewhere (e.g., Feigenbaum 2018).[9]

Figure 4A shows that there was substantial task mobility in the economy. The persistence of task content was generally smaller than the persistence of occupational income. The estimate of occupational income persistence is 0.57, which indicates that 57 percent of the differences in percentile rank persisted from one census to the next. The only measure that was similar in magnitude to occupational income was physical labor. Overall, task content appears to be weakly associated across censuses such that workers often ended up in jobs performing different tasks each decade.

Interestingly, we find sharply different predictions for persistence across the task return distribution in 1940. In fact there is a U-shaped relationship between task returns and task persistence. Physical labor, the lowest-ranked task in Figure 3A, is by far the most persistent over workers' lifetimes. The next most-correlated tasks were the highest ranked. Task specialization may have affected social mobility at the top and bottom of the income distribution. In contrast, the tasks in the middle of the compensation rankings, those related to routine work, were the least likely to persist across censuses, indicating a role for technological change in altering workers' task intensities.

Task mobility decreased throughout the lifecycle as occupations became more stable. For 18-24 year olds, only 30 percent of the difference in routine manual content persisted ten years later; for 40-45 year olds, this rate increased to 53 percent (Appendix Figure A7). The fact that older individuals were less likely to transition to different task content suggests that there was task-specific human capital built over working lives (Gathmann and Schonberg 2010). In contrast to the sharp increase in task persistence throughout the lifecycle, the persistence of occupational income was more stable. For 18-24 year olds, 55 percent of income differences persisted, in contrast to 58 percent for 40-45 year old. These results suggest that early in the lifecycle, occupational switches left one in a similar paying job performing different tasks, particularly for those originally working in routine tasks.

We also present estimates of the persistence of task content from father to son, which compares the task content of the son's occupation to that of the father's (instead of comparing an individual to himself ten years later.) To address measurement error in occupational data, we instrument one father observation with a second observation from a census ten years later or ten years earlier (Ward 2021). While this method increases the magnitude of the estimates, it does not alter the qualitative conclusion that occupational income persistence was stronger than task persistence.

[9] While there are a variety of ways to measure occupational income, we use a method similar to Collins and Wanamaker (2021) where we rely mostly on the mean wage income by occupation in the 1940 census. See Appendix D for the construction of occupational income. Our construction follows Collins and Wanamaker (2021) without any adjustment for race or region. While adjusting for within-occupational differences are important for accurately measuring income gaps in the past (Saavedra and Twinam 2020), we prefer the occupation-only scores since the task measures are also defined at the occupation level.

Figure 4B shows that the persistence of task content across generations was low when compared to the persistence of occupational income. For example, only 21 percent of gaps in routine cognitive endured across generations, and only 23 percent of gaps in routine manual. Again, there is a u-shape to these correlations across the task return rankings. The lowest intergenerational mobility coefficients are associated with the highest and lowest ranked tasks in 1940. For both communication and physical labor, though, we find that the correlation between fathers and sons' task intensities is almost twice as large. The highest estimate is nearly 10 percentage points larger than these; the persistence of occupational income was 65 percent.[10] Thus, children mostly ended up in similar status jobs as their fathers with different task content. Since task mobility was so high, these results suggest that task-displacing technological shocks had less impact on socioeconomic positions across generations before 1940.

Racial mobility gaps

Since the transmission of task content was weak but Black-white gaps persisted in the pre-World War II period, there must have been a racial *mobility* gap in task content (Chetty et al. 2020, Margo 2016). That is, Black individuals likely ended up in a different part of the task distribution relative to white individuals who started (or whose father started) in the same rank. Racially biased *income* transitions have been documented elsewhere (Akee et al. 2019, Collins and Wanamaker 2022, Chetty et al. 2020), but we are not aware of similar evidence for *task content*. To measure such mobility gaps and test this hypothesis, we estimate the same within-one and across generation regressions as above but include an indicator variable for one's race being reported as Black.

Figure 5 shows that racial mobility gaps in occupational task content existed for both the intragenerational and intergenerational datasets. First, the data confirm the pattern found by Collins and Wanamaker (2022) that Black sons ended up 15 percentiles lower in the occupational income distribution than white sons (Figure 5B). These mobility gaps are largest for the highest-return tasks in 1940. Black sons were also estimated to end up 20 percentiles lower in the non-routine analytic distribution, 10 percentiles lower in the routine manual distribution, and 18 percentiles lower in the communication distribution. In contrast to these negative mobility gaps for Black sons, there was a positive mobility gap (14 percentiles) for jobs that required physical labor. Black sons ended up 14 percentiles higher than white sons whose fathers had the same physical labor task intensity. The early aggregate decline in white physical labor share can explain these racial differences in the ability to transition into other tasks even among men starting in similarly intensive work.

The direction of the racial mobility gaps across generations were the same as the gaps within one generation, though the magnitudes varied. Figure 5A shows that Black males ended up in more physically demanding jobs and less analytical jobs than white individuals who started at the same location. Since physically demanding jobs had a lower return than analytical jobs, Black individuals also ended up lower in the occupational income distribution. Differential task mobility, therefore, undergirds the lack of upward occupational mobility for Black men in this time period

[10] The estimate of intergenerational persistence of occupational income (0.65) is higher than intragenerational persistence (0.57), which is surprising since the intergenerational estimates are across different individuals. This pattern is due to the instrumental variables strategy aimed to purge measurement error in the intergenerational regression, a method that we cannot use for the intragenerational estimates. If one does not use an instrumental variables strategy, then the father-son persistence estimate is 0.38, lower than the within-lifetime correlation.

(Collins and Wanamaker, 2022). Note that these racial mobility gaps also hold when controlling for observable characteristics, such as state of residence and human capital.

A provocative implication of these results is that task-displacing technological shocks had disparate impacts by race across the skill distribution. For example, if a routine manual task is automated, and therefore eliminated, then white individuals are expected to end up in a job that is more routine manual than a Black individual. Similarly, if a father's job is automated, then a white child is expected to end up in a more routine-intensive job than a Black child even when in the same initial conditions. Declines in the demand for routine workers altered labor market outcomes across racial groups over multiple generations.

The lack of convergence in the Black-white task gap between 1900 and 1940 discussed in Section 3 contrasts with estimates of income convergence during the same period (Margo 2016). The key force driving Black-white convergence during this earlier period was the first Great Migration. In fact, Collins and Wanamaker (2014) estimate that if the Great Migration during the interwar period had not occurred, black-white income gaps may have *widened*. With the linked data, we can test the importance of migration out of the South for Black-white gaps in occupational task content. We do so with a brother fixed-effects methodology that compares migrant brothers out of the South to brothers who remained in the South, like Boustan (2016) and Collins and Wanamaker (2014).[11]

Within-brother variation suggests that the Great Migration did not counteract the widening Black-white task gap before 1940; in fact, it appears to have increased the gap. Figure 6A shows that migration out of the South was associated with a *decline* in non-routine analytic, routine manual and communication task content. In contrast, there was a slight increase in physical task content (see Figure 6, Panel A). The results are surprising since the Migration was from rural agricultural jobs in the South to the urban unskilled work in the North, which potentially opened new opportunities for routine manual as well as non-routine analytic/communication tasks. However, our task measures place agricultural work relatively high in the routine manual and non-routine analytic distribution, reflecting the wide range of tasks performed in agriculture. Even if one drops the sons of farmers and farm laborers (80 percent of the sample), the directions of results are similar, except for a decline in physical task content. Overall, it appears that the Great Migration improved incomes due to movement to higher wages in the North and urban areas, but Black workers who migrated did not transition into more complex occupations.

Broadening the focus from the Great Migration, internal migration for the whole population was associated less routine manual and physical task content, and little change in communication and non-routine analytic work. The estimates in Figure 6B are for interstate migration when using the whole sample and not just Black sons who grew up in the South.[12] However, if one drops the sons of farmers and farm laborers, then interstate migration was associated with an increase in non-routine analytic and communication tasks.

---

[11] Specifically, $y_{ih} = \beta_1 Migration_{ih} + \theta_h + f(Age_{ih}) + \varepsilon_{ih}$, where y_{ih} is the percentile rank of task in either 1930 or 1940, and the childhood household is observed between 1900 and 1920. We control for a quartic in age. The sample is limited to Black sons whose father was in the South census region in childhood and the son was outside of the South region in adulthood. The sample contains 37,350 brothers. 7,782 were sons of non-farmer/farm laborers.

[12] The shift in focus from the Great Migration increases the number of observations from 37,350 to 1,940,833 observations. After dropping the sons farmers and farm laborers, there are 889,948 observations.

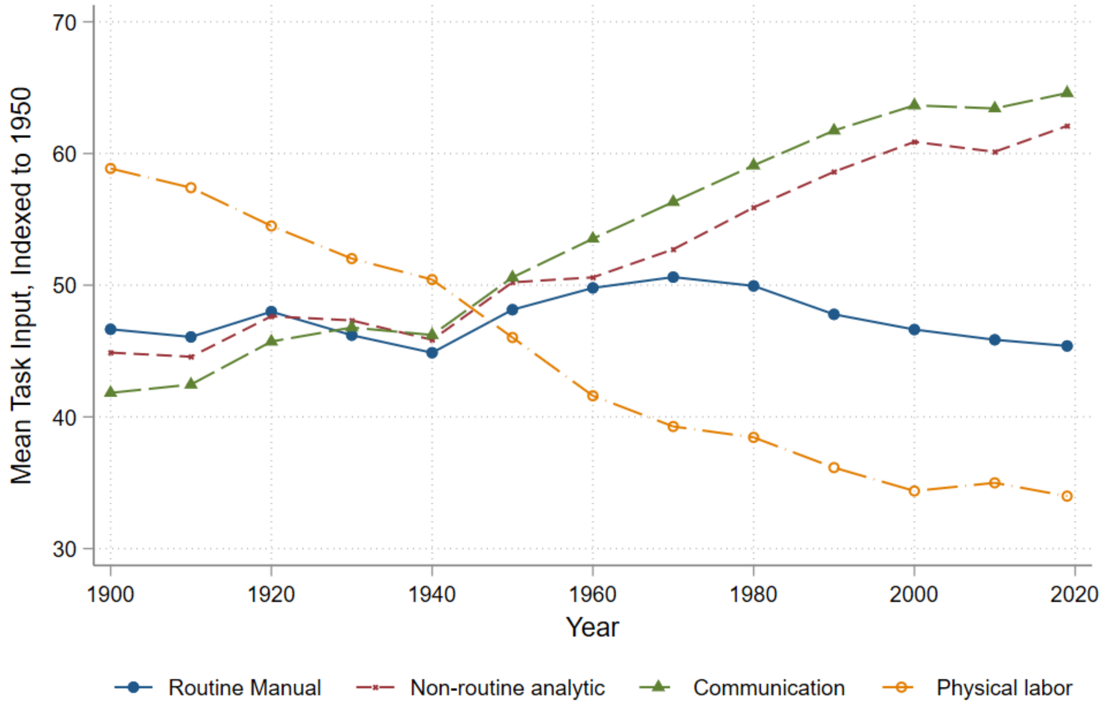
How then do we reconcile the occupational standing mobility gap with the differences in routineness operating in the opposite direction? White workers' higher levels of entering and remaining in white-collar tasks are key. The sizeable within and across-generation mobility differences associated with communication and non-routine analytic work can explain how white workers were more exposed to routine-replacing technology but also more upwardly mobile on average. Although a segment of white workers persisted in these tasks while the rest of the white occupational distribution disproportionately shifted into complementary, higher return work. These gaps may not remain after 1960, given the rapid convergence in the Black-white gap in task content documented in Figure 2. To the extent that recent technological changes parallel those in the past, however, early differences in task persistence may still echo today.

[Potential PSID Comparison]

Conclusion

White men had quite a different work experience during the early 20th century, compared to other groups. They began transitioning right from 1900 towards we think of as modern jobs, characterized by higher level cognitive skills involving communication and analysis. As they left routine work behind, their place was taken by female and Black workers. In turn those groups have followed the same trends, although for Blacks this transition occurred a full half-century later. Building on previous work that showed income gains for Blacks were substantive from 1940 onwards, this paper shows the that the types of tasks done by Black workers converged at the same time. The result reinforces that the Civil Rights Movement was necessary to integrate the American workplace so that going to work means a very similar thing for all groups by 2019 compared to any other time over the long 20th century.

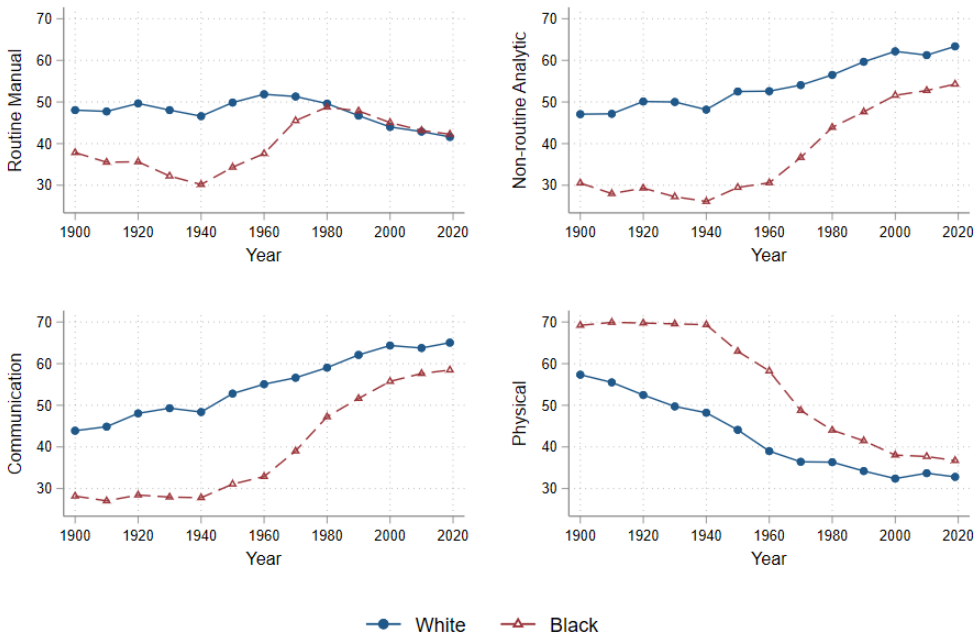
Figure 1. National trends in task content



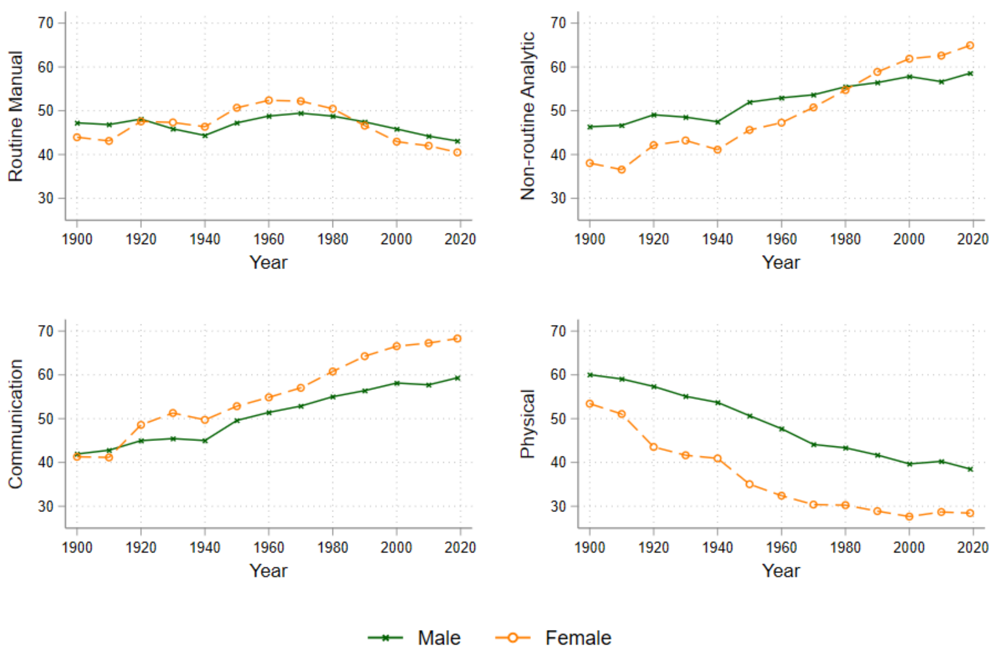
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. Since task content by occupation is fixed, an increase in task content over time reflects changes in the occupational distribution but not changes to task content within occupation. See Table X for task definitions.

Figure 2. Trends in task content by demographic group

Panel A. By race



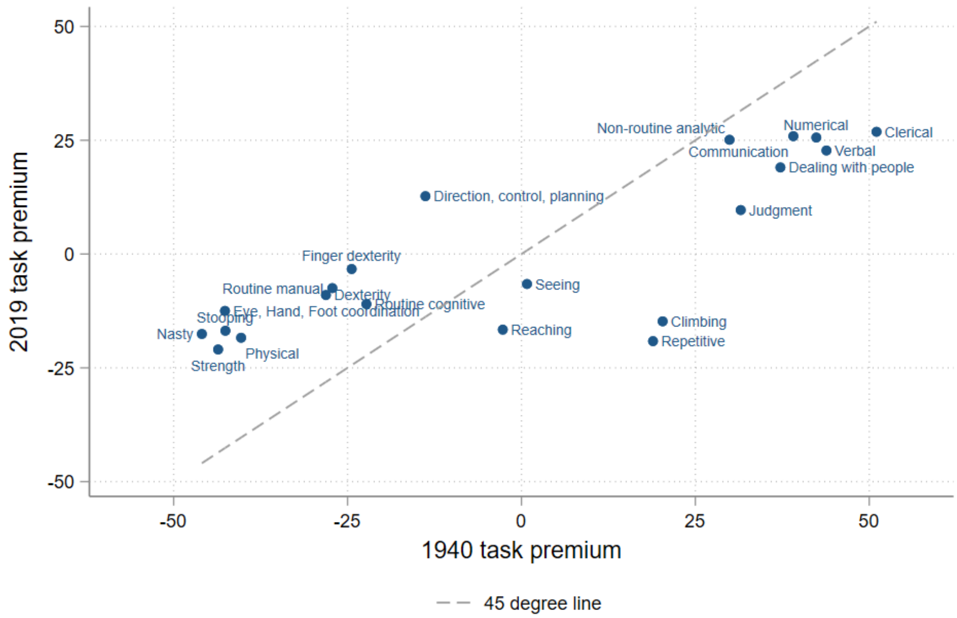
Panel B. By Sex



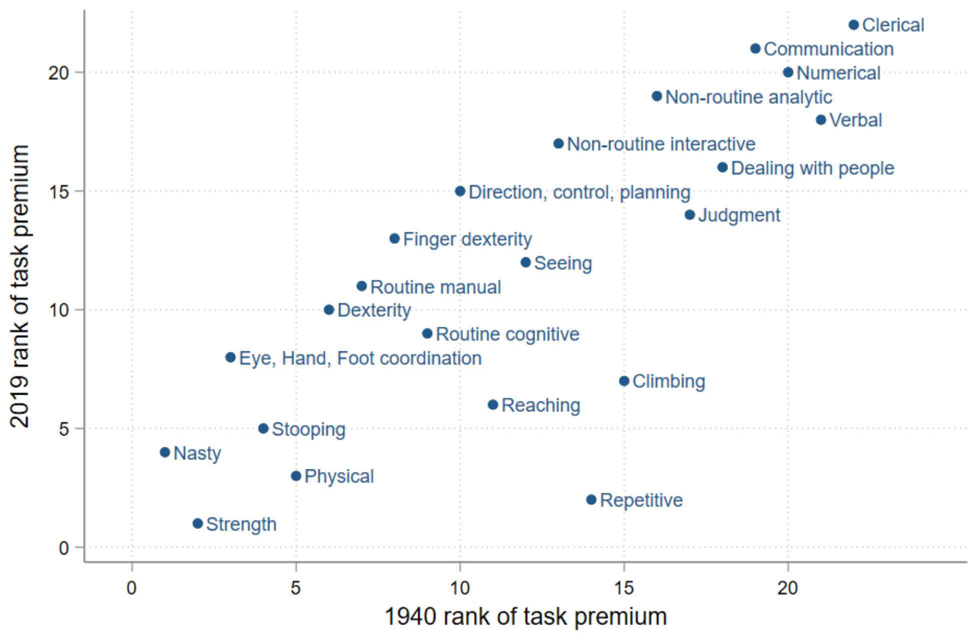
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. Since task content by occupation is fixed, an increase in task content over time reflects changes in the occupational distribution but not changes to task content within occupation. See Table X for task definitions.

Figure 3. Stability of relative task premium across 1940 and 2019

Panel A. Task premia

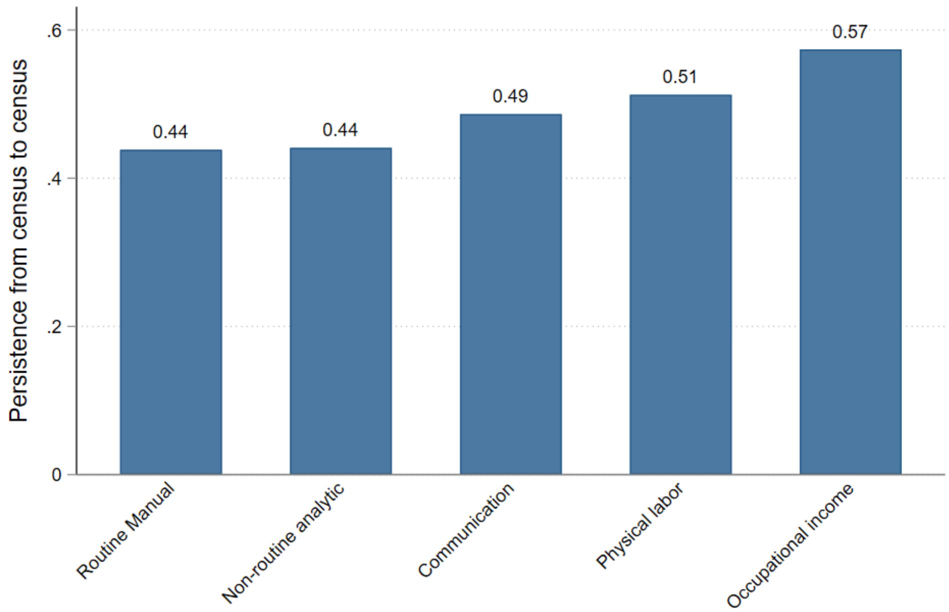


Panel B. Rank of task premia

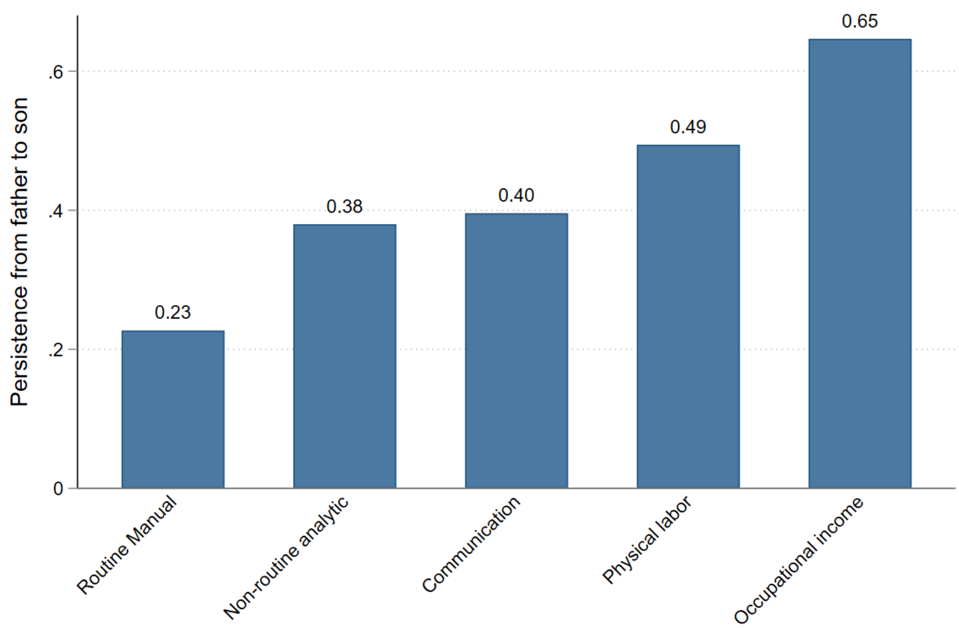


Notes: Data are from the 1940 1% percent sample and the 2019 ACS (Ruggles et al. 2021). Sample is 30-45-year-old male wage workers with an occupation. Task premia are estimated by regressing the percentile rank of wage income on percentile rank of task, a quadratic in age, and education. Panel A plots the estimate for the task premium in 1940 against the estimate for the task premium in 2019. Panel B plots the rank for task premium in 1940 against the rank in 2019.

Figure 4. Task persistence
Panel A. Within one generation



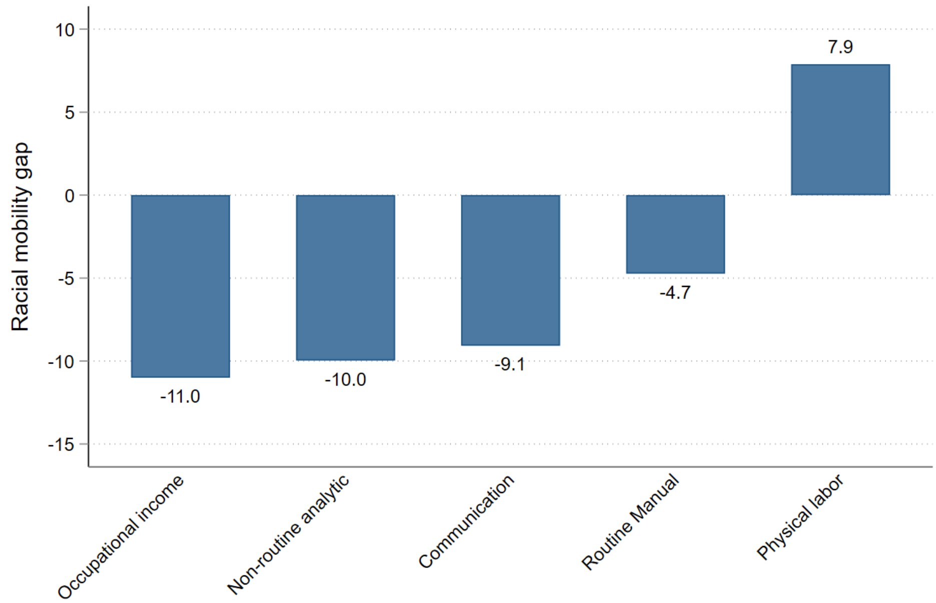
Panel B. Across generations from father to son



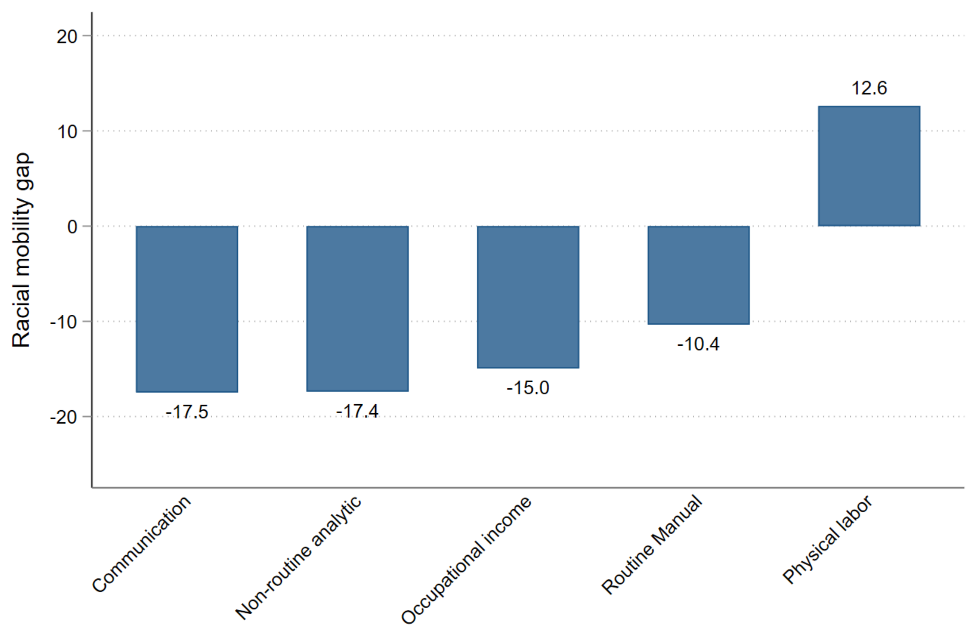
Notes: Underlying data are from the 1900-1940 US Censuses (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2020). Panel A shows the point estimate from a regression of the outcome in census *t+10* on the outcome in census *t*. Panel B shows the point estimate from an 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 (2021). All measures are percentile ranked. Note that measurement error attenuates estimates.

Figure 5. Black-white mobility gaps in the early 20th century

Panel A. Within one generation



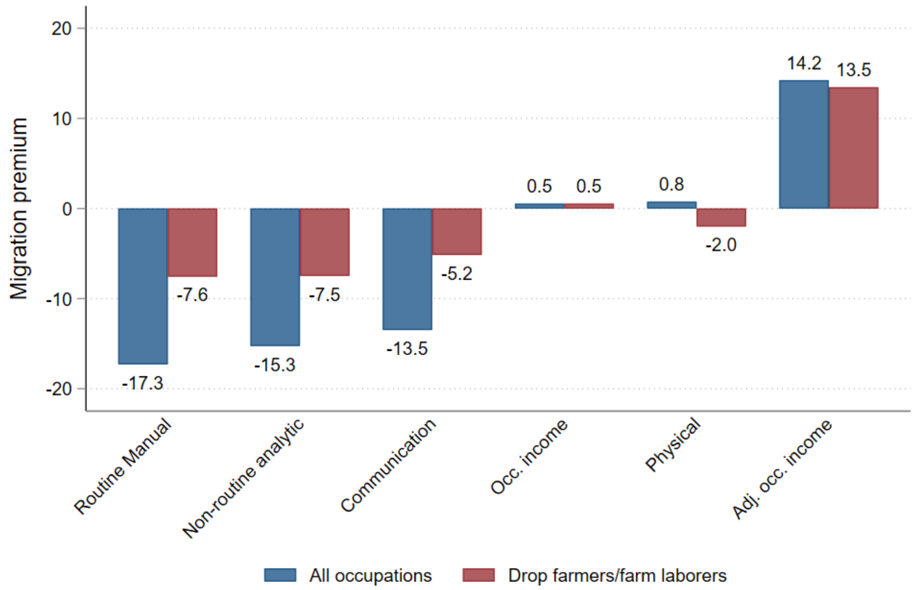
Panel B. Across generations from father to son



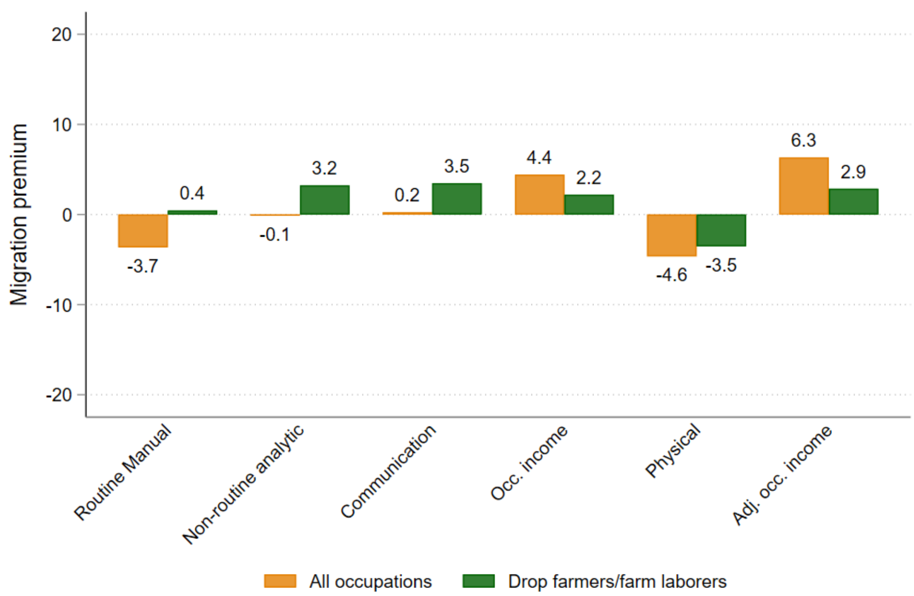
Notes: Underlying data are from the 1900-1940 US Censuses (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2020). The figure shows the point estimate from a Black indicator variable. Panel A is a regression of the outcome in census *t+10* on the outcome in census *t* and a Black indicator. Panel B shows the point estimate from an IV regression of the son's outcome on the father's and a Black indicator. The father's outcome is instrumented with a second observation to address potential measurement error, per Ward (2021). All measures are percentile ranked. Note that measurement error attenuates estimates on the initial location in the distribution. Occupational income is a 0-100 percentile ranked measure that imputes income by occupation.

Figure 6. The association between migration and task content

Panel A. Great Migration out of the South



Panel B. Interstate migration



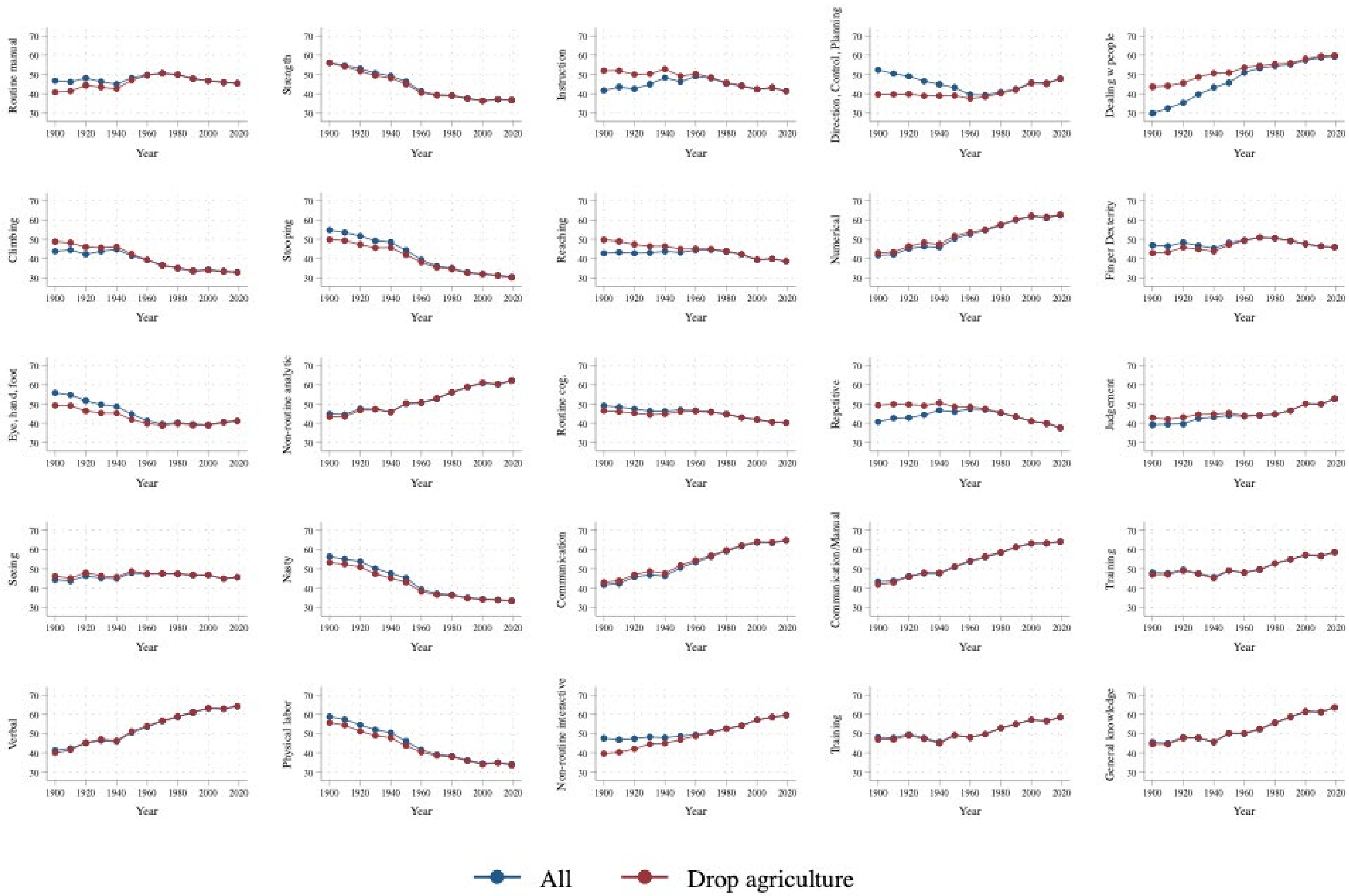
Notes: Data are intergenerational links from Ward (2021). Each bar is from a different regression of a brother's adult percentile rank on a migration variable, age controls, and childhood household fixed effects. In Panel A the sample is limited to Black brothers who grew up in the South; the migration variable is an indicator for whether one left the South by adulthood. In Panel B, the sample includes everyone, but the migration variable is for the son living in a different state than childhood. Occupational income is the main one used throughout this paper. Adjusted occupational income adjusts for regional and Black/white differences within occupation.

Online Appendix, not for publication.

Table of contents

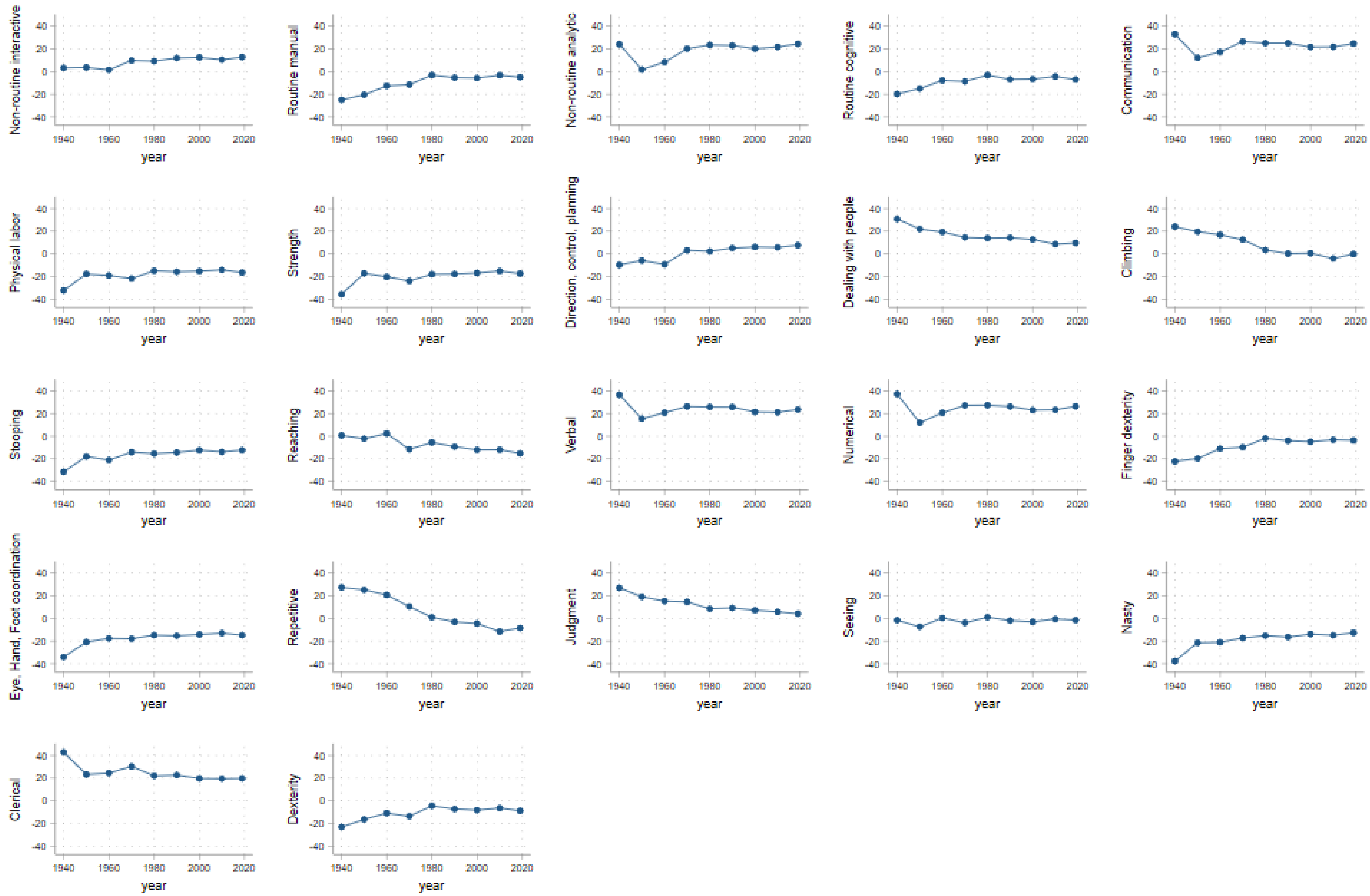
Appendix A. Additional figures

Figure A1. National trend in task content



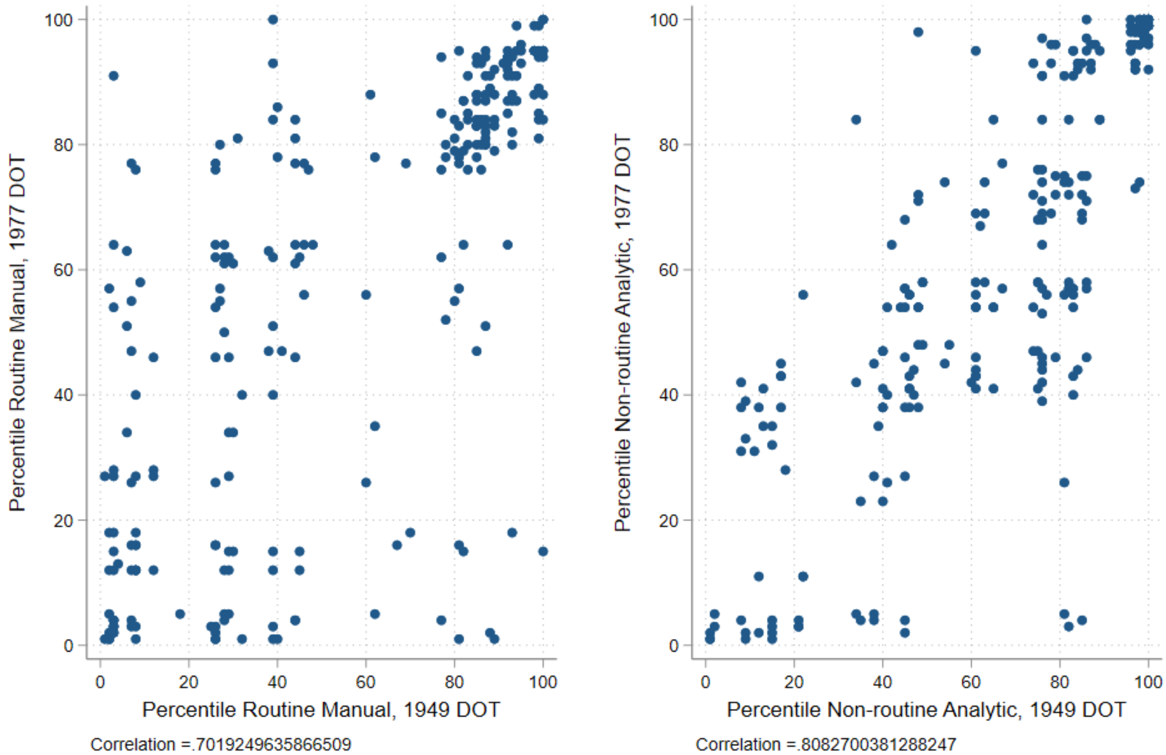
Notes: Data are from the 1900-2000 Censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021).

Figure A2. Trend in task premia between 1940 and 2019



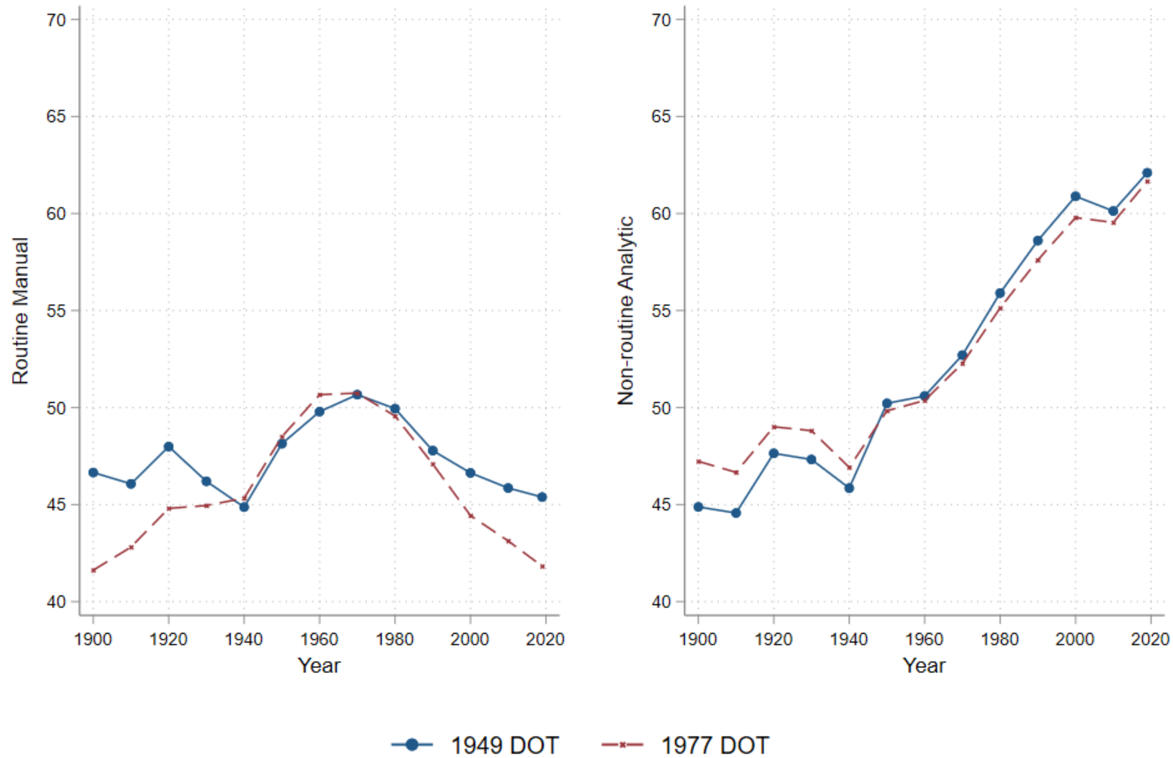
Notes: Data are from the 1940-2000 Censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021). Sample is 30-45-year-old male wage workers with an occupation. Task premia are estimated by regressing the percentile rank of wage income on percentile rank of task, a quadratic in age, and education.

Figure A3. Correlation between 1949 and 1977 Dictionary of Occupational Titles Data



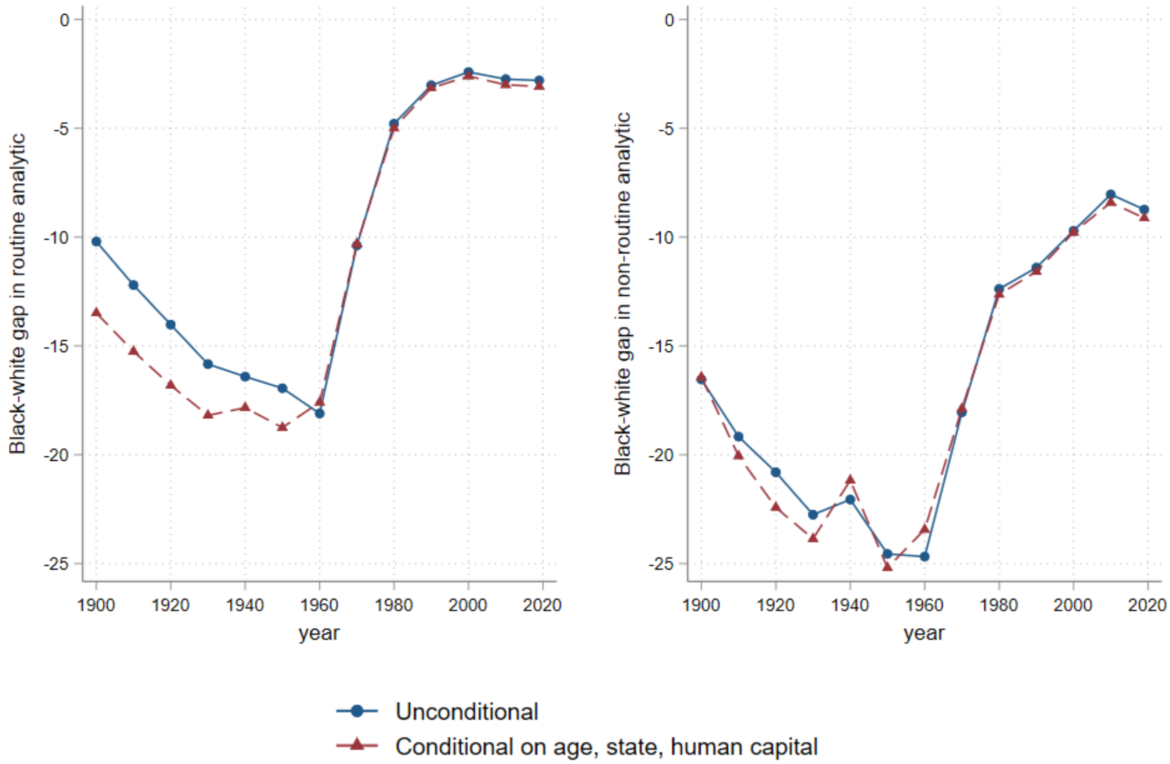
Notes: The unit of observation is an occupation (occ1950 code). This figure plots the distribution of routine manual and non-routine analytic task ranks when using the task content based on the 1949 Dictionary of Occupational Titles, versus the task content based on the 1977 Dictionary of Occupational Titles.

Figure A4. Trend 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 content based on the 1949 Dictionary of Occupational Titles, versus the task content based on the 1977 Dictionary of Occupational Titles.

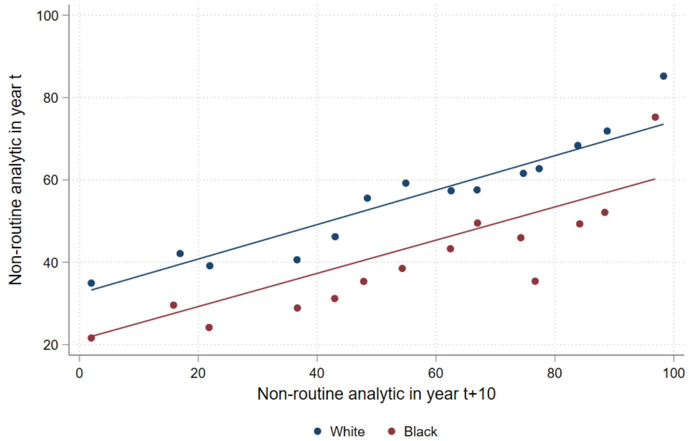
Appendix Figure A5. Black-white differences in task content conditional on observables



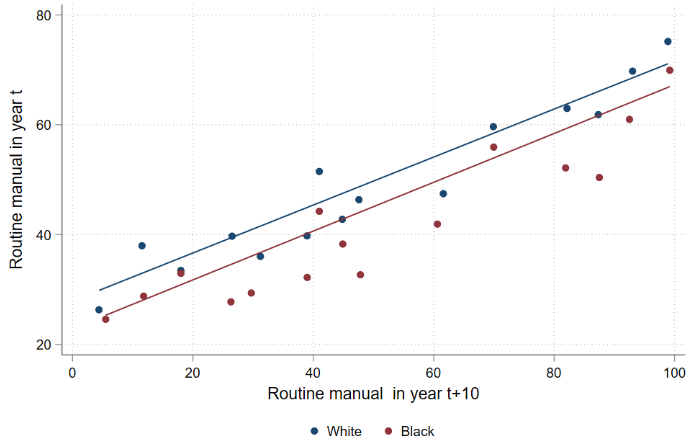
Notes: Data are from the 1900-2000 Censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2020).

Figure A6. Binscatter plots by race

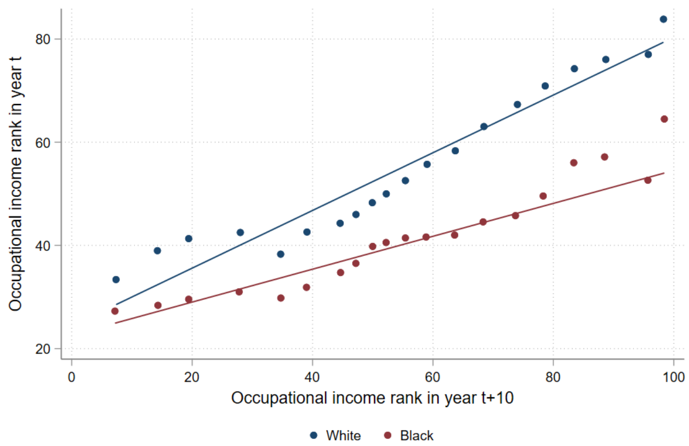
Panel A. Non-routine analytic



Panel B. Routine manual

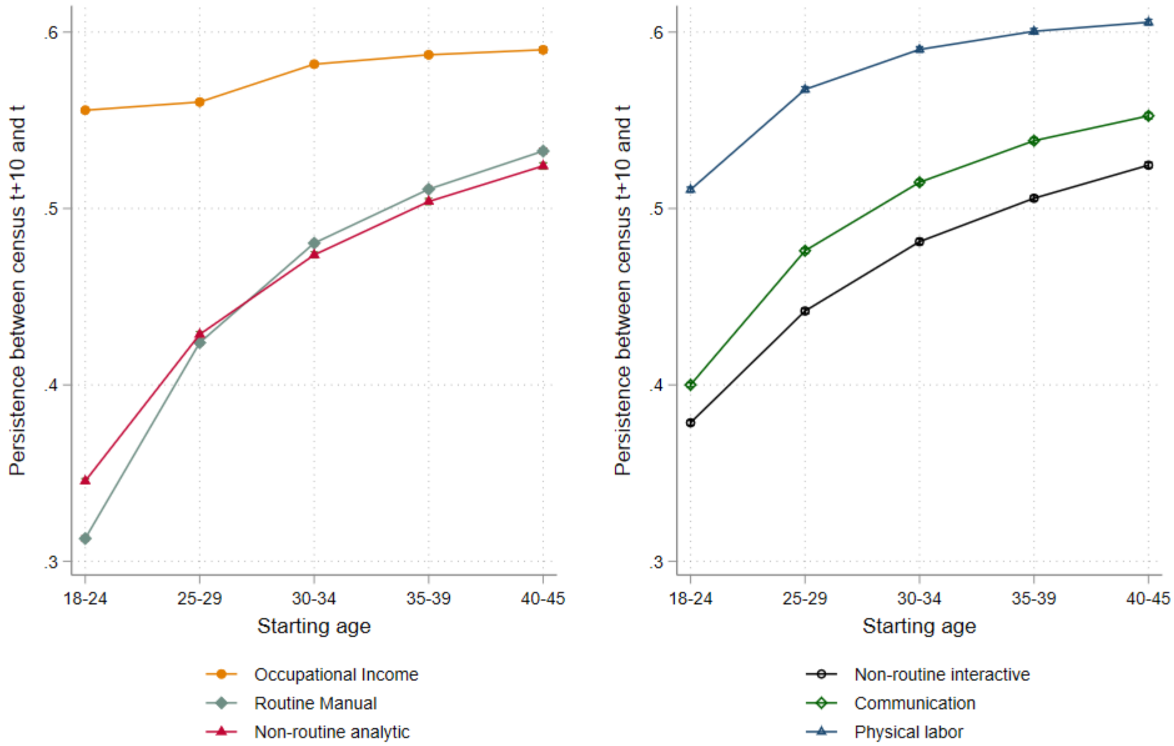


Panel C. Occupational income



Notes: Data are from linked censuses between 1900-1910, 1910-1920, 1920-1930, 1930-1940. The figures show the binscatter plot by race.

Appendix A7. Persistence of task content throughout the lifecycle.



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 lifecycle.

Appendix 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 went out and observed people performing these jobs. The Dictionaries described about 12,000 jobs, and 4,000 of those ended up with more formal coding for tasks performed 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 4000 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. In that paper the job descriptions were checked against an earlier set of job descriptions used by the U.S. military, in Swan (1918).

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, routine cognitive, 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, which is what we used then throughout the paper. [13]

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.

[13] 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 2- Short demonstration-30 days 3- 30 days to 3 months 4- 3-6 months 5- 6 months-year 6- 1-2 years 7- 2-4 years 8- 4-10 years 9- 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
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:
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:

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
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	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	Grain stacker, garbage man, lead kettleman,

	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	

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
Physical2	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**

Figure B1. Example rating from the 1956 DOT

ALPHABETICAL ARRANGEMENT OF JOB TITLES

Line No.	D. O. T. Job Title	Vol. II Code	Part IV Code	Train. Time GED	SVP	Aptitudes GVN	SPQ	KFM	EC	Temperaments (1 2 3 4 5 6 7 8 9 0 X Y)	Interests (1 2 3 4 5 6 7 8 9 0)	Physical Capacities (1 2 3 4 5 6)	Working Conditions (1 2 3 4 5 6 7)	Industry Code	OAP No.	OOH Page	Line No.
	A																
1	Able Seaman	5-48. 040	3-X8.70	4	6	344	334	333	24	1 8	1 9	H 2 4 6	O 6	944			1
2	Abrasive Grader	4-70. 301	4-X2. 035	4	5	344	324	444	54	0 Y	1 9	L 6	I	651			2
3	Abrasive-Wheel-Friction-Saw.-Mach. Operator.	6-78. 613	6-X2. 416	4	3	343	434	343	45	2 Y	1 9	M 4 6	I 5	561		191	3
4	Absorberman	6-52. 711	4-X6. 601	4	5	333	324	443	54	0 Y	1 9	L 4 6	I	237			4
5	Absorption-Plant Operator	4-55. 010	4-X6. 697	4	6	343	234	333	55	0 Y	1 9	L 4 6	I 7	679			5
6	Abstractor	1-01. 31	1-X1. 1	4	3	343	542	344	55	2 3	1 3	S 4 6	I	249			6
7	Abstractor	0-68. 45	0-X7. 12	6	5	224	552	544	55	9 0	6 0	L 4 6	I	695			7
8	Accordion Maker	5-13. 351	4-X6. 309	4	6	333	224	432	52	9 Y	9 0	L 4 6	I	594			8
9	Accountant, Audit	0-01. 20	0-X7. 11	6	7	121	542	444	55	4 0	1 2	S 4 6	I	695			9
10	Accountant, Cost	0-01. 10	0-X7. 11	6	8	121	542	444	55	4 0	1 2	S 6	I	695	5	116	10
11	Accountant, General	0-01. 20	0-X7. 11	6	8	121	542	444	55	4 0	1 2	S 4 6	I	695	5		11
12	Accountant, Public	0-01. 30	0-X7. 11	6	8	111	542	444	55	4 0	1 2	S 4 6	I	695	5		12
13	Accountant, Tax	0-01. 40	0-X7. 11	6	7	121	542	444	55	9 0	1 2	S 4 6	I	695	5		13
14	Account Checker	1-01. 31	1-X1. 1	4	3	332	542	433	55	2 3	1 3	S 6	I	249			14
15	Account-Classification Clerk.	1-01. 03	1-X2. 0	4	3	333	543	444	55	0 Y	1 3	S 6	I	249			15
16	Accounting Clerk	1-01. 31	1-X2. 0	4	4	332	542	333	55	1 3	1 3	S 4 6	I	249			16
17	Accounting-Machine Serviceman.	5-83. 121	4-X2. 106	4	7	333	223	322	54	0 Y	9 0	L 4 6	I	138	15	161	17
18	Accounts-Payable Clerk	1-01. 31	1-X2. 9	4	4	333	542	334	54	1 3	1 3	S 4 6	I	249			18
19	Accounts-Receivable-Balancing Clerk.	1-01. 33	1-X2. 9	4	4	332	542	334	55	2 3	1 3	S 4 6	I	249			19
20	Account-Transfer Clerk	1-17. 01	1-X4. 0	4	4	334	452	334	54	2 3	1 3	L 4	I	532			20
21	Acetylene-Burner Operator	6-85. 215	4-X6. 283	4	4	344	334	343	44	2 Y	1 9	H 3 4 6	B	138			21
22	Acid-Correction Man	4-51. 010	4-X6. 641	4	5	344	534	444	53	0 Y	1 9	L 4 6	I 7	737			22
23	Acid Craneman	5-73. 010	4-X2. 493	4	5	344	345	343	34	2 Y	1 9	M 4 6	I	475		372	23
24	Acidizer	5-20. 420	4-X6. 694	6	7	233	334	444	44	0 Y	1 9	L	O	677			24
25	Acid Maker	6-41. 260	6-X2. 601	3	4	344	344	443	55	2 Y	1 9	L 4	I 7	667			25
26	Acid Mixer	6-55. 530	4-X6. 694	4	5	343	343	443	55	2 Y	1 9	L 4	I 7	679			26
27	Acid Patrolman	4-51. 030	4-X6. 641	4	4	344	424	443	53	0 Y	1 9	L	I 7	737			27
28	Acid-Plant Lead Burner	4-95. 031	4-X6. 285	4	7	344	335	343	34	2 Y	1 9	H 2 3 4 6	I 6 7	679			28
29	Acid-Retort Operator	6-55. 550	4-X6. 694	4	5	334	334	443	55	2 Y	1 9	L 4	I 7	679			29
30	Actor	0-02. 11	0-X4. 2	5	7	225	444	444	35	5 X	5 6	L 5	I	133			30
31	Actuarial Clerk	1-08. 01	1-X1. 1	4	3	232	552	445	55	2 3	1 3	S 6	I	473			31
32	Adding—Mach. Operator	1-25. 12	1-X2. 9	3	2	343	553	234	55	2 3	1 3	S 4 6	I	249	12		32
33	Adding-Machine Serviceman.	5-83. 122	4-X2. 106	4	7	343	224	333	54	0 Y	1 9	L 4 6	I	138	15	164	33
34	Additions and Betterments Clerk.	1-01. 31	1-X2. 0	4	2	333	552	334	55	2 3	1 3	S 4 6	I	724			34
35	Addresser I	1-04. 01	1-X2. 9	3	3	335	543	334	55	2 3	1 3	S 4 6	I	249			35

1

Figure B2. GED

State of development involving *capability* to immediately function in *one or more* of the following ways:

Level	Reasoning Development	Mathematical Development	Language Development
7	Apply principles of logical or scientific thinking to a wide range of intellectual and practical problems. Deal with nonverbal symbolism (formulas, scientific equations, graphs, musical notes, etc.) in its most difficult phases. Deal wi.h a variety of abstract and concrete variables. Apprehend the most abstruse classes of concepts.	Work with a wide variety of theoretical mathematical concepts and make original applications of mathematical procedures, as in empirical and differential equations.	Comprehension and expression of precise or highly connotative meanings, as in —Journal of Educational Sociology. —Scientific Monthly. —Works in logic and philosophy, such as Kant, Whitehead, Korzybski. —Literary works, such as Stein, Elliot, Auden.
6	Apply principles of logical or scientific thinking to define problems, collect data, establish facts, and draw valid conclusions. Interpret an extensive variety of technical instructions, in books, manuals, mathematical, or diagrammatic form. Deal with several abstract and concrete variables.	Make standard applications of advanced mathematics, as differential and integral calculus.	Comprehension and expression as of —Saturday Review of Literature, Harper's. —Scientific American. —Invitation to Learning (radio program).
5	Apply principles of rational systems [2] to solve practical problems. Interpret a variety of instructions furnished in written, oral, diagrammatic, or schedule form. Deal with a variety of concrete variables.	Perform ordinary arithmetic algebraic, and geometric procedures in standard, practical applications.	Comprehension and expression as of —Popular Science. —America's Town Meeting of the Air (radio program).
4	Apply common sense understanding to carry out instructions furnished in written, oral, or diagrammatic form. Deal with problems involving several concrete variables.	Make arithmetic calculations involving fractions, decimals and percentages.	Comprehension and expression as of —Readers' Digest. —American Magazine. —Lowell Thomas (radio program).
3	Apply common sense understanding to carry out detailed but uninvolved written or oral instructions. Deal with problems involving a few concrete variables.	Use arithmetic to add, subtract, multiply, and divide whole numbers.	Comprehension and expression as of —"Pulp" detective magazines. —Movie Magazines. —Dorthy Dix. —Radio "soap operas".
2	Apply common sense understanding to carry out spoken or written one- or two-step instructions. Deal with standardized situations with only one or two, very occasional, variables entering.	Perform simple adding and substracting.	Comprehension and expression of a level to —Sign name and understand what is being signed. —Read simple materials, such as lists, addresses and safety warnings. —Keep very simple production records.
1	Apply common sense understanding to carry out very simple instructions given orally or by demonstration. No variables.	None	No speaking, reading, or writing required.

Figure B3. Sample data sheet

SAMPLE DATA SHEET

FUNCTIONAL OCCUPATIONAL CLASSIFICATION PROJECT

DATA SHEET

(Physical Capacities & Working Conditions)

Title: REVERBERATORY-FURNACE OPERATOR. Code: 4–91. 441.

Physical Capacities

1. Strength.............. S L M H V

2. Climb. and Bal.........	
3. Stoop., Kneel..........	X
4. Reach., Handl.........	X
5. Talk., Hear...........	
6. Seeing...............	X

Working Conditions

1. Inside, Outside............... I O B

2. Cold......................	
3. Heat......................	X
4. Wet, Humid................	
5. Noise, Vibr...............	X
6. Hazards..................	X
7. Fumes, Dust..............	X

Comments: Physical Demands Form, 1946, same job; Job Description 1944, same job; Volume Job Descriptions for Job Foundries, 1948.

Reviewer: ....

1. Encircle the appropriate symbol for STRENGTH and for INSIDE-OUTSIDE for every job.
2. Mark an "X" in the box alongside all other factors that are significant.

Appendix 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.

Intragenerational data

First, we downloaded the census links available from the Census Linking Project (Abramitzky et al. 2020). 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. We 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 (2021), 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
   - Whether one is foreign-born.

(3) Based on the probit coefficient, we calculate the probability of being linked, $\hat{p}$. Figure X1 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 17,XXX,XXX individuals.

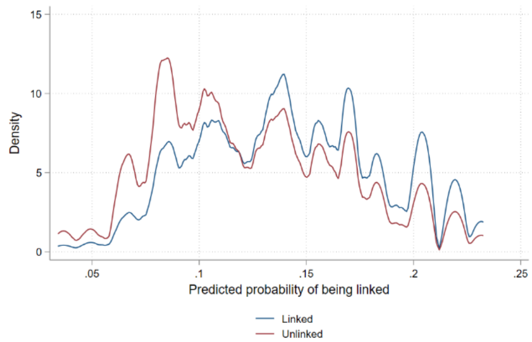
Intergenerational data.

The intergenerational data are from Ward (2021), 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 25-55 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.

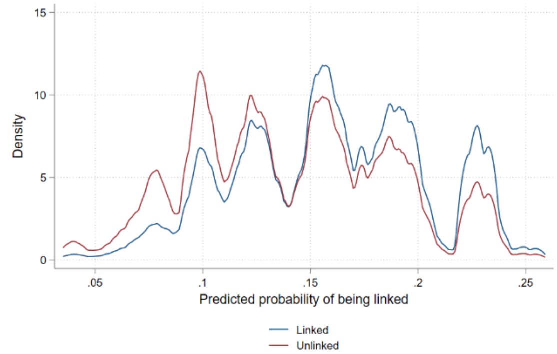
See Online Appendix X of Ward (2021) for details on representativeness of the intergenerational sample.

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

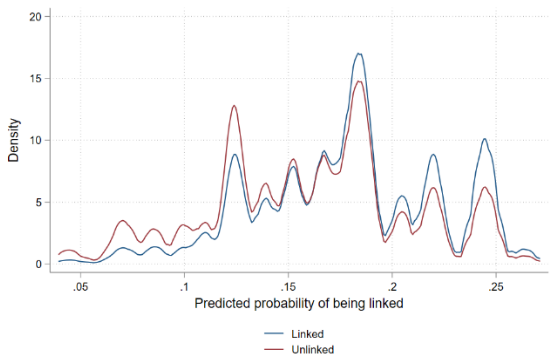
Panel A. 1900-1910 Census



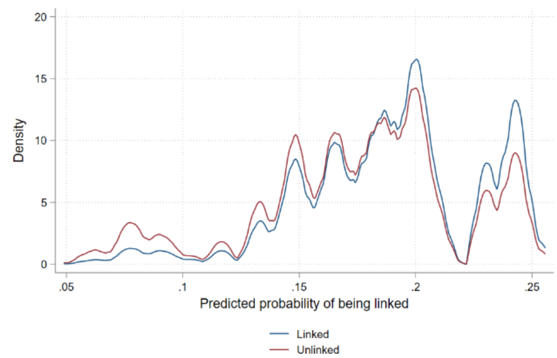
Panel B. 1910-1920 Census



Panel C. 1920-1930 Census



Panel D. 1930-1940 Census



Notes: These figures plot the densities of the predicted probabilities $\hat{p}$ 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	Weighted	Population	Linked (1910-1920) Unweighted	Weighted
Black	0.090	0.044	0.093	0.090	0.039	0.092
	(0.287)	(0.205)	(0.290)	(0.286)	(0.195)	(0.289)
Age	39.494	40.057	39.706	39.849	39.890	39.948
	(7.883)	(7.980)	(7.910)	(7.825)	(7.908)	(7.862)
Northeast	0.298	0.275	0.291	0.296	0.268	0.290
	(0.457)	(0.447)	(0.454)	(0.457)	(0.443)	(0.454)
Midwest	0.331	0.400	0.330	0.332	0.394	0.331
	(0.470)	(0.490)	(0.470)	(0.471)	(0.489)	(0.470)
South	0.267	0.230	0.276	0.270	0.225	0.279
	(0.442)	(0.421)	(0.447)	(0.444)	(0.418)	(0.448)
West	0.104	0.095	0.102	0.101	0.112	0.100
	(0.306)	(0.293)	(0.303)	(0.302)	(0.316)	(0.300)
Migrant	0.478	0.601	0.483	0.497	0.613	0.499
	(0.500)	(0.490)	(0.500)	(0.500)	(0.487)	(0.500)
White Collar	0.156	0.193	0.159	0.159	0.194	0.161
	(0.363)	(0.395)	(0.365)	(0.365)	(0.396)	(0.368)
Farmer	0.226	0.282	0.229	0.201	0.245	0.203
	(0.418)	(0.450)	(0.420)	(0.400)	(0.430)	(0.402)
Unskilled	0.207	0.142	0.201	0.181	0.125	0.177
	(0.405)	(0.349)	(0.401)	(0.385)	(0.331)	(0.382)
Skilled	0.225	0.204	0.223	0.246	0.224	0.244
	(0.418)	(0.403)	(0.417)	(0.430)	(0.417)	(0.429)
Observations	16,506,501	2,404,341	2,404,341	19,340,363	3,271,896	3,271,896

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)

		Linked (1920-1930)			Linked(1930-1940)	
	Population	Unweighted	Weighted	Population	Unweighted	Weighted
Black	0.090	0.036	0.091	0.088	0.035	0.088
	(0.287)	(0.185)	(0.288)	(0.283)	(0.185)	(0.283)
Age	40.225	40.263	40.291	40.485	40.462	40.495
	(7.834)	(7.865)	(7.863)	(7.989)	(7.967)	(7.987)
Northeast	0.294	0.268	0.290	0.288	0.266	0.287
	(0.456)	(0.443)	(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	0.212	0.275	0.285	0.217	0.287
	(0.444)	(0.409)	(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	0.515	0.612	0.515	0.583	0.630	0.582
	(0.500)	(0.487)	(0.500)	(0.493)	(0.483)	(0.493)
White Collar	0.206	0.245	0.208	0.271	0.305	0.273
	(0.404)	(0.430)	(0.406)	(0.445)	(0.461)	(0.445)
Farmer	0.154	0.178	0.154	0.122	0.136	0.121
	(0.361)	(0.382)	(0.361)	(0.327)	(0.342)	(0.326)
Unskilled	0.195	0.142	0.193	0.219	0.176	0.218
	(0.396)	(0.349)	(0.394)	(0.413)	(0.381)	(0.413)
Skilled	0.257	0.251	0.256	0.332	0.342	0.332
	(0.437)	(0.433)	(0.437)	(0.471)	(0.474)	(0.471)
Observations	22,687,570	4,443,807	4,443,807	25,038,344	5,441,882	5,441,882

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.

Appendix D. Details on the construction of occupational income

We compare estimates of task persistence to estimates of occupational income persistence. In this Appendix, we describe how we create the measure of occupational income. Broadly, we follow the method of Collins and Wanamaker (2022), but do not adjust for within occupational differences by race or region of residence.

First, we use Black and white 25-55 year olds who are observed in the 1940 Census (Ruggles et al. 2021). We keep only those who hold an occupation, as measured by the IPUMS code *occ1950*. For wage workers who have a top-coded wage income of 5,000, we multiply it by 1.4 (Goldin and Margo 1992). Since the 1940 Census does not include business or farm income, we need to impute income for self-employed workers in 1940. To do so, we use information from the 1960 Census. Specifically, we calculate the ratio of total income for self-employed workers to total income for wage workers by occupation in the 1960 Census. We impute the income for self-employed workers by occupation by multiplying the mean wage income for wage workers by this ratio.

For farmers and farm laborers, we additionally adjust their income upwards to reflect perquisites in 1940. Since we do not have farmer income in 1940, we must again use information from the 1960 Census. We first multiply total 1960 income for farmers by 1.35, and by 1.19 for farm laborers, to take 1960 perquisites into account (Collins and Wanamaker 2022). This gives us the ratio of farmer to farm laborer income (inclusive of perquisites), which we apply to 1940. To apply this ratio to the 1940 Census, we first boost farm laborer income by 1.26 to reflect the earlier perquisite rate. Then we multiply the farm laborer income (inclusive of the 1940 perquisite rate) with the 1960 ratio to uncover farmer income.

The final occupational income score is the average adjusted income by occupation. The adjusted income includes perquisites and the self-employed imputation. When we merge the score into the data, if there are no matching occ1950 codes in the 1940 Census, we use the average income based on the first digit of the occ1950 code. To provide an idea of this score in comparison to the most commonly used 1950 occupational income score, the correlation between the two is 0.88.