Task Inequality and Racial Mobility over the Long Twentieth Century

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Abstract

We present a new series on the trend of occupational task content between 1900 and 2020. We find that Black workers were concentrated in tasks that declined in demand over the last 120 years, while white workers were concentrated in tasks that increased in demand. We then use longitudinal data to show that transitions across occupational task content were racially biased, where Black workers ended up in occupations with lower-rewarded task content than their white counterparts. This bias also existed across generations in pre-World War II data, but not for post-World War II years. These results suggest that a given task-displacing technological shock will impact Black-white inequality within one generation, but not across generations.

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The fear that technology will automate tasks and lead to mass unemployment is not new. The most recent version of this anxiety concerns the impacts of artificial intelligence, robots, and computers on wage inequality (Autor et al. 2003, Acemoglu and Restrepo 2022). Rates of technological progress were even higher before World War II (Field 2003, Gordon 2010), sparking similar concerns over the mechanization of the tasks of craftsmen and the elimination of demand for farm labor (Autor 2015, Jerome 1934, Gray 2013). As technology evolves, a persistent question is whether the latest advances, and their impact on the nature of work and wage inequality, are different from the past (Mokyr et al. 2015, Autor 2015).

Recent research has documented the persistence of racial inequality throughout American history (Derenoncourt et al. 2022, Margo 2016, Wanamaker 2017). We now understand some of the key institutional drivers of the Black-white wage gap over the course of the 20th century, such as changing school quality and minimum wages, but less is known about the role of technology and the changing demand for tasks.[2] Dicandia 2022 and Hurst et al 2021 argue that Black-white differences in tasks help to explain racial wage inequality since 1960, but the importance for the long-run gap remains unclear. Furthermore, key to understanding the impact of task-biased technologies is how workers *transition* to occupations with different task specializations.[3] If barriers in the labor market cause transitions away from tasks to vary by race, then a given technological shock will influence long-run Black-white gaps. Moreover, transitions may differ across generations, as identified in the income mobility literature (Chetty et al. 2020, Collins and Wanamaker 2022). Yet, the small literature on Black-white differences in tasks primarily examines cross-sectional rather than longitudinal data that tracks workers over the lifecycle or across generations.

To understand long-run changes in task content and racial inequality over the past century, we first develop a new long-run series of occupational task content between 1900 and 2020. We focus on four key tasks that describe the nature of work—routine manual, physical, non-routine analytical, and communication—using descriptions of task content from the *Dictionary of Occupational Titles* (DOT). We develop measures using ratings of over 4,000 jobs from 1939 and 1949 in the earliest DOT

[2] For recent work on the institutional drivers of Black-white wage gaps, see Carruthers and Wanamaker (2017) on school quality, Derenoncourt and Montialoux (2021) on minimum wages, Aneja and Avenancio-Leon (2019) on political power, and Bayer and Charles (2018) on mass incarceration.

[3] Acemoglu and Restrepo (2022) estimate the relationship between task displacement and between-group inequality when collapsing data into demographic groups by race/ethnicity (White, Black, Asian, Hispanic, other), gender, educational attainment, age, and nativity. Task data on routineness are used to identify which occupations are subject to task displacement. When using 1980-2016 data, they estimate that 50 to 70 percent of changes in the wage structure between groups can be attributed to task displacement. Our paper highlights that Black and white workers have different transitions to new work within the lifecycle.

manuals (Gray 2013), and then combine these with later versions of the DOT more familiar in the economics literature (Autor et al. 2003).[4] After merging data on task content by occupation to 1900-2019 cross-sectional census data, we then measure differences in occupational task content between Black and white workers, which captures each group's relative exposure to long-run changes in demand for tasks. Finally, we combine these task measures with longitudinal data over the 20th century to measure whether there are racial biases in task transitions.

Using these data, we document that one of the most important trends is the decline of *physical* tasks, which involve strength, pushing, reaching, or climbing. This finding is consistent with Kogan et al. (2022), who find that physically intensive occupations have been the most exposed to technological advance since 1850. Using wage data from 1940-2019, we show that physical tasks were consistently at the bottom of the distribution, such that declining physical jobs helped push individuals into higher-wage occupations. In contrast to a decline in occupations with physical tasks, there has been a long-run increase in demand for occupations with analytical and communication tasks. These tasks were at the upper end of the wage distribution throughout the 20th century.

We also measure the long-run change in demand for routine-manual tasks, which have been of significant interest due to the hollowing-out of the wage distribution since the 1980s (Autor et al 2003). Over the 20th century, routine manual tasks saw their relative demand rise and then fall. At the same time, the aggregate economy was shifting toward higher-wage jobs, a result that is consistent with Katz and Margo's (2014) long-run examination of occupation categories. Despite the similarity of these episodes of technological change in altering tasks, we find that the most rapid periods of changes in task content were during mass mobilization decades surrounding World War I and World War II (the 1910s and 1940s). The slowest periods occurred during severe interruptions to growth: during the 1930s, and the 2000s. Besides these macroeconomic shocks, the early 20th century does not appear to have had faster changes in aggregate task content than in recent decades.

Turning to trend in tasks by race, we find that racial task gaps were wide in the early 1900s: Black workers were more likely to do physical tasks and less likely to do analytic, routine-manual and communication jobs. Based on these gaps, Black workers were relatively exposed to long-run declines

[4] 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. 2022). We crosswalk our ratings to census occupational codes and percentile rank each occupation based on their physical, routine manual, non-routine analytic, and communication task usage, each indexed to the 1950 census distribution. This process yields an updating measure of task content for a consistent set of occupational categories for a wider range of tasks over a longer window than other methods.

in demand (physical tasks), and less exposed to long-run increases in demand (analytic and communication tasks). However, racial gaps were not constant over time: Black-white task gaps stagnated between 1900 and 1940, converged significantly between 1940 and 1980, and then stalled again since 1980, which mirrors the convergence trends in racial income gaps (Jacome et al 2021). Out of the four tasks we focus on, only the gap in routine-manual tasks completely converged and there remain gaps in physical, analytical and communication tasks. There are several forces that could have contributed to rapid convergence of Black-white task gaps between 1940 and 1980, but it appears that the decline in low-rewarded physical tasks helped push Black workers into occupations with higher-rewarded routine-manual, communication, and analytical tasks.

Given that Black workers were concentrated in occupations that were exposed to long-run declines in demand, we then analyze Black-white differences in task transitions using longitudinal data. To measure differences in task transitions, we adopt the approach used in the intergenerational mobility literature by regressing the current task content percentile rank on a prior percentile rank and an indicator variable for being Black (Collins and Wanamaker 2022, Jacome et al. 2021). We create this measure when tracking men across the lifecycle, where we compare task ranks ten years apart; we also create this measure across generations, where we compare the son's and father's task content. For the early 20th century, we use linked data across the 1900-1940 complete-count censuses; for modern data, we use the Panel Study of Income Dynamics (PSID) for 1968-2019.

We estimate large racial gaps in task mobility within the life cycle where, conditional on initial task content, Black and white workers end up in occupations with different task content. Specifically, we find that Black males are more likely to end in occupations that require intensive use of physical tasks, and less likely to do analytical and communication tasks. These results suggest that the convergence of racial gaps in task content across the last 120 years has been much slower than we might have observed in the absence of bias. However, a comparison of racial gaps in task mobility by decade suggests that racial bias has declined over time. For example, we do not find a racial bias for routine-manual task content since 1990, such that Black and white workers end up in similarly ranked routine-manual jobs ten years later. However, there remains a racial bias for the highest and lowest paid tasks even for the 1990-2010 period.

While there remains racial bias for mobility within a generation, we estimate that racial bias across generations has narrowed substantially. For historical census data, we find that there were sizeable intergenerational gaps where, conditional on the father's task content, Black sons ended up doing lower-rewarded tasks relative to white sons. Black-white intergenerational gaps narrowed during the civil rights movement, but there is some evidence that this convergence stalled out after 1980.

There are two limitations to our approach. The most important limitation is that the trend in task content is primarily based on across-occupation shifts in tasks rather than within-occupation changes. Within-occupation changes in tasks and new jobs have certainly been identified (Autor et al 2022, Atalay et al. 2020), and we can account for changing measures based on different editions of the DOT between 1939 and 1977. However, there is evidence that we are accurately capturing trends in the early 20th Century since there is stability in many job descriptions—for example, those from the 1939 DOT are similar to those in a 1918 US Army publication (Gray 2013, Swan 1918). A second limitation is that, due to limited wage data prior to 1940, we are unable to explicitly link changes in task measures to changes in wage inequality before that census so we cannot fully compare our results to the research on modern automation (Autor et al. 2003, Acemoglu and Restrepo 2021). In contrast to the decline of middle-income jobs today, we find a decline in the share of occupations with low-premium tasks (physical) and an increase for high-premium tasks (analytic and communication), which reflects a rightward shift in the wage distribution.

Our study contributes to both the growing literature on the nature of work and the impact of technological change, using the lens of workplace tasks, and the literature on racial gaps in outcomes, providing a longer run perspective which each of these bodies of research mostly lacked until now. We thus capture task changes driven by the previously examined specific cases such as electrification 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). Like related research by Katz and Margo (2014) on broad occupations, Michaels et al (2019) on urbanization's role in interactive tasks development, Autor et al (2021) on post-1940 employment in new work, and Kogan et al (2022) on historical patent descriptions and recent earnings, we find evidence of a shift out of physical work and into communication-based work in the long-run in our dataset. We contribute not just a more comprehensive depiction of task employment over the past 120 years, but also measure whether the *rate* of task changes evolved over time, yielding a new understanding of the timing of the rise of modern work. By covering four major task quantities and earnings for a long time frame, this paper provides a unified analysis of tasks from the structural transition out of agriculture and subsequent urbanization (e.g. Gaggl et al 2021) through the invention of the computer or the rise of the services sector whose impacts have been identified post-1960 (Autor et al 2003, Autor and Dorn 2013).

The paper also highlights that the shifts just described began in 1900 only for white workers, and that the shift to modern work for Black men began only from about 1950. Task data has been used to analyze racial gaps since 1960, either emphasizing different task premia across Black and white workers (Hurst et al. 2021) or differences in employment shares across tasks (Dicandia 2021), providing intuition behind differences in current racial differences in automation exposure (Lerch 2022, Aizer et al). We present novel information on long-run racial task gap trends before that period and use those to inform the racial income gap debate which has previously lacked a task perspective (Aneja and Avenancio-Leon, 2019, Bayer and Charles, 2018, Collins and Wanamaker 2022, Derenoncourt and Montialoux 2021, Derenoncourt et al. 2022, Margo 2016). Specifically, we emphasize that Black workers remain more exposed to task displacement shocks due ot hieghteind probabilities of being in routine manual and physical jobs, but that the nature of this persistence has swung from being an intergenerational process to one occurring within workers' own lifetimes.

Another key contribution is to examine how Black and white tasks differ not just in the cross-section, in longitudinal or linked data. Our use of longitudinal data relates to the small literature that have used modern-day panel data to relate task content across the lifecycle (Cortes 2018, Ross 2017 Yamaguchi…); our contribution is to measure differences across race, which has not been examined before. Not only do we extend this literature by comparing historical linked data to modern data, we also contribute by further estimating across-generation mobility. All these additions are related to the literature on long-run measures of intergenerational economic mobility, by race, which has only recently started to include Black men (Collins and Wanamaker 2022, Jácome et al. 2022, Ward 2023). Our results suggest that there are barriers in the labor market such that Black and white workers do not transition in a similar way

2. Measuring Task Mobility in the Long Run

2.1 Analytical framework

For the purposes of this analysis, we follow Acemoglu and Autor (2011) and define a task as an aspect of a job. Each job, then, is a bundle of tasks depending on the firm's production function. Changes in technology alter the need for labor to perform each task, inducing shifts in the bundle of tasks within an occupation as well as changes in labor demand across occupations. Innovation, therefore, affects both the quantities and returns to each task, depending on whether it is a complement or substitute to the new technology. As capital replaces labor in the performance of a task, workers utilizing that task face a reduction in labor demand. To the extent that these technology shocks are economy-wide, as in the case of a general-purpose technology, displaced workers may experience prolonged difficulty relocating into another type of job.

We focus on four major task definitions, further explained in Section 2.2, to track these effects in a relatively reduced-form way over the past 120 years. Because our analysis is long-run, we update our task definitions over time for each occupation. Then, we analyze task prices over time to quantify the income convergence deriving from shifts in the income distribution over time, such as through "hollowing out" (Autor et al 2003). Finally, we examine the degree to which workers adjust their tasks over time and over generations to provide new evidence on the persistence of these sorts of labor demand changes.

Given our focus on racial disparities in the long run, it is important to take into account both technologically driven shocks affecting the entire labor market and changes in racial discrimination which might shift relative demand for Black and white workers within occupations (Bayer and Charles 2018). By mapping workers' occupations and incomes to historically accurate task intensities, we summarize changes in workers' wages and on-the-job skill requirements which are flexible with respect to the evolution of each of these two influences over the past 120 years. Comparisons of these task prices and quantities, reflect the similarity, or lack thereof, between Black and white workers' places in the labor income distribution, perhaps due to barriers to entry. Then, we examine task persistence by race to examine whether Black and white workers transition similarly when exposed to a labor demand shock.

2.2 Occupational Task Definitions

Our paper examines the long-run evolution of occupational-based task measures and how they differ across Black and white workers. Descriptions of tasks required in an occupation were created during the Great Depression to help match workers to jobs and address long-term unemployment. We use data from the original *Dictionary of Occupational Titles* (DOT), (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). The data, first compiled in Gray (2013), estimate worker traits required for different jobs, such as a worker's aptitudes (e.g., verbal skill, motor coordinate, finger dexterity), temperament (e.g., situations involving repetition, working in isolation, or dealing with people), and physical capabilities (e.g., amount of lifting or climbing). Ratings are sometimes on a one to five scale, such as the variable for strength separating work into sedentary, light, medium, heavy or very heavy.[5] Other variables are dichotomous, such as whether the job involves repetitive tasks or whether dealing with people is a prominent feature of a job.

We create four composite measures that reflect the changes in task content and technology over time: routine manual, non-routine analytic, communication, and physical. These measures allow us to measure the shift away from traditional tasks such as physical strength and factory-style work, towards more cognitive-skill work in the modern period. These measures also allow us to compare to other research on task changes in the modern period. For instance, Autor et al. (2003) highlight the peak and fall of routine-manual jobs since 1960 while Michaels et al. (2019) and Deming (2017) show that communication and social tasks have risen in employment share and task premium.

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. Tool makers, medical technicians, and blacksmiths score highly on this measure. Non-routine analytic averages a measure of the education-level required to do a job, the intensity with which a job involves numerical skills, and whether evaluating situations based on measurable criteria is a key feature of a job. Occupations associated with intensive use of non-routine analytic work are chemists, inspectors, and engineers. 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. High communication intensity jobs include insurance agents, ticket agents, and store managers. Finally, physical tasks are the average of how much strength is required in a job and requirements for climbing, reaching, and stooping. Plumbers, welders, and baggage handlers are all physically intensive occupations by this measure.

After creating the composite task measures by DOT code, we then map them into 3-digit occupation codes (*occ1950*) following the process in Gray (2013) and create an average task measure by occupation. We then merge these measures into a 1% sample of the 1950 US Census by occupation

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[5] For example, the *strength* variable describes the level of physical strength needed in an occupation on a scale of one to five where five includes the heaviest-lifting occupations. 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 unimportant is a machinist.

code (Ruggles et al. 2022).[6] The four tasks are measured on different ordinal scales but we wish to make comparisons across measures, so we percentile rank each occupation based on their position in the 1950 Census -- this means that any changes in the task variables are relative to the 1950 baseline.[7]

To describe modern task content, we follow the modern-day literature and use information from the 1977 DOT (Autor et al. 2003, Autor and Price, 2013).[8] There was a revision to the 1977 DOT released in 1991, but updates were limited such that the correlation of task measures across versions was high (Atalay et al. 2020). We compute the same composite task measures with the 1977 DOT, which we also merge to the 1950 Census to percentile rank them. Based on these measures, we do find some intra-occupational change: the correlation of task content by occupation is about 0.78-0.83 across versions (Figure A3). Figure A4 demonstrates the implications of using a historical DOT are particularly important for capturing the shift in routine manual work overtime. Hence, for our main results, we will use the historical DOT for the period between 1900 and 1950, a weighted average of the two measures in 1960, and then use the 1977 DOT for census years 1970 onwards.

An important thing to note is that the data include ratings for farmers, who represented a large share of the economy in the early 20th century (though declining from 20% in 1900 to 10% in 1940). Therefore, our methodology allows us to capture the structural shift away from agriculture. In the early DOTs, farmers were ranked at the 67-70th percentile in physical and routine manual tasks, as well as for non-routine analytic. 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.

2.3 Historical Occupation Transitions

After creating task content measures at the occupational level (*occ1950),* we merge them to cross-sectional census data between 1900 and 2019 using data from IPUMS (Ruggles et al. 2021, Ruggles et al. 2022). 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

[6] The sample is limited to 18–55-year-olds with an occupation.
[7] The normalization was conducted such that, in 1950, a value of 0.34 indicates that 34% of the population in 1950 worked in an occupation which was equally or less intensive in the use of that task.
[8] The update to the DOT measures, O*NET, has been used elsewhere (e.g., Peri and Sparber 2009). However, Autor (2013) notes that the O*NET measures are more complex than DOT measures such that it is difficult to merge measures over time, which is our objective.

measure task content for the entire occupational distribution, so we place limited restrictions on the sample: we include all individuals of prime age (18-55) who listed an occupation. We follow Alston and Ferrie (2004) and re-code Black southern farmers as laborers since most Black farmers were sharecroppers whose tasks were more similar to laborers than farmers.

In addition to the cross-sectional census data, we use longitudinal data to measure how occupational task content is stable across the lifecycle or across generations. Tracking individuals over time is possible in historical censuses by searching for combinations of name, birthplace, and birth year, characteristics which should be stable across censuses. Note that females are not included in the data because their surnames often change after marriage. We use the links created by the Census Linking Project (Abramitzky et al. 2021), which are then merged into full-count data from IPUMS (Ruggles et al. 2022). For the intragenerational analysis, we limit the sample to 18-55-year-old males in the 1900-1930 US censuses, and then link them forward to the next decennial census. For intergenerational data, we link 0-14-year-old sons' parental status forward 20, 30, or 40 years to their adult labor market outcomes in the 1920-1940 US censuses.[9] All of these data are weighted for representativeness using inverse probability weights (Bailey et al. 2020). Full details on linking, weighting and representativeness are given in Appendix C.

2.4 Mid-Century Occupational Data

In order to investigate task persistence in the period between the historical census and the PSID, we turn to the Occupational Changes in a Generation (OCG) survey (Blau et al 1994). These data were collected in 1962 and 1973 by the Census Bureau as a supplement to the March Current Population Survey. Respondents were asked about their own occupation and what type of occupation their father held when they were 16 years old, facilitating an intergenerational task analysis. We follow Collins and Wanamaker (2021) and restrict the sample to men who report living with a parent at 16. All other sample selections (ages 18-55, black or white, with an occupation) are consistent with our other analyses.

2.5 Modern Occupation Transitions

We use longitudinal data from the Panel Study of Income Dynamics (1968-2019) to compare mobility estimates those constructed with linked historical data (1900-1940). We create two different

[9] These are the same data as in Ward (2023). Ward (2023) takes 0-14-year-old children in the 1850-1920 censuses and uses the CLP links to observations in censuses 20, 30, and 40 years onwards, keeping those between 25 and 55 years of age in the latter wave. Fathers are also linked to a second observation 10 years earlier or later. Conservative links are used (exact first and last name strings that are unique within plus/minus 2 years of birth) to address issues of false positives (Bailey et al. 2020). The data is also weighted to be representative of the underlying population using inverse proportional weights.

datasets from the PSID: an intragenerational dataset that tracks males over their lifecycle, and an intergenerational dataset that compares fathers and sons' occupational standing as adults. We aim to make the PSID sample as comparable as possible to the historical data: for example, we limit the PSID to the same age ranges and only keep males. For the intragenerational dataset, we compare occupations ten years apart, similar to the historical analyses. For the intergenerational PSID dataset, we use the sample constructed by Ward (2023), where the son's occupation is taken at the mid-point of the lifecycle (closest to age 40). Further, we acquire two different father occupations, usually at ten years apart, in order to address potential measurement error in task measures. Occupations in the PSID are recorded at a 3-digit level, which the same specificity as the historical data. We crosswalk PSID occupations to 1950 occupation codes and then bring in the task measures based on these codes (note that we only use task measures from the 1977 DOT in the PSID). We also weight the PSID to be representative of the population, since some in the literature have argued that the PSID has become less representative over time due to selective attrition (Schoeni and Wiemers 2015).[10]

The 1968-2019 PSID dataset is not fully comparable to the linked historical data for two reasons. First, the historical censuses likely recorded occupations with greater error, perhaps due to less careful enumerators (Ward 2023). Second, since links across historical censuses are not perfect, there can be false matches (Bailey et al. 2020). Both of these issues will bias estimates toward greater mobility in the linked censuses relative to the PSID. One way to address these errors are to use multiple reports of the father's task content, or an IV approach to correct for measurement error, but these methods only work for intergenerational mobility estimate and not intragenerational mobility estimates. Therefore we focus more on the *gap* in mobility across Black and white individuals, rather than the absolute level.

3. Long-Run Trends in Tasks

3.1 Aggregate Task Content

Mapping workers' occupations to task content allows us to summarize the overall impact of 120 years of labor demand shifts. Figure 1A shows the broad trends in the four summary task

[10] We pool the PSID with the 1980-2020 CPS-ASEC. We then use a probit model to determine which observable characteristics are associated with appearing in the PSID relative to the CPS-ASEC. This method is the same suggested by Bailey et al. (2019). The observable characteristics are age (in 10-year bins), race (Black or white), region of residence interacted with Black, occupational category interacted with Black, (white collar, farmer, unskilled or skilled). All of these are interacted with five-year dummy variables in case selection into the PSID varies over time. We winsorize weights at the 5th and 95th percentile to reduce outliers biasing results. This weighting method is the same as that in Ward (2023), who shows that estimates of intergenerational mobility are similar when using these weights or PSID-provided weights.

measures, looking at data for all workers in each year—communication, routine manual, physical, and non-routine analytic. The average occupation in 1900 was near the 60th percentile for the physical task measure (which is indexed relative to the 1950 census), which then declined to near the 30th percentile by 2020. A long-run decline in occupations specialized in physical tasks is consistent with new innovations reducing labor demand as reflected in patent data (Kogan et al., 2021). Offsetting this decline was a steady rise in communication and non-routine analytic tasks, reflecting increasing urbanization and skill-biased technological change (Michaels et al 2019, Deming 2017, Katz and Goldin 2008, Katz and Goldin 1998, Autor et al 2020). We show that this long-run pattern is not solely driven by the structural shift away from agriculture since we also find a decline in physical task intensity if we drop farmers and farm laborers (Figure A1). We find that these stylized facts are geographically broad-based and hold within all census regions (North, South, Midwest and West) in Figure A6. The trends we find in workers' employment experience thus reflect innovation-based shifts in labor demand over the long run rather than regional shifts in economic activity and population.

By extending routine manual task intensities back to 1900, we show that there was a similar – albeit shallower – rise and fall between 1900 and 1940 as studied in the modern "hollowing out" episode. First, there was a small rise in routine manual task intensity between 1900 and 1920, as steam-powered machinery helped to replace tasks performed by hand (Atack et al. 2019, Atack et al. 2022). However, the increase is not large; it may be that a stronger increase in routine manual occupations occurred earlier in the 19th century when steam first started to power machinery and operatives began replacing artisans (Atack et al. 2008, Goldin and Sokoloff 1982, Katz and Margo 2014). After a rise in routine-manual tasks between 1900 and 1920, there was a fall between 1920 and 1940. Interestingly, during this 1920-1940 period, many expressed concern that mass unemployment in part reflected industrial mechanization (Jerome 1934); however, we document a fall in routine manual labor. The fall between 1920 and 1940 was about 4 points, which contrasts with a 9-point drop in the index from 51 to 42 between 1970 and 2020. The early reversal of routine-manual intensity 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.[11] 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 for the period.

[11] See Appendix A for these results.

To compare the speed of task changes more clearly across the long 20th century, Figure 1B plots the decadal change in task input. First, we note that recent shifts in task content are by no means unusual regardless of the specific task considered. The current era of technological advance, in fact, is similar to the early 20th century as modern tasks rose over several decades prior to the postwar computer revolution and physical work declined prior to the 1930s. The most rapid shifts in task input occurred during the 1940-1950 decade as physical work fell and the other three measure rose by roughly five ranks. While differences across regions accelerated after World War II (e.g. (Wright 1986)), we also document rapid shifts in task content during the 1940s within census region (Figure A6.[12] Our measures include females, whose labor force participation changed considerably over the 120 years, but we also find an increase when limiting the sample to males (Figure A11). A similar rapid shift in task content occurred during the 1910s. In contrast to these fast rates of change, the slowest rates occurred during the Great Depression (1930-1940) and in the decade of the Great Recession (2000-2010), complementing work on the latter period by Beaudry et al (2016). These results may suggest that macroeconomic shocks halt task transitions in the aggregate economy, even while large technological shifts within certain sectors alter the nature of work (Gray 2013, Jaimovich and Siu 2020).

3.2 Task Returns Over Time

Next, we compare the shift in the task content of American labor to trends in the wage returns to each task. To examine this question, we estimate task premia using the 1940 census, the earliest date where this exercise is possible, and for each cross section through the 2021 ACS. Specifically, we regress the log of weekly wages on the percentile rank of task intensity, a quadratic in age, and years of educational attainment for male 30-45-year-old wage workers using the following equation.[13]

$$ln(WeeklyWage_i) = \beta_0 + \beta_1 Rank(Task_i) + \beta_2 Educ_i + \beta_3 A_i + \beta_4 A_i^2 + \varepsilon_i \qquad (1)$$

We estimate the regression for each census wage.[14] Finally, note that these results do not include business or farm income due to data limitations in the 1940 census.

[12] See Jaworski (2017) for an argument that World War II mobilization does not explanation industrialization in the American South.

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

[14] We find 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.

Figure 2A compares the returns to each task in each census. Consistently, we see the highest returns for communication and non-routine analytic-oriented work, as in the modern labor market (Peri and Sparber 2009, Deming 2017). After some declines during the Great Compression between 1940 and 1950, there are consistent rises in both series after 1980 such that these tasks have premia roughly equal to their 1940 levels. Physical work's renumeration almost exactly mirrors these higher-paying tasks, with a rise during the 1940s offset by decades of slow declines back to the pre-war level. In contrast, routine manual task premia did not reverse their Great Compression trend, instead they are no longer associated with high incomes, denoted by a positive coefficient. The modern hollowing out period, then, has continued a longer-run pattern of routine manual incomes falling while reversing the convergence in task premia from the 1940s.

Next, 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. Each of our 4 main measures separately aggregates reflects a combination of 21 total tasks. We show that across these finer task intensity variables, there is remarkable stability between 1940 and 2021 in Figure 2B. A simple regression between task premia across years yields an R-square of 0.71. We plot a 45-degree line to clarify which tasks' returns have moved over time. For example, routine manual is to the right of the line, illustrating it was higher paid in 1940 than in 2021. Though we focus in this paper on four summary variables, the changes in returns for individual tasks, such as *reaching* and *direction*, indicate that there are important shifts in the underlying tasks as well. Tasks associated with greater interpersonal interaction like *dealing with people* and *direction, control, planning*, as well as those requiring non-standardized evaluation of situations, like *judgment* rose between 1940 and 2021, clarifying how communication and non-routine analytic intensive work has remained the highest-paying tasks over time.

3.3 Workers' Task Persistence

One 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. As firms substitute capital to perform some tasks, workers become unemployed, so we might expect low levels of persistence. However, high task mobility may also reflect that workers could easily switch between jobs, which would mute negative welfare impacts from innovation-induced falls in relative demand. In this section, we complement longitudinal modern labor data with linked data in the early 20th century, also a time of significant structural and technological change, to estimate how task content persisted not only within one male worker's lifetime, but also over time from father to son.

Looking first at intragenerational changes, we measure task mobility via the rank-rank association across censuses and PSID waves for the same worker:

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

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 changes in the magnitude of the task persistence estimates over time, we compare them to the persistence of the percentile rank of occupational income, which has been used elsewhere due to its availability before 1940 (e.g., Feigenbaum 2018).[15] Figure 3A plots estimates for workers' task persistence over their own lifetimes while Figure 3B displays results for intergenerational task mobility.

Across all of our task measures in Figure 3A, modern lifetime task mobility is lower than it was before World War II. This stands in contrast with the small decline in occupational standing persistence in the literature, indicating that workers' reduced propensities to change task are not strictly equivalent to changes in economic opportunity. Routine manual task persistence is the lowest of the four tasks in the historical and PSID data, both of which have been associated with periods of hollowing out in prior work (Gray 2013; Autor et al 2003). Figure 3A demonstrates that conditional on being in routine manual occupations in the first period, workers transition out of it in the second more than for other tasks. The gap between routine manual persistence and other tasks' lifecycle correlations, however, has remained stable over time. Workers have increased their tendency to remain

[15] While there are a variety of ways to measure occupational income, we use a method similar to Collins and Wanamaker (2021) and report full details in Appendix D. We follow Collins and Wanamaker (2021) in using mean wage income by occupation from the 1940 census, without any adjustment for race or region. While adjusting for within-occupational differences is 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. We also note that this measure is constructed separately from the task intensity data, making them not entirely comparable.

in each task from 1940 to today, but these changes are not specific to the task currently being hollowed out.

3.4 Intergenerational Task Mobility

While workers were somewhat mobile across tasks over time, the above results do not speak to the transmission of labor market experiences across generations. We thus 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. 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 2023). While this method, presented in Figure A8, increases the magnitude of the estimates, it does not alter the qualitative conclusions.

In both time periods, Figure 3B shows that task mobility is higher across generations than within a lifetime, regardless of the task measure. As in Figure 3A, we see persistence has slightly increased over time in non-routine analytic and communication work over time. At the other end of the task return spectrum, physical labor has a marginally lower intergenerational correlation in the PSID compared to the historical censuses. Unlike these largely stable mobility estimates, we see marked reductions in both the occupational income measure (corroborating Ward (2023) and Jacome et al (2022)) and routine manual work. While those working in routine manual jobs are increasingly likely to remain in those jobs, their children have particularly low propensities for this technologically displaced task compared to other types of work. This suggests that task demand shocks have had less impact on socioeconomic positions across generations than within the same generation, especially in the present.

4. A Century of Racial Task Disparities

4.1 Racial Task Content Differences

A key focus of our paper is how task gaps across race changed over the course of the last 120 years. Though the *average* worker's tasks shifted in ways commensurate with technological change, we find that this masks substantial differences by race. Figure 4 plots the difference in task intensity between Black and white workers, with the dashed line conditioning on other labor market characteristics. Positive numbers indicate that the average Black worker has a higher task intensity than the average white worker so that, starting in 1900, it is clear that Black workers held jobs that were more physically demanding than white workers, for example.

Racial disparities in task content have narrowed overall from 1900 to 2019 but this shift was hardly monotonic. Particularly before 1940, we find very little evidence of any sort of convergence, commensurate with high levels of occupational segregation. These labor market frictions took many forms, including white workers' overt intolerance for Black co-workers or supervisors (Dewey 1952, Banks and Whaley 2022, Maloney 1995, Fishback et al 2020). As a result, Black workers were often excluded from unions and sorted into less-protected work, like working in the Ford foundry instead of on the assembly line (Norrell 1986; Foote et al, 2003). This kept Black workers from being promoted up the job ladder to occupations that were more communication or analytic intensive (Sundstrom 1994; Borghans et al 2014). These channels likely generated the stark patterns of task segregation we find through 1940, especially between modern and physical tasks.

Then, after decades of stalled progress towards racial labor market equality, Figure 4 finds partial convergence occurred from 1940 up until 1980 across our four summary measures. In Figure A5, we show that the racial task gap does not wholly close in this period even when factoring in improvements in Black access to educational attainment which workers' ability to qualify for analytically intensive jobs as perceived skill affects workers' potential set of occupations (Autor and Acemoglu 2011, Card and Krueger 1992, Carruthers and Wanamaker 2017).[16] In general, the economy has experienced a shift away from middle-wage routine manual jobs to low-wage service jobs after 1980 (Autor and Dorn 2013). Our results indicate this transition varied by workers' race, indicating potential disparities in exposure to labor demand shocks between Black and white workers.

We find marked differences by race in workers' physical task intensity, despite the sustained long-run decline in demand for physical labor. White workers transitioned toward jobs with fewer physical demands 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 matched the physical content for white workers in 1900 – a 60-year lag. The timing of this decline in Black physical task intensity corresponds to shifts in both Black labor supply and Southern labor demand induced by increases in Black workers' geographic mobility and technological advances in agriculture. Black workers' movement out of the rural South during the Great Migration led to occupational upgrading (usually corresponding in our sample to routine manual tasks) and higher incomes for Black male

[16] Information on human capital is scarce in the 1900-1930 census records, where only the ability to read or write recorded. However, between 1940 and 2019 we can observe educational attainment. Figure 4B shows the trend of the Black-white gap when conditioning not only on educational attainment, but also on age and state of residence. Task gaps are smaller when conditioning on education, but the historical gaps between 1940-1980 did not close by much. Further, gaps remain for analytic, communication and physical jobs today when controlling for education.

workers in this period (Collins and Wanamaker 2014, Boustan 2016, Ward 2021). [17] Then, as labor scarcity increased in the Cotton Belt, so did the incentive for agricultural mechanization, which had been delayed in the South (Hornbeck and Naidu, 2014, Whatley 1985). Included in our physical task measure is whether the job includes reaching or stooping, which were important tasks for Southern farm laborers in the 1939 DOT. Thus, the introduction of the mechanical cotton picker in 1949 and subsequent adoption during the 1950s helped to reduce farm labor and physical work for those remaining in agriculture.[18]

While the gap in physical tasks has narrowed substantially since World War II, there remains a positive gap in 2019 as Black workers are still more likely to work in jobs with greater physical demands. To the extent that modern innovation aims to replace human physical labor, these results reveal the century-long roots of current depictions of relatively high Black exposure to technological change (Mason 2022, Muro et al. 2019, Lerch 2022, Wrigley-Field and Seltzer 2020).

Just as Black workers were concentrated in tasks that declined in demand early in the 20th century, they were less concentrated in tasks that increased in demand. For both communication and non-routine analytic tasks, Black workers were far behind white workers in 1900. As the century progressed and the aggregated share of communication and analytic jobs increased, Black workers were slow to catch up to the average white worker's task intensity. Certainly some of this was due to the prohibition of outright discrimination based on race in 1964 with the passage of the Civil Rights Act. This helped to open jobs in new sectors, e.g. textile production or the public sector (Heckman and Paynor 1989; Aneja and Avenancio-Leon 2019). Over time, taste-based discrimination also appears to have decreased, prompting Black workers' entry to factory work in the 1940s and 1950s, and later, public-facing service employment (Aizer et al. 2020; Ferrara 2022; Hurst et al. 2021). Though the two decades up to 1980 saw some convergence, today, there remains a gap across Black and white workers in both communication and non-routine analytic tasks.

The only task that completely converged in average intensity between white and Black workers over the 20th century is routine manual. Black workers' routineness increased dramatically towards the white rate after 1940 and completely converged by 1980. As is well known, this 1940-1980 period was

[17] Boustan (2010) and Derenoncourt (2022) estimate that the share of land planted in cotton helped to predict out-migration from the South. Displacement of farm labor and sharecroppers occurred earlier, as the Agricultural Adjustment Administration's policies of paying farmers to remove land from production displaced Black workers (Fishback et al. 2006, Whatley 1983).

[18] One contemporary commentator put it: "It was the invention of the cotton gin by Eli Whitney that set the stage of the development of the slave plantation economy. It was not the Civil War, but the tractor and mechanical cotton picker that are freeing the Negros from the plantation economy." (Neal 1953)

one of rapid wage convergence for full-time workers, in part due to significant occupational upgrading for Black workers (Aizer et al. 2020, Margo 2016, Wanamaker 2017). After 1980, both white and Black workers had declines in routineness as computerization and robots automated middle-skill jobs at a fast rate (Autor and Salomons 2018).

4.2 Relative Task Returns By Race

Racial differences in the returns to each task exacerbated the gulf in task quantities by race over time. We re-estimate Equation 1 separately by race and plot the results in Figure 5A. The difference between the white and Black coefficients represents the disparity in income for performing the equivalent intensity of a given task. For instance, the gap between white and Black premia for communication and non-routine analytic work indicates that conditioning on entry into modern work, Black workers earned lower incomes than their white counterparts. These differences fell to near-zero by 1980, before widening slightly between 1990 and 2010 as the return to both tasks increased (Deming 2017). Black workers' returns in both communication and non-routine analytic work have converged to those for white workers in 2020 due to a continued Black worker-specific rise in renumeration in the last decade.

Over the past eighty years, the fall in Black physical task returns has been steady, turning physical labor from a positive premium task for Black men in 1940 into low-paid work. Unlike Black workers, white workers experienced a rise in physical task premia during the 1940s. In comparison to Black task compensation, white physical task returns fell less slowly after 1950 before converging to the Black physical return in 1980. Similarly, we see differences in white and Black workers' relative return to routine manual work in the decades surrounding hollowing out. Unlike white workers, Black workers' returns to routine manual work rose from 1940 to 1960, constituting a reversal of fortune. These racial disparities indicate that Black and white men had different incentives to sort into tasks as both physical and routine manual labor demand fell, all other labor market frictions held constant.

Over time, there has been a decline in the gulf between white and Black workers' wage returns to the same tasks. In Figure 5B, we plot the correlation between white and Black specific task premia for our disaggregated task measures.[19] In 1940, the Black and white premia for the same task were very different; even if racial differences in task quantities were erased, there would still be an income gap between Black and white workers. After 1950 we see successive increases in this correlation,

[19] We plot these detailed race-specific task premia in 1940 and 2021 in Figure A9.

especially in the civil rights era, with near total convergence occurring by 2000. White and Black workers therefore have similar income-based incentives to sort into the same tasks ex ante, making their actual task content especially important for understanding the persistence of racial income gaps.

4.3 Black-White Mobility Gaps Over the Life Cycle

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 tasks. Since white men transitioned to modern tasks much earlier than Black men did on aggregate, we next examine the size of racial task gaps over workers' lifetimes and across generations. To measure such mobility gaps and test this hypothesis, we modify Equation 2 to include an indicator variable for one's race being reported as Black. Each point on a plot, therefore, is the gap between Black and white task persistence where the second observation occurs in time t with the associated 95 percent confidence interval. A positive number indicates Black men's task intensities were more similarly ranked between census waves than white task intensities, implying a lower task mobility estimate for Black men.

First, we focus on the Black-white difference in task persistence over workers' own lifetimes in Figure 6A for our four main task measures. Black men were more likely to persist in physical work between 1900 and 1910, with continued divergence through the start of World War II. In contrast, they were less likely to continue in other tasks, with some closure of the racial persistence gap during the Great Depression. Between 1940, our last historical observation, and 1980, our first PSID observation, the modern task persistence gaps halved. Without additional longitudinal data, however, we cannot rule out that this is a trend which began in 1930. Like the racial income gap, however, these disparities have stalled in recent years. Despite the similarity of Black and white returns for both non-routine analytic and communication work, Black men's intensities of these tasks fall by 10 ranks more than white men.

We see contrasting evidence of continued racial differences in the two tasks most likely to experience reduced demand due to technological advance. There is evidence of total convergence in the PSID for routine manual mobility. After the Black-white gap turned positive between 1940 and 1980, this coefficient has fallen to zero. However, the physical correlation remains higher for Black men than white men, as it has throughout history. The most recent census wave has the same magnitude gap as in 1910, indicating race-specific exposure to physical task demand shocks still exists today. Combined with the continued gap in persistence in technology-complementary work like non-routine analytic and communication-intensive work, we interpret these results as evidence of extant racial disparities in exposure to automation going forward.

4.4 Black-White Mobility Gaps Over Generations

We find that intergenerational mobility differences by race have narrowed substantially over time in Figure 6B. In and before 1940, we find estimates in line with the own lifetime correlation; Black men were far more likely to be in physical work if their fathers were, and far less likely to be in any other task. Though not directly comparable with occupational standing estimates, these differences in task mobility corroborate the lack of upward occupational mobility for Black men over time (Collins and Wanamaker, 2022). Putting the lifetime and intergenerational results together in this historical period indicates that Black fathers' low probabilities of entering and remaining in high-return and modern tasks intensified for the next generation as their sons fell further behind white sons.

We do not see the same compounding of initial differences across generations in the modern period. Beginning with sons' observations in 1960, we document task mobility differences fell towards zero for all of our four tasks. Most of the convergence in intergenerational task mobility occurred in the 1960 and 1970 periods, identified above as the periods associated with both reductions in labor market barriers and convergence in labor market returns. In the decades immediately following World War II, all of the mobility gaps fell in magnitude by roughly ten points, constituting almost all of the progress made in leveling the intergenerational difference in tasks. By 1990, the mobility gap had fallen for all tasks but we find some evidence that this convergence in intergenerational mobility is incomplete.[20]

4.5 Black-White Task Transition Differences

A potential 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 was automated in the early 20th century, and therefore eliminated, then white individuals were expected to end up in a job that is more routine manual than a Black individual in the past. Similarly, if a father's job was automated, then a white child was expected to end up in a more routine-intensive job than a Black child even when in the same initial conditions. Now, if anything, the opposite is true, though the earnings-based differences remain large. and it may be that Black and white workers transition differently to new work. For example, Lerch (2022) estimates that the introduction of industrial robots

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

leads to greater dis-employment for Black workers than white workers. Similarly, Gould (2021) shows that the decline of manufacturing jobs since 1960 led to more negative effects among Black workers than white workers. In future iterations of this paper, we plan to test for these differences over time more this directly.

5. 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 what we think of as modern jobs, characterized by higher level cognitive skills involving communication and analysis. As they left routine and physical work behind, their place was taken by Black workers, whofollowed the same trends a full half-century later. Task prices were relatively stable over time but convergence in race-specific returns only occurred after 1950. Changes in task quantities are key inputs for understanding the evolution of relative wage income over time.

In particular, this paper argues that task mobility, both within and across workers' lifetimes, contributed in meaningful ways to the lingering difference in white and Black men's labor earnings. We find that Black men were more likely to remain in physical tasks than white men and, at the other end of the task compensation spectrum, were less likely to remain in non-routine analytic and communications work than white men both in the early 20th century and today. These within-lifetime task barriers remain larger in the modern context than in the past, though we see evidence of greater intergenerational convergence relative to the past.

Building on previous work that showed substantial income gains for Black men from 1940 onwards, this paper shows that the types of tasks done by Black workers converged to those of whites at the same time. By linking these occupational outcomes to income measures, we show that these shifts contributed to the changes in Black-white labor market outcomes. 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.

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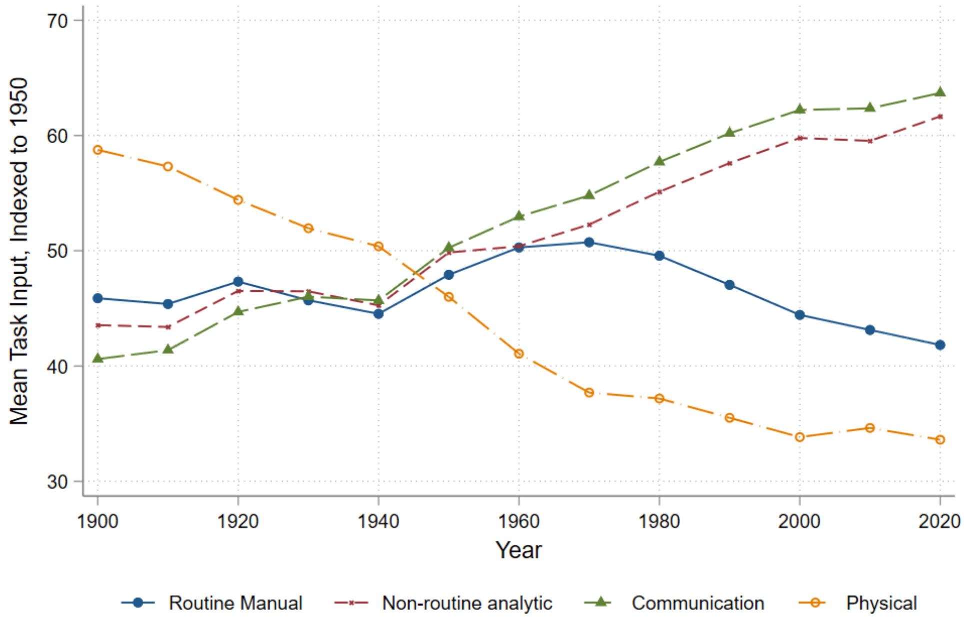
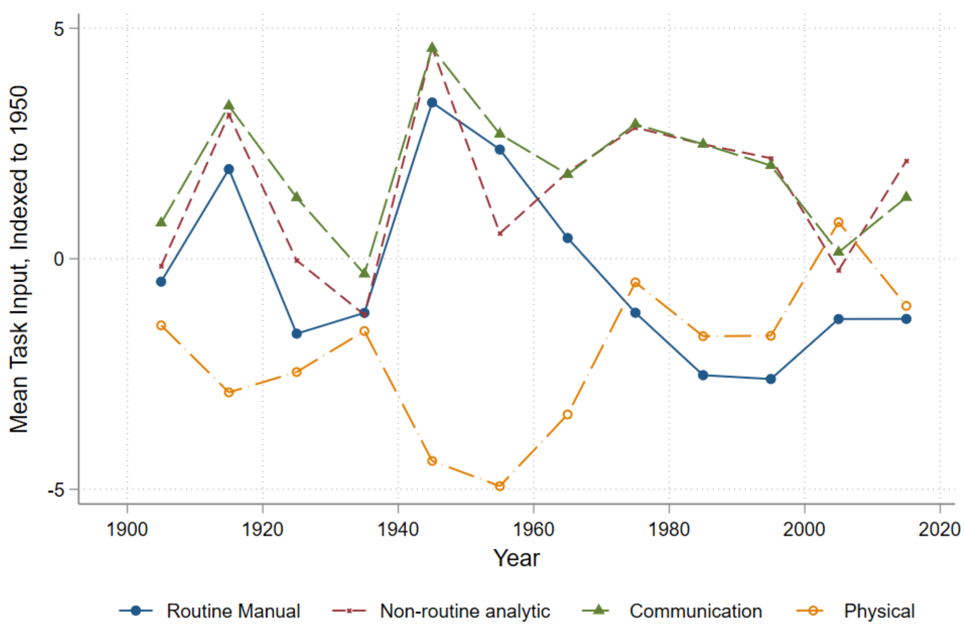
Figure 1. National trends in task content

Panel A: Level of task content



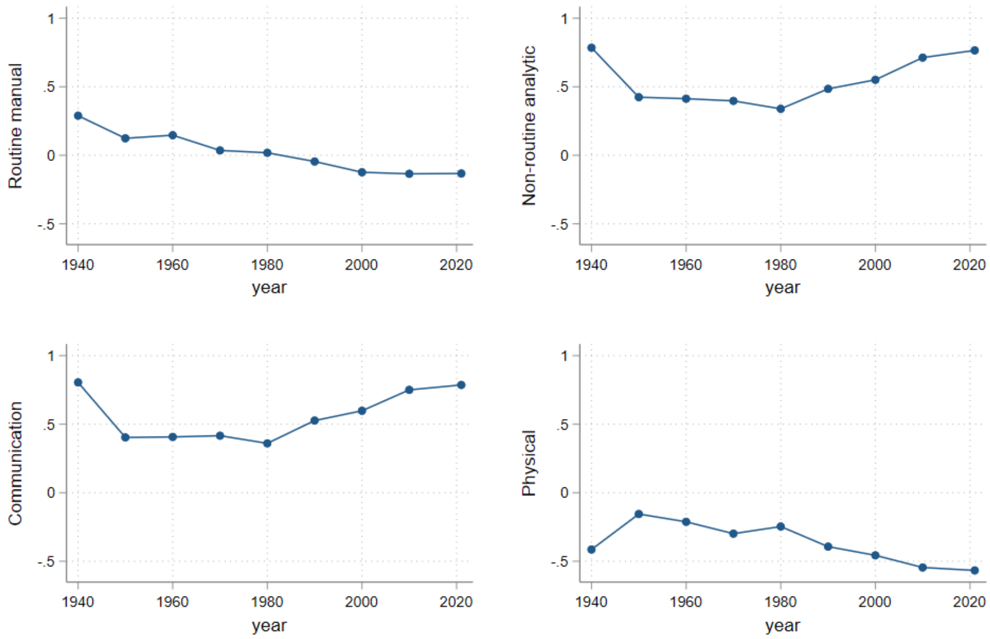
Panel B: Decadal changes in task content



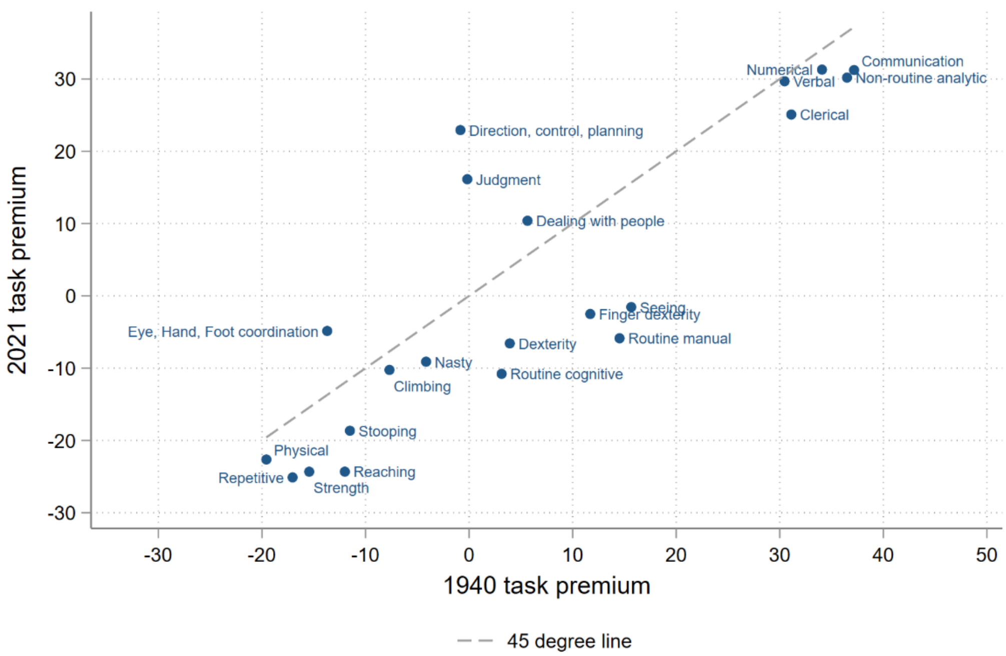
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. Since task content by occupation 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 B6 for task definitions.

Figure 2. Task premia over time

Panel A. Mincerian task premia , 1940—2021

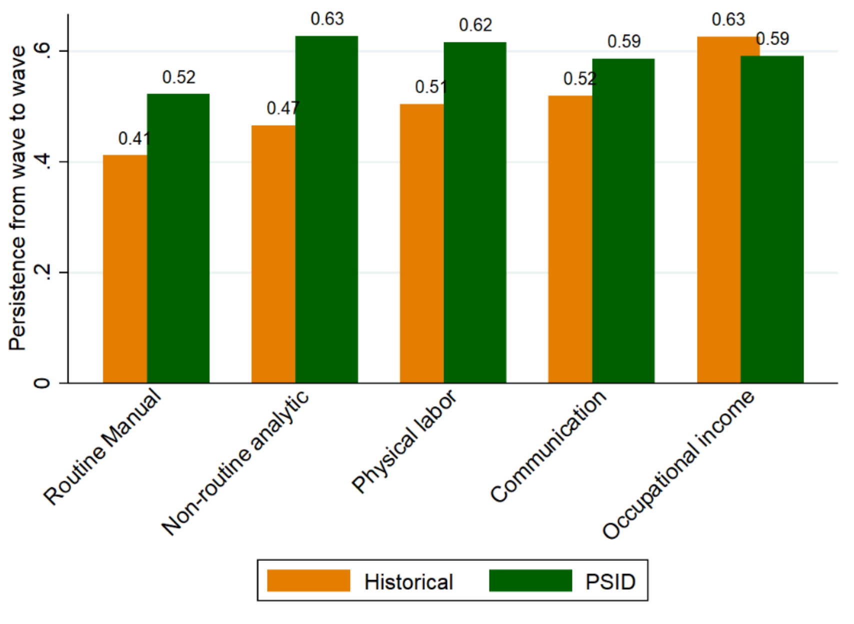


Panel B. Stability of task premia 1940—2021

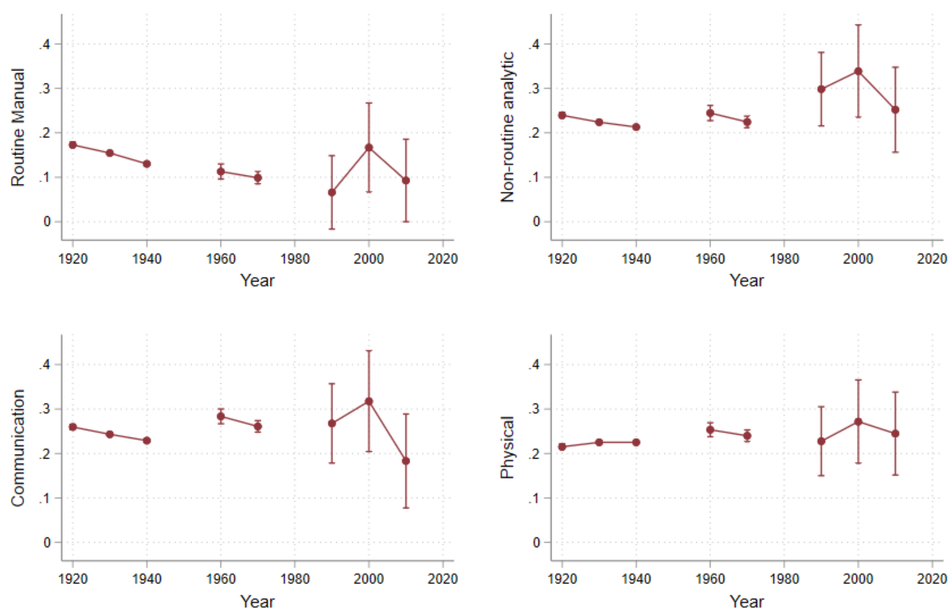


Notes: Data are from the 1940 IPUMS and the 2021 ACS (Ruggles et al. 2021). Sample is 30-45-year-old male wage workers with an occupation. Task premia are estimated by regressing the log of weekly wage income on percentile rank of task, a quadratic in age, and years of education. See Tables B1-B6 for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

Figure 3. Task persistence, then and now
Panel A. Within one generation

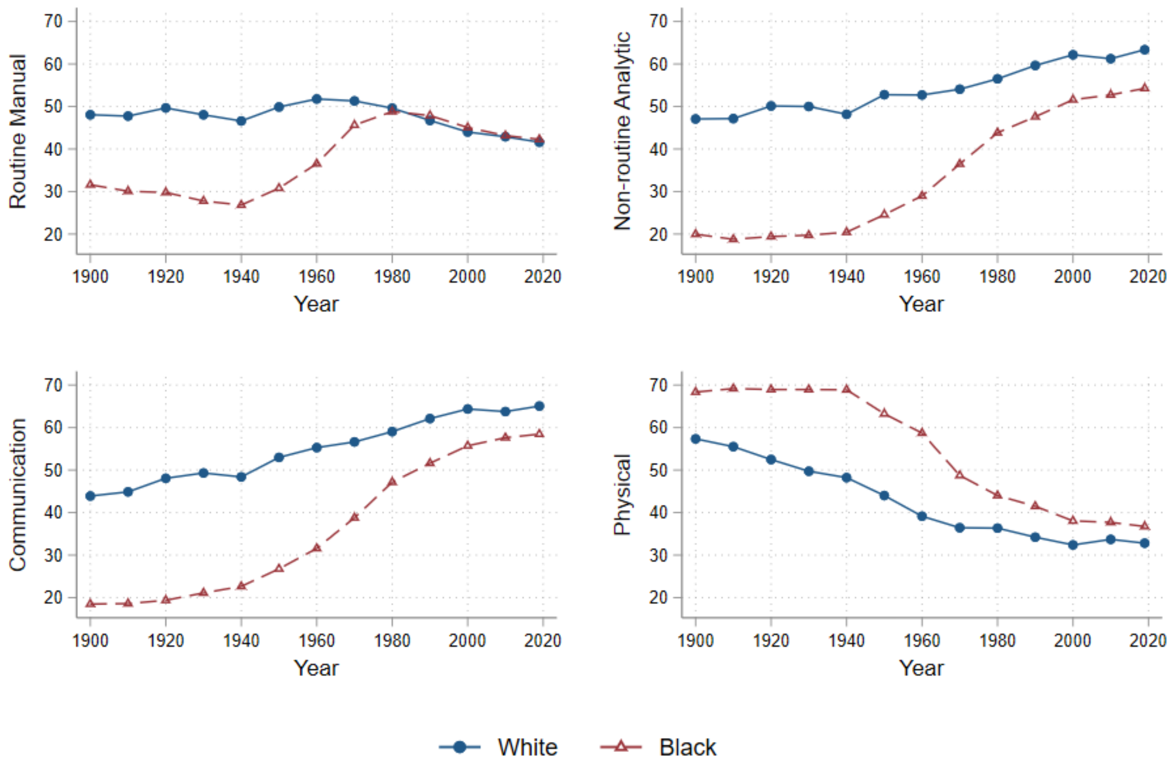


Panel B. Across generations from father to son



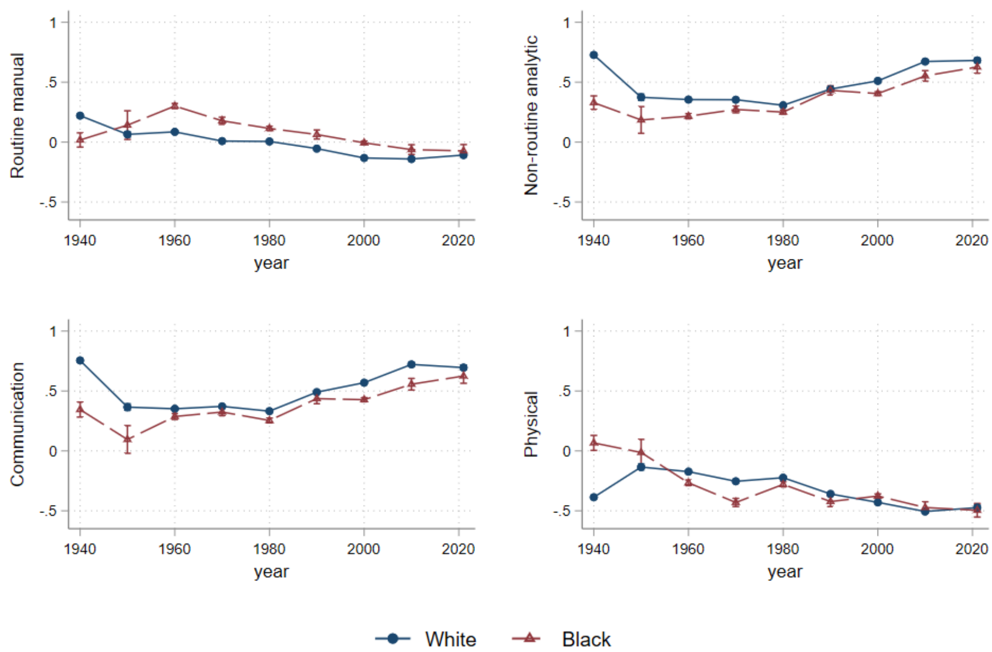
Notes: Underlying data are from the PSID, OCG, and 1900-1940 US Censuses (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2020) in Panel A and Ward (2023) in Panel B. Panel A shows the point estimate from a regression of the outcome in census *t+10* on the outcome in census *t*. Panel B shows the point estimate from an OLS regression of the son's outcome on the father's. All measures are percentile ranked.

Figure 4. Trends in task content by race

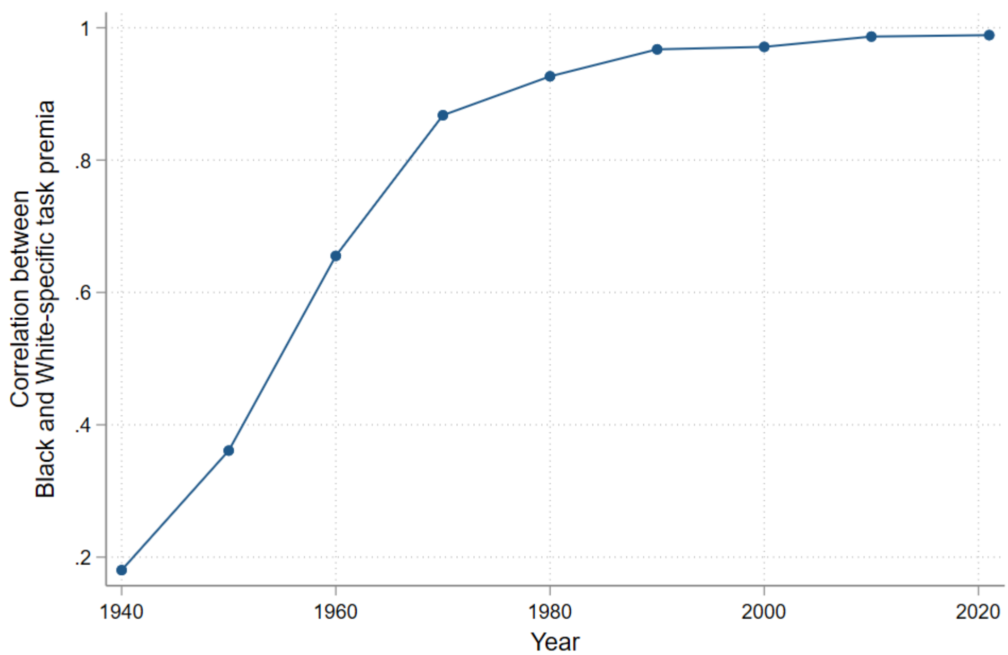


Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. Since task content by occupation 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 B6 for task definitions.

Figure 5. Racial differences in task premia
Panel A. Mincerian task premia by race



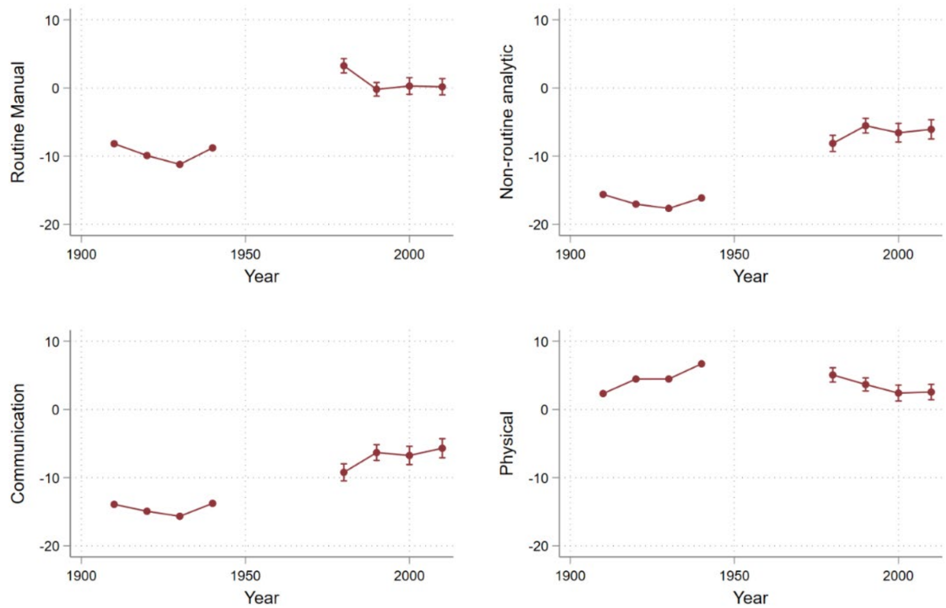
Panel B. Black-white correlation of component task premia over time



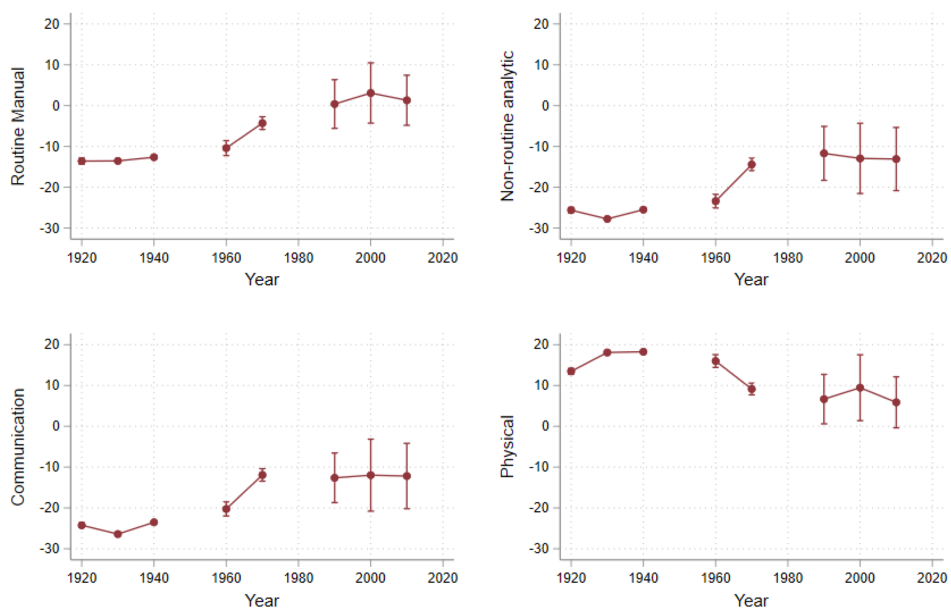
Notes: Data are from the 1940 IPUMS and the 2021 ACS (Ruggles et al. 2021). Sample is 30-45-year-old male wage workers with an occupation. Task premia are estimated by regressing the log of weekly wage income on percentile rank of task, a quadratic in age, and years of education separately by reported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

Figure 6. Black-white mobility gaps across the 20th century

Panel A: Own lifetime



Panel B: Intergenerational



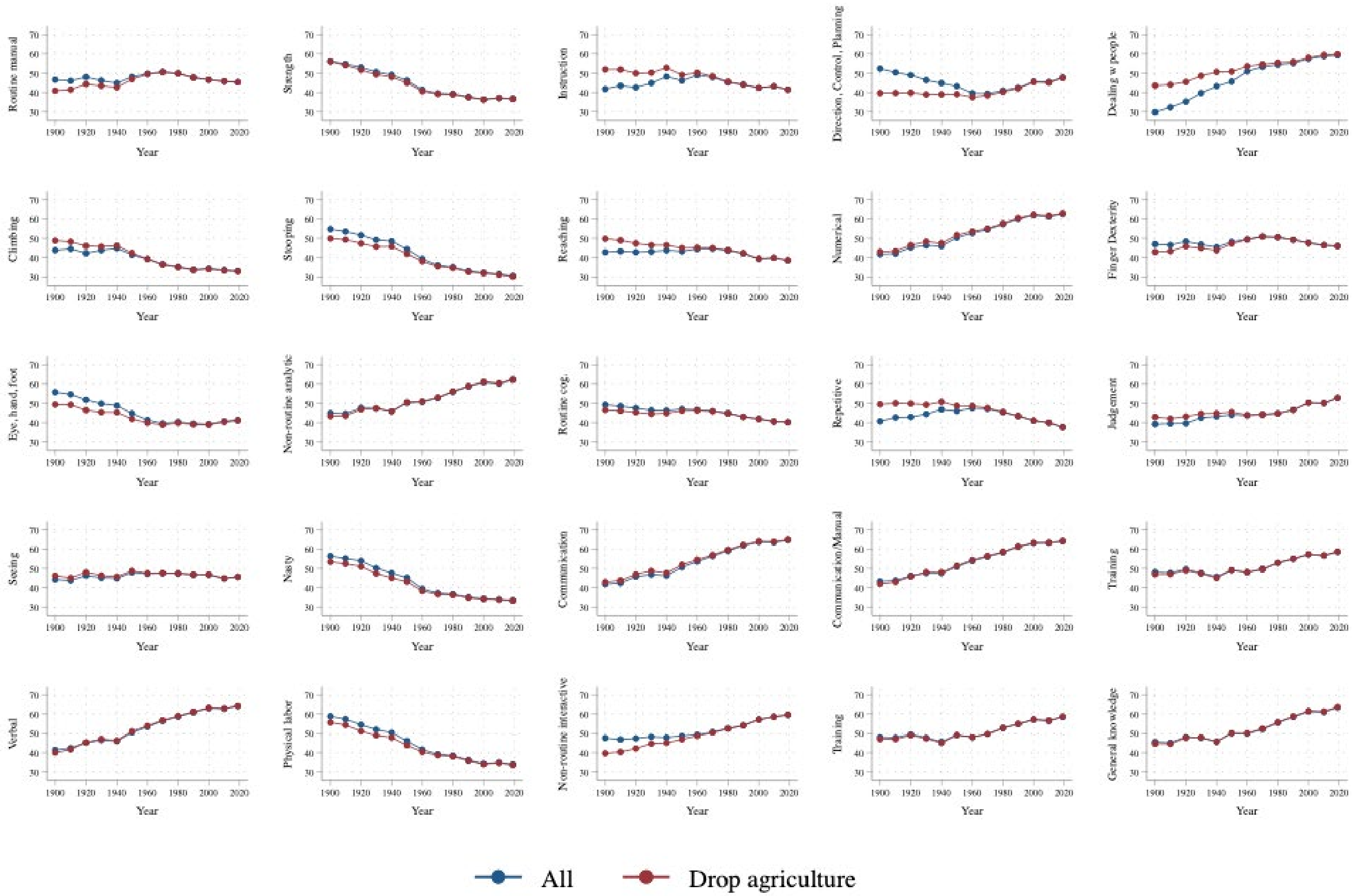
Notes: Underlying data are from the PSID, OCG, 1900-1940 US Censuses (Ruggles et al. 2021) and links from the Census Linking Project (Abramitzky et al. 2020) in Panel A and Ward (2021) in Panel B. The figure shows the point estimate from a Black indicator variable. Panel A is a regression of the outcome in census *t+10* on the outcome in census *t* and a Black indicator. Panel B shows the point estimate from an OLS regression of the son's outcome on the father's and a Black indicator. All measures are percentile ranked. Occupational income is a 0-100 percentile ranked measure that imputes income by occupation.

Online Appendix, not for publication.

Table of contents

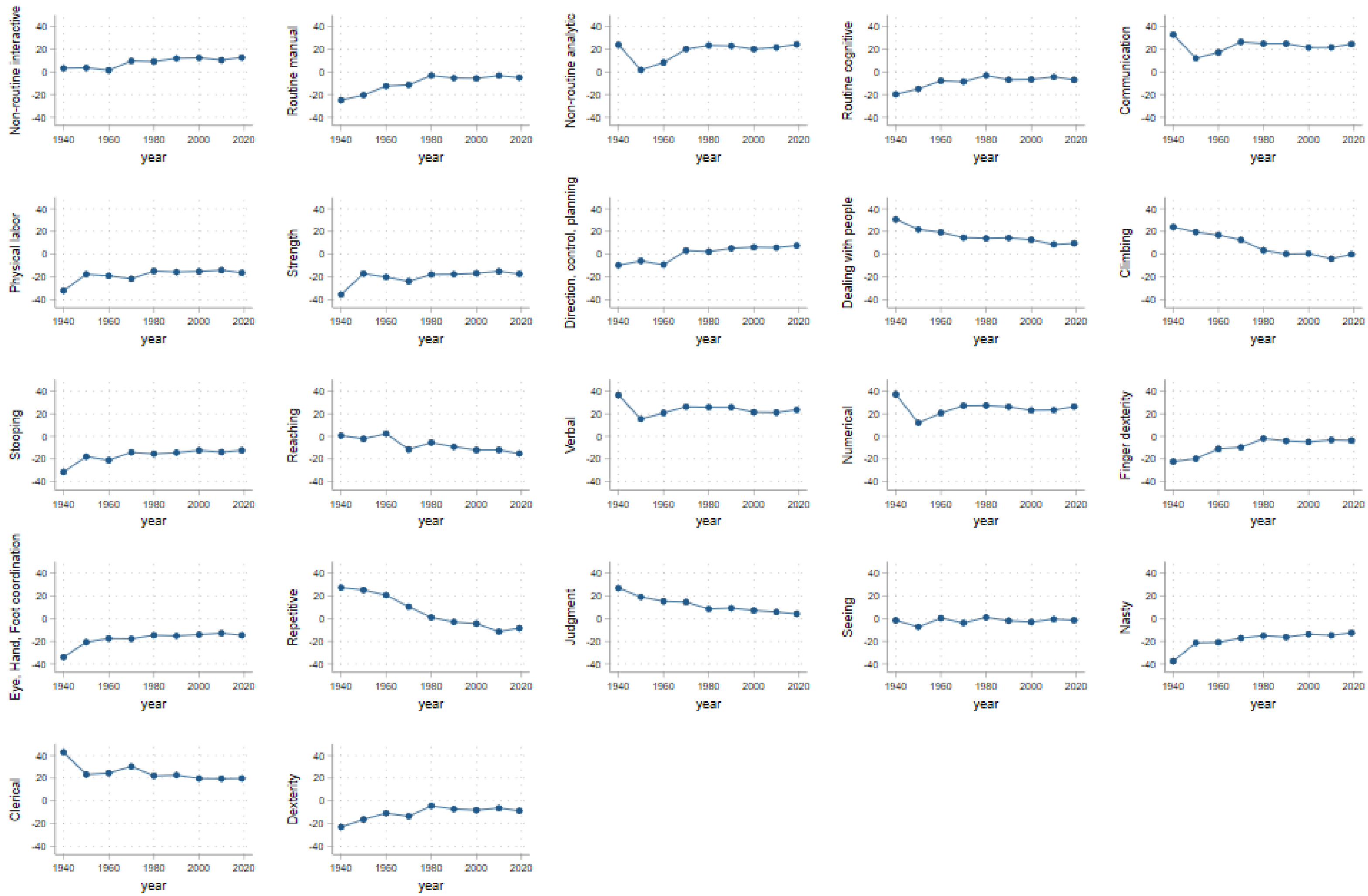
Appendix A. Additional figures

Figure A1. National trend in task content



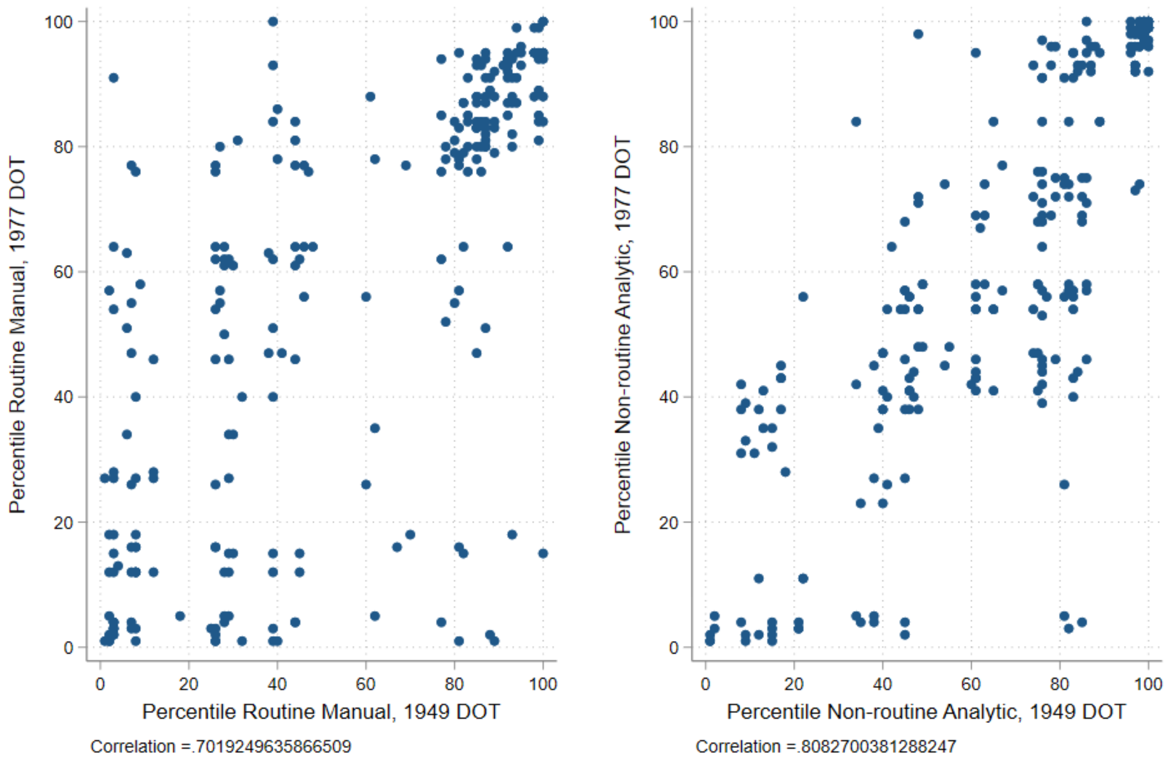
Notes: Data are from the 1900-2000 Censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021).

Figure A2. Trend in task premia between 1940 and 2019



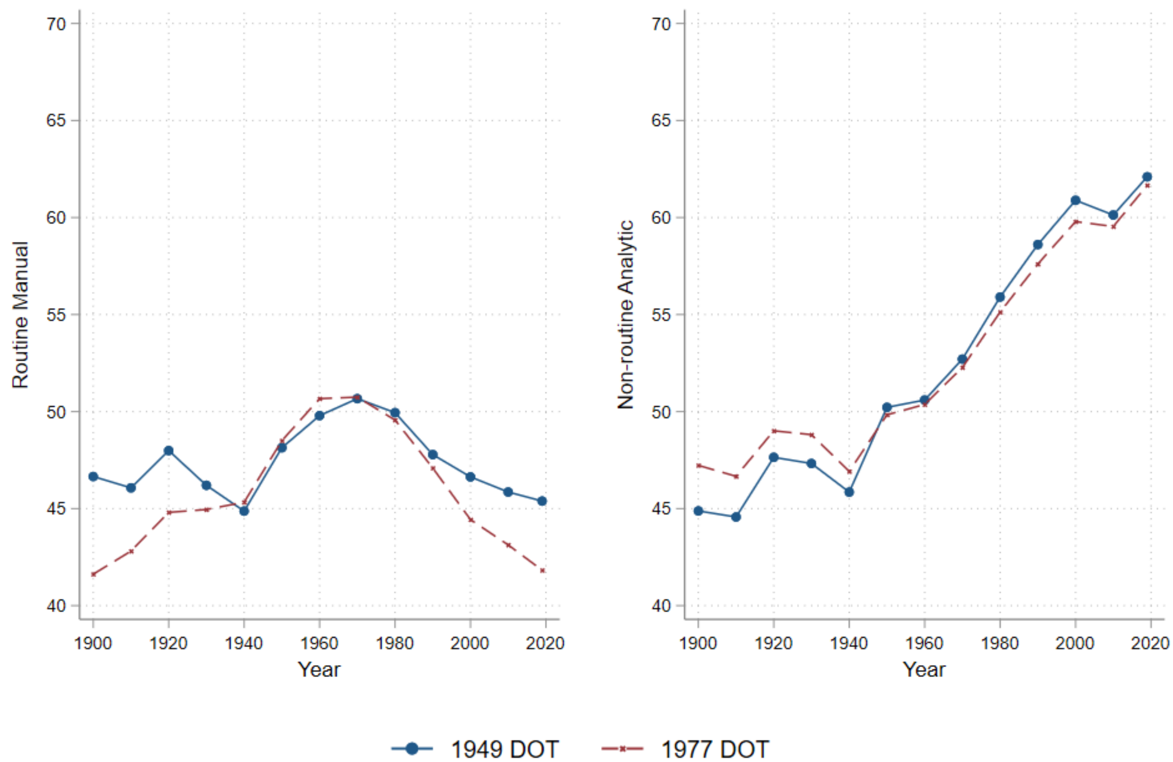
Notes: Data are from the 1940-2000 Censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021). Sample is 30-45-year-old male wage workers with an occupation. Task premia are estimated by regressing the percentile rank of wage income on percentile rank of task, a quadratic in age, and education.

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 percentile ranking of each occupation in 1949 against its percentile rank in 1977.

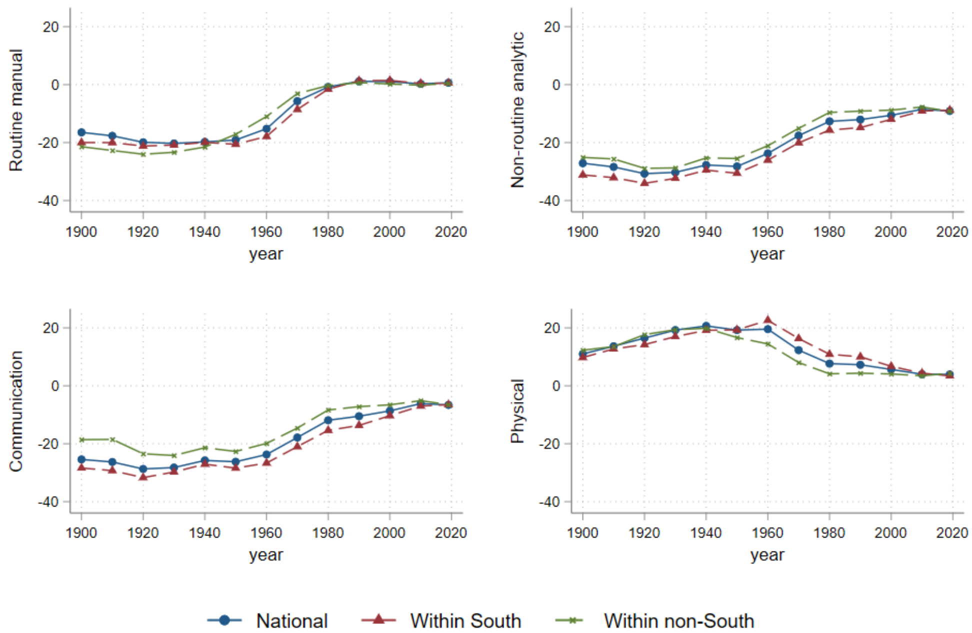
Figure A4. Trend in occupational task content when using the 1977 DOT



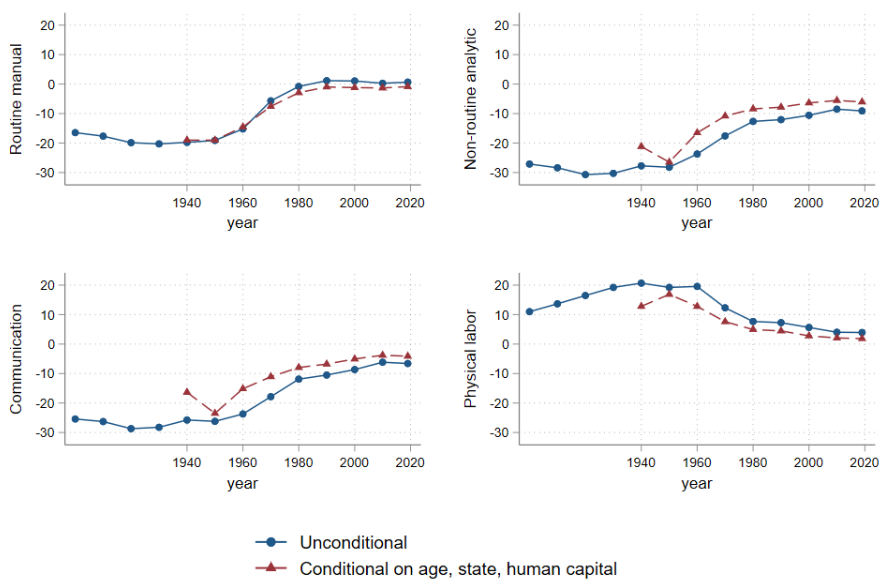
Notes: This figure compares the trend in routine manual and non-routine analytic when using the task intensity measures based on the 1949 *Dictionary of Occupational Titles*, versus the task content based on the 1977 *Dictionary of Occupational Titles*.

Figure A5. Black-white trends using observable differences

Panel A. By region

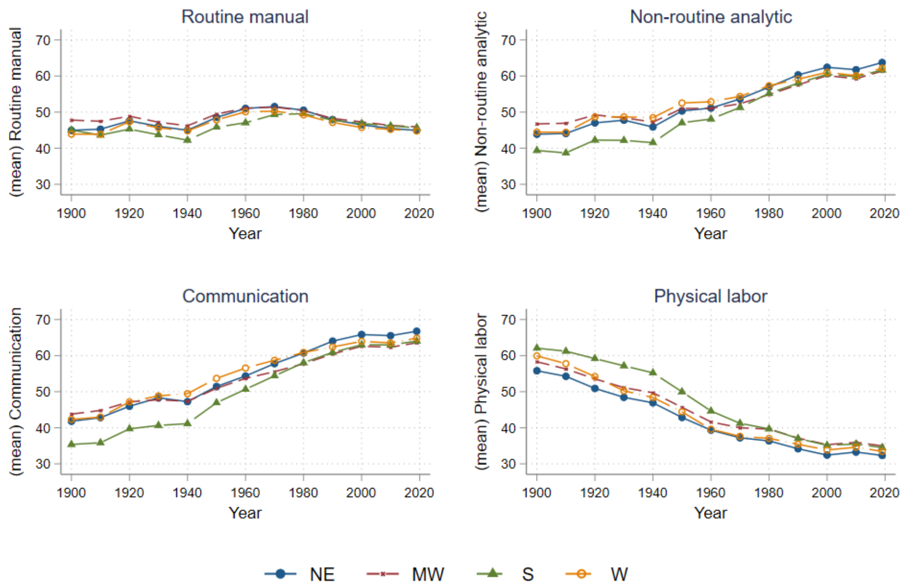


Panel B. Conditional on observables



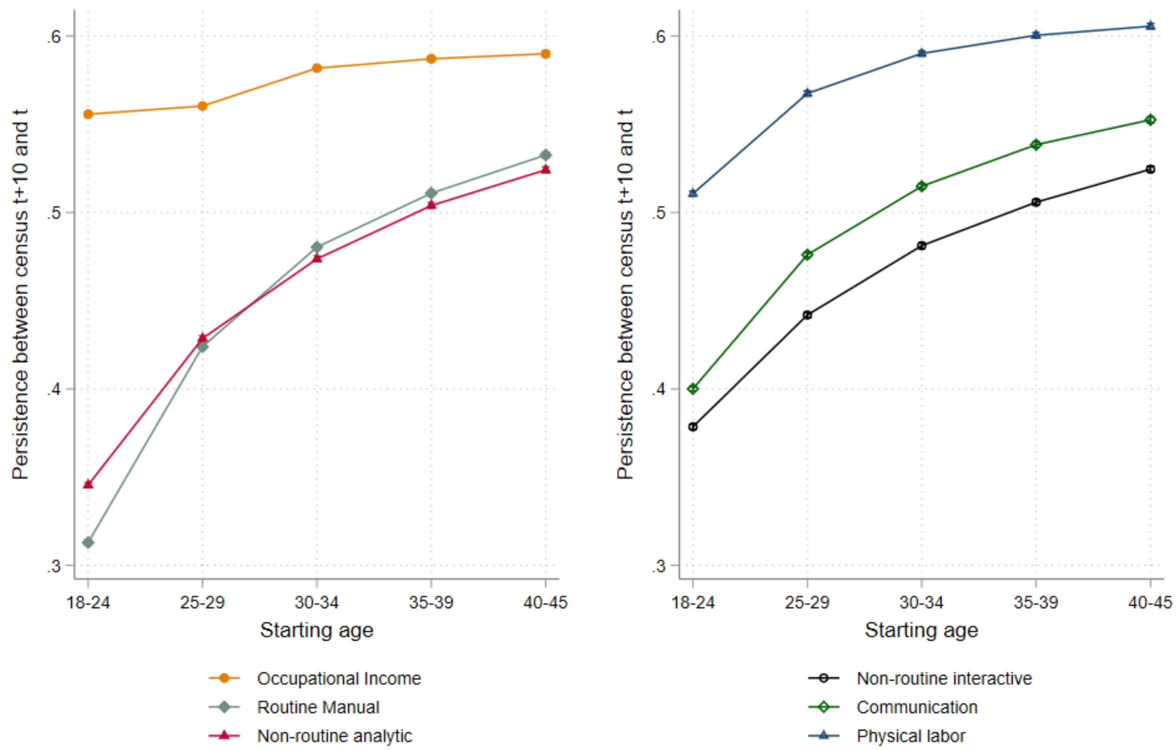
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. Since task content by occupation 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 B6 for task definitions.

Figure A6. Task measures by census region



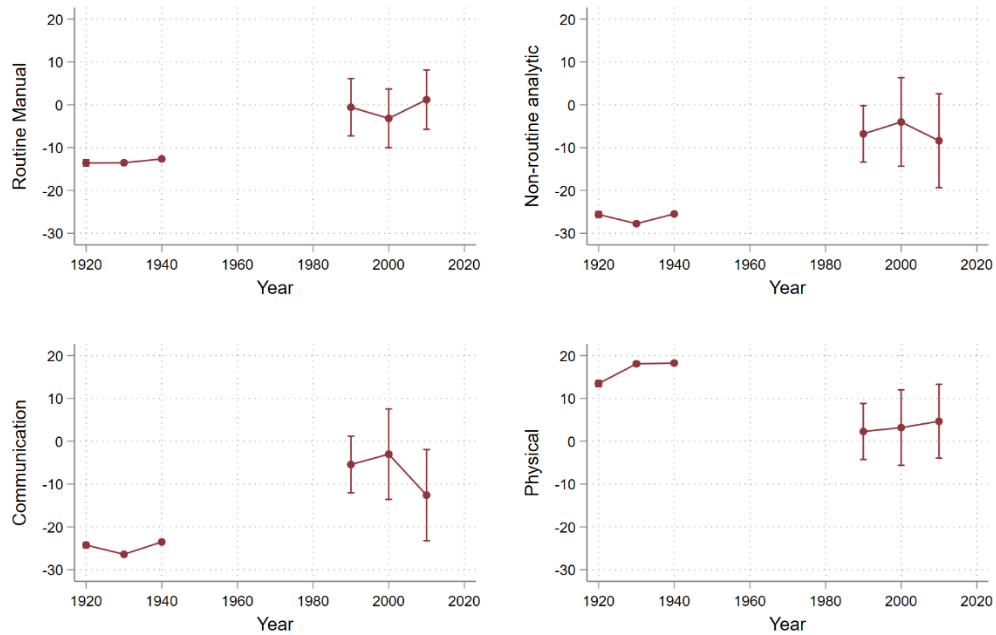
Notes: Data are from the 1900-2000 censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021). Data are of 18-55-year-olds with an occupation. Occupational task content is indexed to the 1950 Census such that the 50th percentile reflects median task content in 1950. Since task content by occupation 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 B6 for task definitions.

Figure A7. Persistence of task content throughout the lifecycle

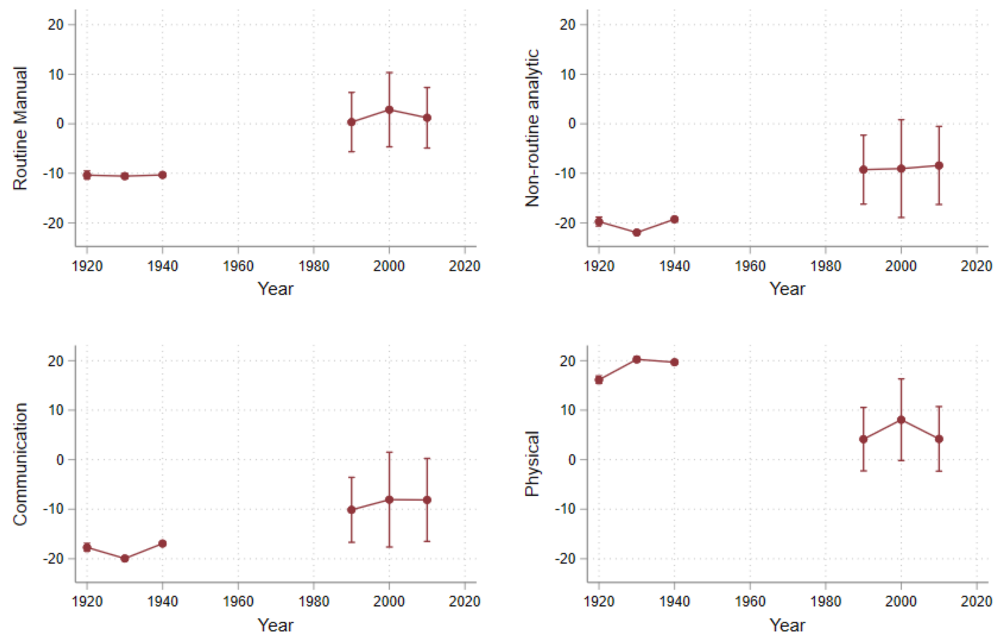


Notes: Data are from the 1900-1940 censuses (Ruggles et al. 2021). Each point plots a separate regression of the task content in time *t+10* on the task content in census *t* by age and task. The main point of the figure is that the occupational task content was more persistent across a 10-year period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

Figure A8. Instrumental variable approach to IGM
Panel A. Overall

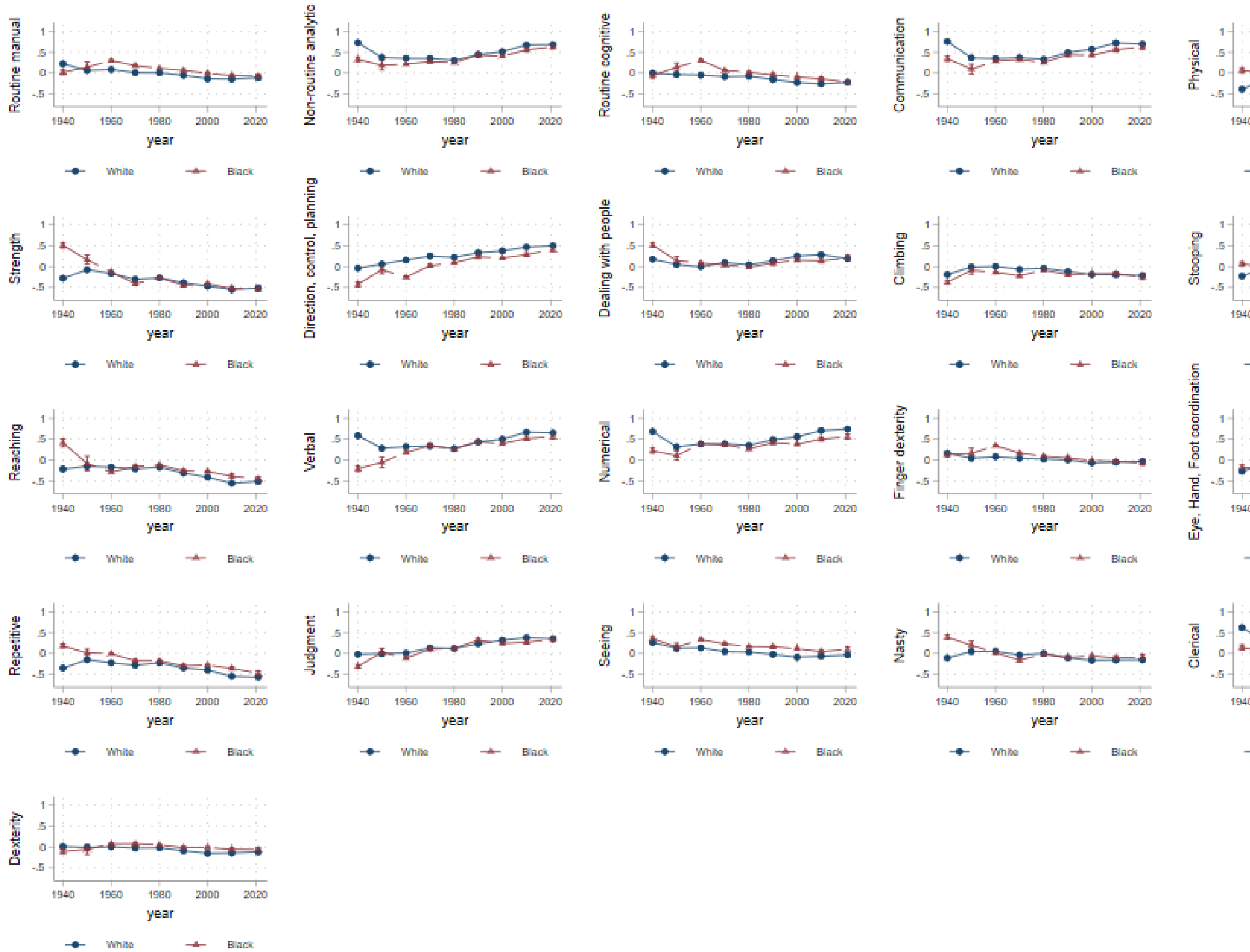


Panel B. Black-white differences



Notes: Underlying data are from the PSID and 1900-1940 US Censuses (Ruggles et al. 2021) and links from Ward (2023). Each panel shows the point estimate 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 (2023). All measures are percentile ranked. Note that measurement error would attenuate estimates. Panel A is overall mobility while Panel B is the coefficient on a Black indicator.

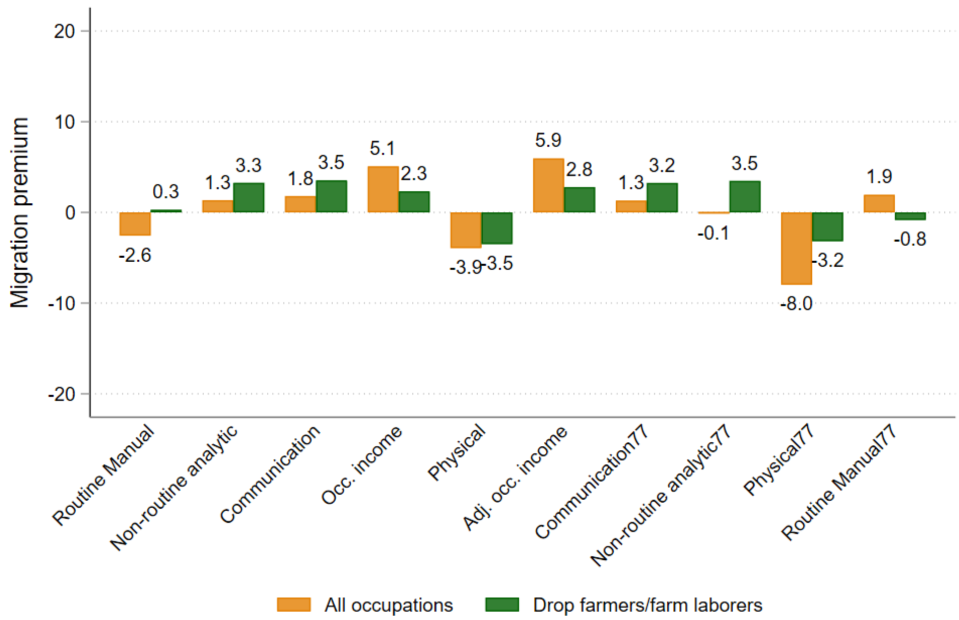
Figure A9. Trend in task premia between 1940 and 2019



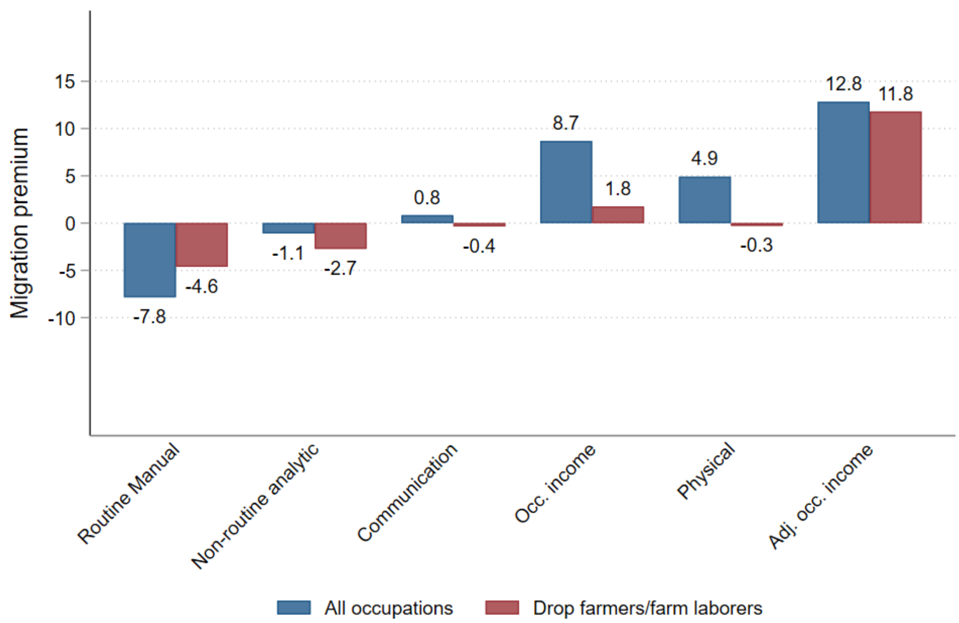
Notes: Data are from the 1940-2000 Censuses, the 2010 ACS and the 2019 ACS (Ruggles et al. 2021). Sample is 30-45-year-old male wage workers with an occupation. Task premia are estimated by regressing the percentile rank of wage income on percentile rank of task, a quadratic in age, and education.

Figure A10: Historical migration and task intensity

Panel A. All internal migrants



Panel B: Great Migration



Notes: Data are intergenerational links from Ward (2023). 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 B 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 A, 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.

Figure A11: National task intensities by sex

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

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. [21]

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.

[21] 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
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	Train. Time: SVP	Aptitudes: GVN	Aptitudes: SPQ	Aptitudes: KFM	Aptitudes: 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			20
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 with 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.

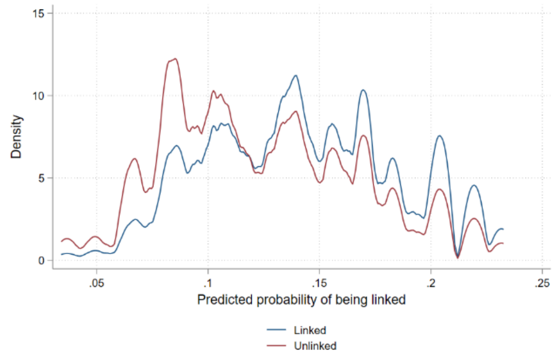
Intergenerational data.

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.

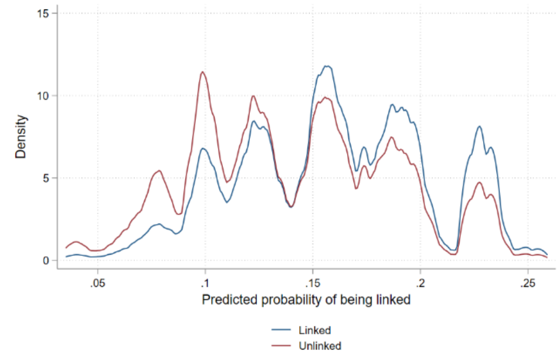
See the Online Appendix of Ward (2021) for details on representativeness of the intergenerational sample.

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

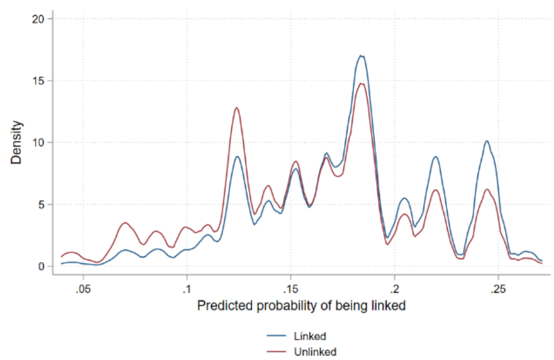
Panel A. 1900-1910 Census



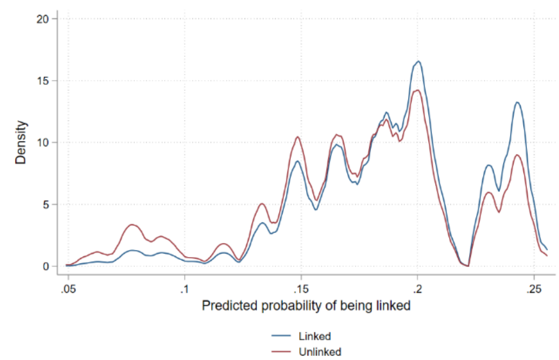
Panel B. 1910-1920 Census



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)

		Linked (1900-1910)			Linked (1910-1920)	
	Population	Unweighted	Weighted	Population	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.