The Evolution of Black-White Differences in Occupational Mobility Across Post-Civil War America*

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Abstract

We study long-run differences in intergenerational occupational mobility between Black and White Americans using a Markov-Chains-based approach, combining linked historical census data and contemporary survey data. We highlight the pivotal role of the changing mobility dynamics, especially among the 1940-1950 cohort, in shaping contemporary occupational distributions and reducing occupational segregation by race. We further explore the properties of remaining cross-sectional racial inequalities and offer a novel perspective on this persistence using measurements of mobility bottlenecks and the extent of parental influence on offspring outcomes examined for each mobility regime.

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Keywords: Black-White Inequality, Intergenerational Occupational Mobility, Markov Chains, Structural vs. Exchange Mobility

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1 Introduction

Disparities in intergenerational mobility between Black and White individuals constitute a fundamental dimension of racial inequality in the United States. Recent research on these differences has drawn attention to how Black-White mobility gaps have evolved over time (Chetty et al., 2020; Collins and Wanamaker, 2022; Jácome et al., 2021). These studies primarily focus on income mobility, measured by individual- or occupation-level income of parents and their offspring. We revisit this growing literature from the perspective of occupational mobility using a Markov chains-based approach.

While related, occupations and income are inherently different measures of socioeconomic status. Income mobility measures changes in earnings from parents to offspring; occupational mobility focuses on changes in job type, prestige, status, and career path across generations. Notably, occupational mobility is sensitive to shifts in societal and economic structures. For example, although industrialization may not have drastically altered income percentile rankings, it significantly changed the occupational compositions of farming versus manufacturing work (Long and Ferrie, 2013; Xie and Killewald, 2013). Despite the wide use of occupation as a proxy for families' socioeconomic status, recent studies on intergenerational mobility have predominantly focused on earnings and income (Sakamoto and Wang, 2020). We argue that studying occupational mobility offers valuable insights into long-term changes in labor market restructuring and their implications for racial inequality, which income mobility alone may not fully capture.

This paper examines long-term trends in racial disparities in occupational mobility by introducing novel mobility measurements based on Markov chains. We leverage a comprehensive dataset that combines linked historical census data (1850 to 1940) and 10 contemporary large-scale survey data (1960s to present). First, we analyze historical patterns in intergenerational occupational mobility between Black and White men across birth cohorts from 1860 to 1970. Second, we study the connection between intergenerational mobility and cross-sectional occupational distributions using the Kitagawa-Oaxaca-Blinder decomposition method and counterfactual experiments. Finally, we investigate the role of occupational mobility in explaining the persistence of Black-White inequality in cross-sectional distributions. We further study properties of persistence embedded in the mobility process using measurements of (i) mobility barriers and (ii) parental memory in mobility.

Sociologists have long modeled mobility using discrete-time Markov chain models (Prais, 1955; Blumen et al., 1955; Matras, 1975). We extend these methods by proposing new ways of characterizing mobility using Markov models with time-varying transition

matrices. Our stochastic analyses allow us to study two major aspects of intergenerational mobility and complement existing regression-based analyses. First, we assess the role of mobility in understanding the racial gap in cross-sectional distributions over time, building on the relationship between mobility and cross-sectional inequality that respects the discrete structure of occupations from Markov chains ($\mu_t = \mathbf{P}\mu_{t-1}$). Our construction of race and birth-cohort specific transition matrices spanning 170 years allows us to identify the periods in which significant changes in the mobility process occur and analyze these historical regimes in terms of their contributions to achieving the current occupational distribution and reducing racial inequality.

Second, we study properties of persistence in Black-White inequality considering both mobility as "movement" and "independence of origin"—a distinction emphasized in Shorrocks (1978) and extensively discussed in a recent study by Blume et al. (2024). Most extant studies conceptualize intergenerational mobility primarily as "movement" using linear regression models (e.g., 1-IGE) or transition probabilities (e.g., calculations using off-diagonal elements). However, the extent to which parental occupations affect the occupational outcomes of offspring—both the magnitude of this influence and the speed at which it dissipates—is also a critical dimension of mobility. In this regard, a Markov chain-based approach presents a key methodological advantage, particularly for analyzing the persistence of inequality over time.

Note that all of our analyses importantly help connect with concepts of "structural" versus "exchange mobility." The distinction, which has long been recognized as fundamental to historical mobility analysis, separates mobility explained by aggregate factors versus mobility stemming from individual effort and merit. In this paper, we propose two different ways to measure structural mobility. Namely, we treat the evolution of mobility regimes from one period to another ($\mathbf{P}_{t-1}$ to $\mathbf{P}_t$) as capturing one form of structural mobility; and mobility that is produced in the process of reaching the steady state of a given Markovian relationship as the other (μ_t to μ^*). Exchange mobility, in the latter case, is then mobility that occurs at the steady state, or immobility that would be observed in the absence of this evolution.

Our analysis presents clear evidence of the essential contribution made by the 1940-1950 birth cohort in reducing the racial gap in mobility. In particular, Black men from this birth cohort show significant progress in increasing (decreasing) the probability of upward (downward) mobility. Our decomposition exercise further reveals that such improvements in the mobility process largely explain the observed changes in occupational distributions, which exhibit a diminution of the degrees of occupational segregation by race. We provide complementary evidence using our counterfactual exercises that the

current occupational distribution, characterized by a notable rise in high-skill occupations compared to historical trends, can predominantly be attributed to the mobility experienced by the 1940-1950 birth cohort. This represents our first form of structural mobility: shifts in the intergenerational mobility process, as captured by the Markov transition matrix, play a crucial role in the occupational advancement of Black men.

Despite substantial improvements, the momentum achieved by the 1940-1950 birth cohort is not maintained in the following generations; the racial gap in cross-sectional occupational distributions remains persistent. The overall degree of occupational segregation by race, albeit a downward trend that begins from the 1920-1930 birth cohorts and accelerates for the 1940-1950 birth cohorts, remains nontrivial. In fact, the rate at which occupational segregation declines levels off for subsequent birth cohorts. Moreover, when we simulate the experiences of Black men to align with that of White men—either by imposing identical mobility dynamics or initial conditions—counterfactual distributions based on identical mobility dynamics, as opposed to equalizing initial conditions, exhibit significantly lower levels of occupational segregation by race. That is, the lack of cross-sectional convergence is largely due to racial differences in the mobility process.

Given the importance of Black-White differences in the mobility process in understanding the persistent nature of racial inequality, we further the analysis by examining the extent of (i) *barriers* and (ii) *parental memory* in mobility. First, mobility barriers to reaching a high-status occupation from a low-status background have decreased substantially for Black men over time, yet they remain significantly higher than those for White men. This disparity is particularly pronounced when examining the barriers to moving from "Semi-Skilled and Unskilled Manual" occupations to "Proprietors, Managers, and Officials." Conversely, when we consider a reverse notion of these barriers—mean first passage times from high-status occupations to low-status ones—Black men exhibit lower mean first passage times than White men. That is, Black men face greater challenges in maintaining high-status occupations across generations, and this gap remains relatively constant over time. These patterns of persistence are not fully captured in our analysis of upward or downward mobility based on transition probabilities alone.

Second, the extent of parental memory on offspring in their occupational sorting and the rate at which this parental influence dissipates do not improve for Black men over time. Even for the 1940-1950 birth cohort, despite its instrumental role in shaping the current occupational distribution and reducing the racial gap demonstrated in previous exercises, the magnitude of parental influence is greater for Black men compared to White men. Our measurement of parental memory is constructed using the distance between the observed cross-sectional occupational distribution and the steady state, in which offspring face

equality of opportunity in sorting across occupations regardless of parental background.

We also show that racial disparities in parental memory vary among occupations and may persist for varying lengths of time. Specifically, Black families positioned at the top and bottom of the occupational hierarchy exhibit stronger memory—namely, a higher tendency to maintain their occupational status over time—than families in the middle. Any racial-specific differences in occupational dynamics, such as those that would arise from discrimination or access to information networks, can produce differential memory. Although our results do not point to specific mechanisms, they help constrain what types of heterogeneities are present.

By assessing the *rate of convergence* to steady state, we show that parental memory dissipates more slowly for Black men relative to White men. When comparing across birth cohort groups, the convergence rates among Black men from the 1940–1950 birth cohorts remain among the lowest in our sample, in stark contrast to White men, whose convergence rates show a marked increase over time, which, in fact, peak for the 1940–1950 birth cohorts. These results reveal a novel dimension of Black-White inequality, whereby mobility, conceptualized as independence of origin, and measured using the rate at which parental influence dissipates for offspring outcome, has only improved for White men.

Finally, we use our measures to distinguish between structural versus exchange mobility. Recall that the exercise introduces our second form of structural mobility. We show that, for both race groups across different birth cohorts, the role of structural mobility—measured using mobility produced in the process of reaching the steady state of a given Markov chain—is quite limited, with magnitudes, however, being relatively larger for Black men than White men. Thus, the overall rate at which parental memory disappears is largely explained by exchange mobility—the convergence rate estimated at the steady state. Our final exercise highlights that Black-White differences in mobility as independence of origin are attributed to the racial gap in exchange mobility: we document a steady improvement for White men but not for Black men.

Literature and Contribution

Our work builds on a growing body of literature on historical trends in mobility. The availability of digitized census data and innovative methods for linking censuses across time periods have significantly expanded the scope and scale of research in this area (Abramitzky et al., 2022; Helgertz et al., 2022). Studies by Song et al. (2020) and Collins and Wanamaker (2022) have leveraged these linked censuses with other survey data to assess patterns of mobility over long time horizons. Jácome et al. (2021) and Buckles et al. (2023) delve deeper into the differences in mobility patterns across gender and racial

groups. Important contributions also include efforts to improve the accuracy of linking methods (Bailey et al., 2020; Olivetti and Paserman, 2015) and measurement of occupations to help address biases in mobility estimates (Ward, 2023).

In complementing these studies, our work constructs a comprehensive dataset combining both the historical censuses from 1850 to 1940 and 10 contemporary surveys from 1962 to 2021 to study the mobility dynamics of post-Civil War America. To construct father-son pairs using the historical data, we reduce false links across census by closely following existing work, test robustness to different linking methods, and apply family reconstitution techniques to reconstruct family lineages.[1] Further combining survey data, which we make extensive adjustments across data sources (weights, variable definitions), we create a sample spanning 170 years with consistent measures of occupations for father-son pairs.

Our analyses based on Markov chains, in combination with the extensive data we construct and produce a range of empirical conclusions that confirm and augment existing studies on Black-White inequality in two important ways.

First, our work extends earlier occupation-based studies (Blau and Duncan, 1967; Duncan, 1968; Featherman and Hauser, 1976; Hout, 1984) to trace out the evolution of the mobility gap over a long time horizon. Our findings confirm the racial disparities in mobility, where the intergenerational transmission of status is both weaker and more heterogeneous among Black men (Bhattacharya and Mazumder, 2011; Mazumder, 2014; Bloome, 2014, 2017; Chetty et al., 2020). We further connect these dynamics to study changes in cross-sectional inequality by assessing the role of intergenerational mobility in shaping changes in occupational distributions, identifying periods when the mobility channel's impact is most pronounced, and examining how these patterns and magnitudes vary across racial groups. Our work complements Collins and Wanamaker (2022), which use a regression-based approach to examine racial disparities in mobility in the long-run, highlighting their significance in explaining changes in Black-White inequality.

Second, our analyses contribute to the strand of important work examining the persistence or lack of convergence in Black-White inequality since the 1960s. Recent studies suggest a stable trend (Lee and Solon, 2009) or no trend in mobility patterns for the whole population of recent cohorts (Chetty et al., 2014; Jácome et al., 2021; Ward, 2023). Black-White convergence in mobility gaps has also stalled for birth cohorts since the 1960s (Bound and Freeman, 1992; Collins and Wanamaker, 2022). This paper offers a new perspective on Black-White inequality using measurement approaches assessing mobility as "movement" and "independence of origin." By accounting for the sequence of transitions to study mobility across occupations, we not only identify regions that pose significant

[1] See Willigan and Lynch (1982); Hammel (1993); Wrigley et al. (1997) for details.

obstacles to moving but also quantify the magnitude of these barriers. Our analysis elucidates the persistent racial gap in maintaining high-status occupations, which remains significant even for the recent cohorts. In addition, by investigating Black-White differences in the rates at which parental memory dissipates, we show greater path dependence in the mobility regimes of Black men, which do not improve over time—unlike those of White men—even for the 1940-1950 birth cohorts.

Finally, this paper contributes to studies examining structural versus exchange mobility. The conceptual distinction dates back to the seminal work of Kahl (1957). The concept of exchange mobility, in particular, has been widely used in the sociological literature to analyze the extent of opportunities to improve status based on individuals' merit and effort (McClendon, 1977; Sobel, 1983; Sobel et al., 1985). In terms of measurements, the conventional practice of using log-linear models to analyze structural versus exchange mobility in a mobility table (Goodman, 1968; Hout, 1983) tries to isolate a component of mobility that is independent of the cross-sectional distribution of occupations among parents. More recently, Blume et al. (2024) uses an imbalance matrix, capturing the difference in inflow and outflow of each occupation, where the imbalances disappear at the steady state (or structural mobility becomes zero).

Our approach takes two separate measurements of structural mobility, by treating the evolution of mobility regimes ($\mathbf{P}_{t-1}$ to $\mathbf{P}_t$) as capturing one form; and mobility that is produced in the process of reaching the steady state of a given Markov chain the other (μ_t to μ^*). The latter, in particular, which conceptually builds on Berger and Snell (1957) focuses on how the cross-sectional distribution of occupations among parents matters for overall observed mobility—these are parallel ideas in the economic growth literature (e.g., Bernard and Durlauf, 1996) that distinguish transitions and steady state dynamic behaviors. These measures importantly allow for a comprehensive assessment of the Black-White differences in long-run mobility patterns as well as an understanding of the role of mobility in explaining the persistence of racial inequality observed in the cross sections.

The rest of the paper is organized as follows. Section 2 describes the methodological approach. Section 3 discusses the data and sample construction. Section 4 presents descriptive patterns of Black-White differences in occupational distributions and mobility. Section 5 studies the importance of the mobility process in explaining the observed changes in occupational distributions. Section 6 proposes our measurements of mobility to study persistence in Black-White inequality and presents results. Section 7 concludes.

2 Methodological Approach: Markov Chains

Our main methodological approach in this paper uses Markov chains, which assume that the outcome state of the present generation only depends on that of the parent generation but not any of the other preceding generations. Thus, in our context, the occupational distribution μ_t evolves according to

$$\mu_t = \mathbf{P}\mu_{t-1} \tag{1}$$

where $\mathbf{P}$ is the time-invariant transition matrix representing conditional probabilities linking parents and children. Assuming that $\mathbf{P}$ is *regular* (irreducible, positive recurrent, and aperiodic) and that the states in the transition matrix communicate over time, given an initial condition (μ_0), there exists a unique long-run equilibrium (μ^*, the steady state vector of the Markov process) for the distribution of descendants: $\lim_{t\to\infty} \mu_0 \mathbf{P}^t = \mu^*$.

We build on this theoretical framework to produce a set of measures that allow us to study two major aspects of intergenerational mobility. First, we assess the role of mobility in understanding the racial gap in cross-sectional distributions over time. As articulated in Durlauf et al. (2022), Equation (1) provides a relationship between mobility and cross-sectional inequality that respects the discrete structure of occupations and so is analogous to the relationship between the intergenerational elasticity of income/earnings (IGE) and inequality in the classic intergenerational mobility regression models.[2] For our purpose of studying long-time horizons, we augment conventional mobility analyses, which are predicated on a time-invariant transition process between parents and children ($\mathbf{P}$), and allow these transition matrices to change over time ($\mathbf{P}_t$).

Our construction of $\mathbf{P}_t$ serves two important objectives. First, we assess the role of changes in the mobility process, namely changes in the transition matrix from one period to another, in explaining changes in the cross-sectional occupational distributions over time. Specifically, we implement a Kitakawa-Oaxaca-Blinder-type decomposition to quantify the contribution of mobility and trace out the evolution of its importance. Second, we study the contribution of each mobility regime, or the period-specific transition matrices, in achieving the current occupation distribution and reducing racial inequality. We do this using a set of counterfactual experiments that capture various scenarios, including counterfactual evolution of mobility processes and counterfactual initial conditions.

Using our time-varying transition matrices ($\mathbf{P}_t$), these exercises highlight the impor-

[2]Consider the intergenerational mobility regression $y_{it+1} = \alpha + \beta y_{it} + \epsilon_{it}$. If $|\beta| < 1$ and $var(\epsilon) < \infty$, then $var(y) = \frac{var(\epsilon)}{1-\beta^2}$ holds. Higher values of β correspond to larger variances in y or higher degrees of inequality.

tance of changes in the mobility process, which reflect period-specific socioeconomic structures influencing intergenerational transitions, in understanding the evolving relationship between mobility and inequality. Here, we capture one form of "structural mobility" through the evolution of these mobility regimes ($\mathbf{P}_{t-1}$ to $\mathbf{P}_t$). We provide a detailed discussion of our analysis in Section 5.

Second, we use the Markov-Chains-based approach to provide a comprehensive assessment of the mobility process, using both mobility as "movement" and "independence of origin"—a distinction emphasized in Shorrocks (1978) and extensively discussed in a recent study by Blume et al. (2024)—and assess racial differences in these mobility measures. The following example illustrates the distinction.

$$P_A = \begin{pmatrix} \epsilon & 1-\epsilon \\ 1-\epsilon & \epsilon \end{pmatrix} \text{ for a small } \epsilon > 0, \quad P_B = \begin{pmatrix} p_1 & p_2 \\ p_1 & p_2 \end{pmatrix}$$

A society with a transition matrix P_A is characterized by greater movement and, therefore, shows higher mobility compared to one with P_B. However, focusing on the extent to which the memory of family background influences occupational sorting, the mobility process under P_A is far less equal or shows greater parental influence compared to P_B. Most existing studies focus on examining mobility as "movement" using linear regression models (e.g., 1-IGE) or transition probabilities (e.g., calculations using off-diagonal elements).

We argue that a comprehensive assessment of the mobility process using both measures is crucial, particularly in the context of understanding the properties of "persistence" embedded in the mobility process—a key advantage of using a Markov-Chains-based approach. Since we construct period-specific transition matrices for each race group, our analysis captures how these measures vary by race and how they evolve over time. Our analysis becomes particularly useful in exploring the lack of Black-White convergence in economic status documented in previous studies (Bound and Freeman, 1992; Fairlie and Sundstrom, 1997; Collins and Wanamaker, 2022).

Our analysis of mobility as "movement" produces measures of mobility bottlenecks using the mean first passage times of Markov chains, which importantly complements our descriptive study of the upward and downward mobility patterns (Section 4). In fact, this concept of the bottleneck has been widely documented in inequality studies. For example, Fishkin (2014) emphasizes the ethical salience of bottlenecks for perpetuating inequalities and limiting access to opportunities (e.g., the gatekeeping role of elite college enrollment). In our context, we measure the expected time it takes to move from one occupation to another and identify regions within the occupational density that pose significant obstacles to moving. By accounting for the sequence of transitions needed to reach, for example, a

high-status occupation from a low-status background for the first time, instead of relying on transition probabilities, which provide only a snapshot of mobility, these measures adding temporal insights effectively reveal information on the persistence in the mobility system, thereby offering policy implications for where interventions are most needed.

Our analysis of mobility as "independence of origin" draws on the *mixing* properties of the Markov chain mobility analyses developed by Blume et al. (2024).[3] Building on this concept, we construct a sequence of mixing curves that measure how long the influence of one generation lasts on future generations and how quickly this influence dissipates over time. Because occupations in our transition matrix all communicate, the occupational density evolves toward a unique steady state (μ^*), in which the advantages or disadvantages of different families, regardless of their initial conditions, will eventually disappear. The difference between the present cross-sectional distribution and the steady state distribution thus serves as a measure of *memory*—the information retained from the initial distribution. When this gap reaches zero, the current distribution no longer retains any information from the past: offspring outcomes become independent of the initial conditions.

In addition to measuring the extent of memory and the rate at which memory dissipates, we further compare (i) mobility that is produced in the process of reaching the steady state of a given Markovian relationship and (ii) mobility that occurs at the steady state or immobility that would be observed in the absence of this evolution. We follow the conceptual approach in Berger and Snell (1957) and treat this distinction as capturing the contrasting concepts of "structural" versus "exchange" mobility. The importance of these mobility concepts has long been recognized as fundamental in earlier sociological work in understanding important determinants of mobility (McClendon, 1977; Sobel, 1983; Sobel et al., 1985). Our measurements quantify these concepts for each birth cohort group by race, which further allows us to study racial differences in structural versus exchange mobility. Note that this is our second form of structural mobility, which is defined for a given structural environment or mobility regime $\mathbf{P}_t$.

We provide detailed descriptions of our measures of mobility as movement and independence of origin in Section 6.2 and Section 6.3, respectively.

[3]The mixing time of a Markov chain is the time until the chain is close to its steady state distribution, μ^*. Technically speaking, mixing analysis evaluates the memory of stochastic processes based on the dependence of probabilities for sets of random variables realized before some time t and those realized at $t+k$ or later. See Bradley (1986) for an exhaustive treatment.

3 Data and Sample Construction

Our analyses of the mobility experiences of several million unique individuals and their families rely on two main sources of data: (i) historical samples from linked complete count censuses covering the periods of 1850-1940 and (ii) contemporary data from 10 large-scale social surveys that cover periods following the 1960s. Appendix C includes details on the data and variables used in our analyses.

3.1 Historical Data, 1850-1940

We first draw on newly released linkages between full-count US Censuses from 1850 to 1940 in the Census Linking Project (CLP version 2.0) (Abramitzky et al., 2022). These linkage data are then merged with age, occupation, race, and household member information in full-count US Censuses 1850-1940 (Ruggles et al., 2020). The CLP linking method relies on several different automated algorithms to create matched individual records across census years based on variables such as first and last names, year of birth, and state/country of birth. Abramitzky et al. (2020) and Abramitzky et al. (2021) discuss in detail the linking methods used for the construction of CLP.

We focus on the decadal links between 1850-1860, 1860-1870, 1870-1880, 1880-1900, 1900-1910, 1910-1920, 1920-1930, and 1930-1940.[4] We implement links based on "Exact" and "Conservative" matching methods, both of which leverage the ABE algorithm with exact names. The "Exact" linking approach, as opposed to the NYSIIS, reduces false positives (Bailey et al., 2020). The "Conservative" links require individuals to be unique within a 5-year age window, which further reduces errors in matching individuals across different census years. Given our focus on race, we use the link that relies on race as a matching variable. We further merge the CLP data with other variables in the full-count censuses, such as age, gender, race, and occupation.

As CLP links individuals' records between censuses but not across generations, we reconstruct family lineages of Black and White Americans by linking family members living in the same households and retrieving records of parents across different census years. This method, often known as the family reconstitution technique, is widely used in historical demography to recreate family histories and events with registry data (Willigan and Lynch, 1982; Hammel, 1993; Wrigley et al., 1997). We construct father-son pairs as follows: we (i) form a panel dataset of individuals by linking their records across different census years; (ii) pinpoint the year in which an individual male resided in the same household as his father and extract the father's historical identification; and (iii) connect

[4]The 1890 Census data are missing because the original files were lost due to a fire.

the father to different census years to assemble a longitudinal dataset for the father.

Appendix Figure C demonstrates four scenarios that help identify parent-offspring pairs. If a father resided with his son in any recorded year between 1850 and 1930 (e.g., 1920), we then trace the father's information to a later census, provided that his individual-level identifier from 1850 to 1930 (e.g., 1920 HISTID) can be found in our 1860 to 1940 multiyear dataset. This tracing method leads to one of two scenarios: the linked father no longer lived with the son in a later census (scenario A), or the linked father continued to live with the son in a later census (scenario B). If the father lived with the son in any year between 1850 and 1930 but is not linked in our 1860 to 1940 multiyear dataset, we keep the father's occupation from 1850 to 1930 (scenario C). In addition, we include male offspring who lived with their fathers in the same household in childhood but whose fathers cannot be found in a later census (scenario D).

As a robustness check, we also construct an alternative sample using linkages of full-count US Censuses from 1850 to 1940 in the IPUMS Multigenerational Longitudinal Panel (MLP version 1.0) (Helgertz et al., 2022). The MLP linking method relies on a probabilistic algorithm based on individuals' sex, place of birth, birth year, first and last names, and household information to find potential matches across census years. Unlike the CLP, the MLP linking technique produces a single linked record for each individual. Helgertz et al. (2022) describes the linking method in detail. We report results using this alternative sample in Section 4.2.

3.2 Contemporary Data, 1962-2021

Our analysis of contemporary periods relies on samples from 10 different large-scale social surveys, including General Social Survey (1972–2021), Occupational Changes in a Generation (1962, 1973), National Survey of Families and Households (1987-1988, 1992-1994, 2001-2003), Panel Study of Income Dynamics (1968-2019), National Longitudinal Study of Youth (1979-2012), National Longitudinal Study–Young Men (1966–1981), National Longitudinal Study–Older Men (1966–1990), Survey of Income and Program Participation (1986-1988), Americans View Their Mental Health (1957, 1976), and National Survey of Black Americans (1979-1980, 1987-1988, 1988-1989, 1992). In each survey, we construct age, gender, race, and occupation variables for sons and their fathers. See Section C for a detailed description of each data source.

3.3 Sample Construction

After combining the linked historical censuses and survey data, we restrict the sample to Black and White men born between 1856 and 1975 and aged between 35 and 55 in six snapshot years 1910, 1930, 1950, 1970, 1990, and 2010. Individuals are grouped into six birth cohorts (1856-1875, 1876-1895, 1896-1915, 1916-1935, 1936-1955, and 1956-1975), which are labeled in our analysis by midyears (1860-1870, 1880-1890, 1900-1910, 1920-1930, 1940-1950, and 1960-1970).[5] Birth cohorts from 1860 to 1910 are drawn from historical censuses, whereas cohorts between 1920 and 1970 are obtained from surveys. As the survey data differ by weighting scheme, we create a standardized weight variable by setting the average to one while preserving the variance of the original weights. We do not apply any adjustment to the census data, as these full-count censuses are self-weighted. Finally, we reweight the sample to match the population distributions (by birth cohort, race, and 7-category occupations) using the Decennial Censuses (from 1870 to 2000, except for 1890) and the American Community Survey (ACS, 2010).[6]

In addition to the alternative sample constructed using MLP linkages for the historical censuses, we construct another version to test the sensitivity of our analysis with respect to changes in the data sources from the linked censuses to these survey data. As the coverage for the 1900-1910 birth cohort overlaps between the two data sources, we examine how the mobility estimates change using the alternate sample based on survey data instead of the censuses for this birth cohort and report results in Section 4.2.

3.4 Measurement of Occupations

For the linked historical censuses, whenever feasible, we maintain multiple observations of occupations in the linked sample and select the modal occupation observed when individuals are aged between 25 and 55. The modal value helps remove measurement errors associated with a snapshot measure of occupations.[7] When no modal value exists, we use the occupation measured in the year closest to age 40 (Haider and Solon, 2006).

We construct occupation variables in survey data in two different ways. In longitudinal studies, in which both offspring and parents are asked to report their main occupations in each survey year, we choose the occupation measured in the year closest to age 40 as the lifetime occupation. In cross-sectional surveys where fathers' information is often not directly observed, we rely on the retrospective information of fathers during the

[5] See Table B.2 for the mapping between birth cohorts and snapshot periods.
[6] See Section 3.4 and Table B.1 for details on the occupation categories.
[7] Ward (2023) shows that such errors in linked censuses may lead to biased mobility estimates.

respondents' childhood or adolescence reported by the respondents.[8] Father's information provided in prospective and retrospective surveys may not always match. However, according to the analysis of Jácome et al. (2021), nationally representative longitudinal surveys such as the PSID demonstrate a high consistency rate—over 80%—between the occupations reported by individuals and those their offspring recall.

We rely on the 1950 three-digit census occupation codes to construct broad occupational categories.[9] Specifically, we collapse the detailed occupations into seven groups (Professional and Semi-professionals; Proprietors, Managers, and Officials; Clerical; Sales; Skilled Manual; Semi-Skilled and Unskilled Manual; and Farming), which are consistent with the Erikson-Goldthorpe-Portocarero (EGP) class scheme widely used in the sociological literature (Erikson and Goldthorpe, 1992).[10] Given the limited number of detailed occupations within broad categories before the 20th century, particularly among Black individuals, we reorganize the occupation data into either three broad categories (Non-Manual, Manual, and Farming) or five distinct categories (Professional and Managers; Clerical and Sales; Skilled Manual; Semi-Skilled and Unskilled Manual; and Farming). From a practical perspective, our measurement approach based on Markov chain models may yield unstable estimates when some cells in the transition matrix have only a few observations or zero entries. Our main exercises rely on these broad categories.

Several recent studies discuss the importance of constructing separate income measures by race (Collins and Wanamaker, 2022; Jácome et al., 2021). Following this line of work, we develop separate transition matrices by race to explore racial disparities in mobility opportunities (see Section 4 for more details). One may further consider incorporating information on region by separately constructing these matrices by region and race. Again, our method using Markov chains is sensitive to cells with zero observations in transition matrices, which can lead to additional measurement issues when disaggregating data. The current scope of our work does not focus on understanding differences in the observed occupation categories between Black and White Americans nor on their implications for mobility patterns. Rather, we focus on the type of job characterized by a set of tasks and skills, and therefore, our results mainly reflect the "between-occupation" component of the Black-White gap in mobility rates given an observed occupation category.

[8] If the occupation information was reported multiple times, we choose the mode of the data values. Otherwise, we use the occupations of fathers when the respondents were 15 or 16 years old.

[9] In the National Survey of Black Americans, parental occupation information is only available in 22 occupation categories, which we map to our categorization of occupations as we discuss below.

[10] See Table B.1 for detailed mapping of three-digit Census occupation codes to our categorization of occupations.

4 Descriptive Patterns: Occupational Distributions and Mobility

We begin by examining the evolution of occupational distributions for Black and White men and changing occupational mobility between racial groups for the 1860 through 1970 birth cohorts. Our descriptive analyses rely on measures of occupational segregation indices and transition probabilities.

4.1 Occupational Segregation by Race and the Historical Context

The occupational distributions for both Black and White Americans change dramatically between the 1910 and 1970 birth cohorts, driven by a structural shift from "Farming" and "Manual" occupations to "Non-Manual" occupations (Figure A.1, top right). The two groups, however, show notable differences in their occupation distributions, which reveal important dynamics over time. Using the segregation index (Duncan and Duncan, 1955), Figure A.2 (solid navy) shows the dissimilarity in the occupational distributions, which increases between the 1860 and 1910 birth cohorts but subsequently exhibits a downward trend. The results using our definition of occupations in 3, 5, and 7 categories yield qualitatively similar trends in occupational segregation by race.[11]

The increasing trends in occupational dissimilarity for our earlier birth cohorts are consistent with the historical characterization of racial inequality during the late 19th and early 20th centuries. Despite the abolition of slavery by the Emancipation Proclamation in 1863 and the 13th Amendment in 1865, Black Americans continued to endure economic, social, and political hardships in the following decades (Black et al., 2015; Collins and Wanamaker, 2014; Derenoncourt, 2022; Logan and Parman, 2017; Margo, 2016).

Occupational segregation between Black and White individuals began to show a decline for the 1920-1930 birth cohort. This decline is further accelerated for the 1940-1950 birth cohort, which can be attributed to pivotal historical events in the mid-twentieth century. The active involvement of Black Americans in World War II ignited a spirit of activism, with many "unwilling to accept the pre-war structure of racial dominance" that characterized the nation (Modell et al., 1989). Civil rights legislation, such as the Civil Rights Act of 1964, which banned discrimination and segregation, and the Voting Rights Act of 1965, which eliminated barriers to Black Americans voting in the South, marked a crucial turning point in the fight against racial discrimination (Donohue and Heckman, 1991; Wright, 2013).

The most recent birth cohort (1960-1970) shows the lowest level of occupational segregation over the entire sample period. The rate of decline over time, however, is slower

[11] We report results in terms of birth cohorts, which is equivalent to using periods when these individuals were prime-age workers.

than that of the previous cohorts.[12] This finding is consistent with prior work that suggests the lack of convergence of Black-White socioeconomic status since the 1960s (Bound and Freeman, 1992). While civil rights legislation represents significant strides in addressing racial disparities, it did not eradicate all forms of discrimination and inequality.

4.2 Trends in Occupational Mobility

Next, we move on to study intergenerational occupational mobility patterns for our sample of Black and White Americans. Here, we use transition matrices constructed separately for our birth cohort and racial groups. Figure 1 shows trends in upward and downward mobility for White (navy lines) and Black men (maroon lines).[13] Solid lines in the plots present upward mobility from "Farming" or "Manual" to "Non-Manual" (Figure 1, left) and downward mobility from "Non-Manual" to "Farming" or "Manual" (Figure 1, right).

The trends show increasing upward mobility and decreasing downward mobility for both Black and White individuals over time. However, consistent with Duncan et al. (1972), the levels of upward (downward) mobility are greater (smaller) for White than Black men across all birth cohorts. Figure A.3 further shows the log differences in transition probabilities between the two groups, $log(p_{black}) - log(p_{white})$, which captures the mobility patterns of Black men relative to White men. Relative upward mobility rates continue to increase with a notable change from the 1920-1930 and 1940-1950 birth cohorts. By contrast, relative downward mobility increases up to the 1900-1910 birth cohort, significantly declines in the subsequent cohorts, and levels off for the 1960-1970 birth cohort. The slowing convergence in Black-White upward (or downward) mobility rates can importantly explain the continuing racial disparities in occupational distributions. Our analyses in Section 6 study this lack of convergence by assessing mobility barriers and examining the persistence of parental influence embedded in the mobility process.

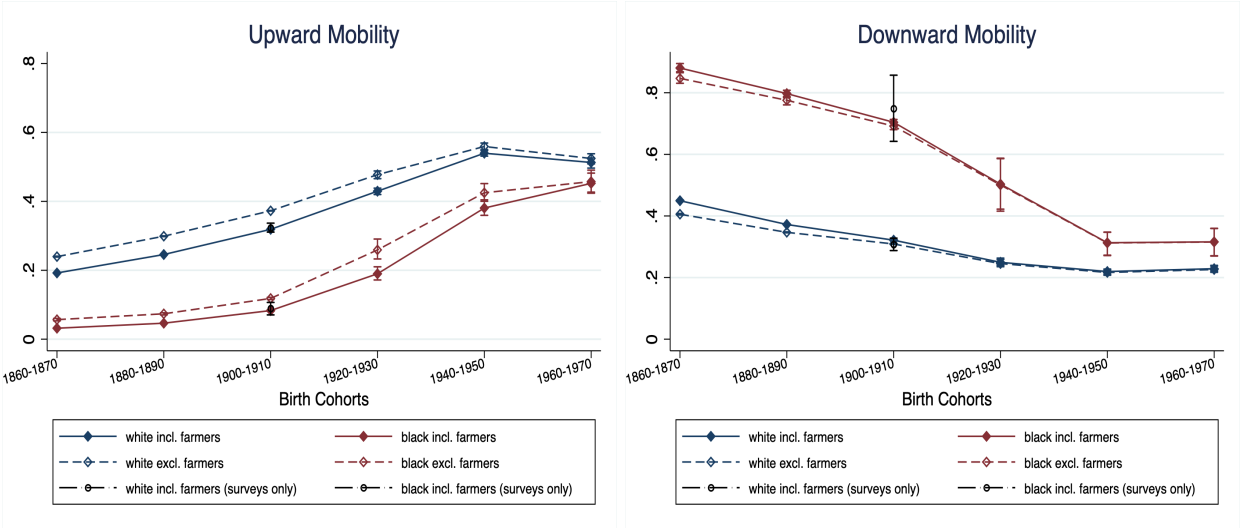
We also conduct analyses excluding farmers (Figure 1, navy and maroon dashes) to assess their role in shaping our results. Note that farmers represent a unique occupation group that not only shows a particularly high rate of status transmission from father to son but also continues to be exposed to the gradual decline of the agricultural sector since World War I (Song et al., 2020). While the results show a slight increase (decrease) in the level of upward (downward) mobility rates for these birth cohorts, the trends remain qualitatively similar to the baseline results.

As a robustness check, we conduct two additional exercises. First, we test the sensitivity

[12] As shown in Figure A.2, the trend is more pronounced, examining the segregation indices calculated using 5- and 7-category definitions.

[13] See Figures A.5 and A.6 for the corresponding full set of transition matrices.

Figure 1: Upward and Downward Mobility Patterns



Notes: The graphs show upward (left) and downward (right) mobility patterns for White (in navy lines) and Black men (in maroon lines) using 3-category occupations. The solid graphs with solid diamond symbols show trends in transitions from Farming or Manual to Non-Manual (left) and Non-Manual to Farming or Manual (right). The dashed graphs with hollow diamond symbols show trends in transitions from Manual to Non-Manual (left) and Non-Manual to Manual (right). The long-dashed graphs with hollow circles use survey data and show trends in transitions from Farming or Manual to Non-Manual (left) and Non-Manual to Farming or Manual (right). Bootstrapped 95 percent confidence intervals based on 200 draws are included.

of our analysis with respect to changes in the data sources from the linked censuses to these survey data. As the coverage for the 1900-1910 birth cohort overlaps between the two data sources, we conduct a parallel analysis using survey data for the 1900-1910 birth cohort (Figure 1, black dots). The upward mobility trends are strikingly similar to those presented as the baseline estimates (Figure 1, navy and maroon solid lines), while those for downward mobility show noticeable deviations, partly due to the small sample size issues. Second, we check how our results change based on the linking methods of the historical sample. Figure A.4 shows results using the historical sample constructed using MLP (Helgertz et al., 2022) instead of our baseline approach of CLP (Abramitzky et al., 2020, 2021). We find quantitatively similar results.

5 Black-White Inequality and The Role of Intergenerational Mobility

We next build on our formulation of the evolution of occupations in Equation (1) and study the connection between intergenerational mobility and cross-sectional occupational distributions. We take two complementary approaches. First, we conduct a decomposition exercise to study the importance of intergenerational transitions in explaining the observed

evolution of racial gaps in occupational distributions over time. Second, we simulate counterfactual scenarios to assess the importance of each mobility regime in explaining the observed cross-sectional distribution.

We also discuss our first form of structural mobility, defined using the change in mobility regimes from one period to another ($\mathbf{P}_{t-1}$ to $\mathbf{P}_t$).[14] The decompositions highlight the magnitude of structural mobility in explaining cross-sectional changes over time; the counterfactual experiments, in addition, show the role of structural mobility in explaining the current cross-sectional distribution or the degrees of occupational segregation by race.

5.1 Decomposition of Dynamics

We adopt the Kitagawa-Oaxaca-Blinder decomposition method to decompose changes in the occupational distribution. Given how we formulate the evolution of occupational distributions, as shown in Equation (1), changes in the occupational structure between periods t and $t+1$ are,

$$\mu_{t+1} - \mu_t = \mu_t \mathbf{P}_t - \mu_{t-1}\mathbf{P}_{t-1}.$$

Then, we further add and subtract terms and obtain the following decomposition,

$$\underbrace{(\mu_t - \mu_{t-1})\mathbf{P}_{t-1}}_{\text{(1) distribution}} + \underbrace{\mu_{t-1}(\mathbf{P}_t - \mathbf{P}_{t-1})}_{\text{(2) transition}} + \underbrace{(\mu_t - \mu_{t-1})(\mathbf{P}_t - \mathbf{P}_{t-1})}_{\text{(3) interaction}}. \tag{2}$$

The first term measures the contribution of overall changes in the occupational structure from periods $t-1$ to t in explaining the changes in the occupational distribution from periods t to $t+1$, fixing the mobility transition probabilities in period $t-1$. The second term, in turn, focuses on the role of changes in mobility transition probabilities from periods $t-1$ to t (or structural mobility) on changes in the occupational distribution from periods t to $t+1$, fixing the occupational distribution in period $t-1$. The last term captures the interaction of changing occupational distribution and mobility probabilities from time $t-1$ to t on the evolution of occupational distribution from periods t to $t+1$.

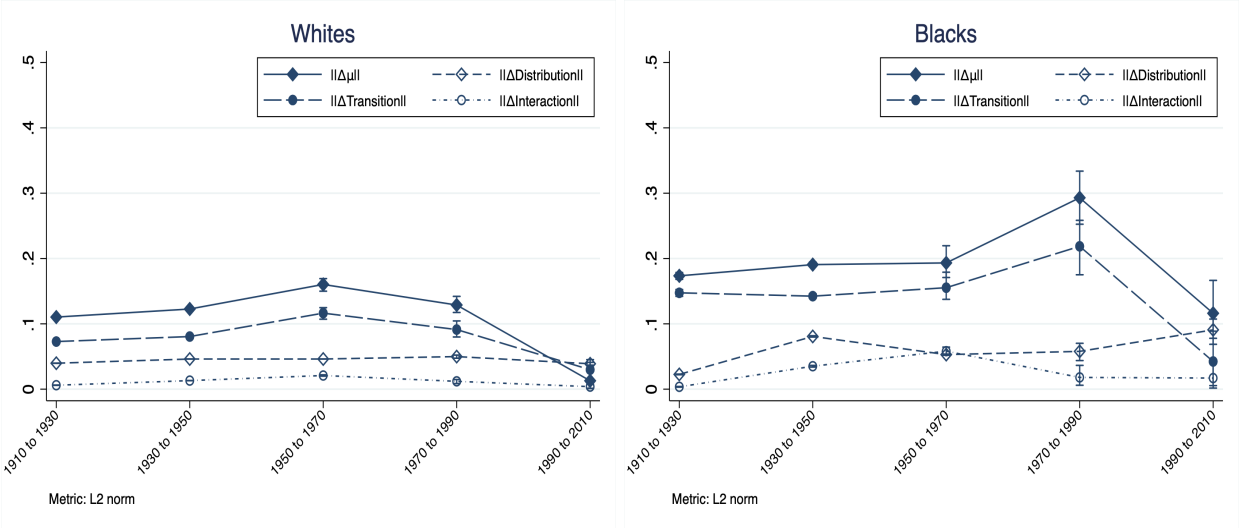
Figure 2 shows the magnitudes of the overall change in occupational distributions from one period to the next, $\|\mu_{t+1} - \mu_t\|$, and the contribution of each component, $\|(\mu_t - \mu_{t-1})\mathbf{P}_{t-1}\|$, $\|\mu_{t-1}(\mathbf{P}_t - \mathbf{P}_{t-1})\|$, and $\|(\mu_t - \mu_{t-1})(\mathbf{P}_t - \mathbf{P}_{t-1})\|$.[15] The solid line, which delineates the aggregate change in the occupational distribution from one period to another, closely follows the long-

[14] Our second form of structural mobility is defined for each mobility regime $\mathbf{P}_t$—mobility that is produced in the process of reaching the steady state in a given Markov chain. See Section 6.3 for further details.

[15] As we take (L2) norms, equality no longer holds for Equation (2):
$\|\mu_{t+1} - \mu_t\| \leq \|(\mu_t - \mu_{t-1})\mathbf{P}_{t-1}\| + \|\mu_{t-1}(\mathbf{P}_t - \mathbf{P}_{t-1})\| + \|(\mu_t - \mu_{t-1})(\mathbf{P}_t - \mathbf{P}_{t-1})\|$

dashed line representing the transition effects. This pattern suggests that the transition effects play a more important role than the distribution effects (short-dashed lines) or the interaction effects (dotted lines) in explaining changes in occupational distributions over time. While the results are similar for both racial groups, where structural mobility significantly explains the overall changes in the cross-sections, the magnitude of these changes is greater for Black men. In particular, notable changes in both the occupational distribution and the transitions occur between the 1920-1930 and 1940-1950 birth cohorts.

Figure 2: Aggregate Measurements of Kitagawa-Oaxaca-Blinder Decompositions



Notes: The graphs show the magnitude of the change in occupational distributions ($\|\mu_{t+1} - \mu_t\|$ in solid lines) and the three components ($\|(\mu_t - \mu_{t-1})\mathbf{P}_{t-1}\|$ in short-dashed lines, $\|\mu_{t-1}(\mathbf{P}_t - \mathbf{P}_{t-1})\|$ in long-dashed lines, and $\|(\mu_t - \mu_{t-1})(\mathbf{P}_t - \mathbf{P}_{t-1})\|$ in dotted lines) shown in Equation (2), separately for White (left) and Black men (right) for our sample of birth cohorts. We take L2 norms. Our calculations are based on 3-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Table 1 further shows the results of the decomposition exercise by occupational group for White (Panel A) and Black (Panel B) men.[16] Each row represents (i) changes in the occupational shares from one period to another (ΔOcc Shares) and (ii) the contribution of each component (ΔDistribution, ΔTransitions, and ΔInteraction) to the occupation-specific change in shares. We report the initial shares of each occupation in parentheses in the first column. For example, for White men, the share of "Non-Manual" and "Manual" occupations in the initial occupational distribution (the 1860-1870 birth cohort) are 0.272 (or 27.2 percent) and 0.512 (or 51.2 percent), respectively. For black men, the corresponding occupational shares are 0.038 (or 3.8 percent) and 0.570 (or 57.0 percent).

[16]Due to space constraints and the focus of the current discussion, the results for Farmers are omitted. These results are available upon request.

Table 1: Kitagawa-Oaxaca-Blinder Decompositions by Race

Occupation (Initial Share)	Cohorts (from)	Cohorts (to)	(1) ΔOcc Shares	(2) ΔDistribution	(3) ΔTransitions	(4) ΔInteraction
Panel A: **Whites**						
Non-Manual (0.272)	1860-1870	1880-1890	0.079 (.078, .08)	0.02 (.02, .02)	0.056 (.055, .057)	0.004 (.003, .004)
	1880-1890	1900-1910	0.096 (.095, .097)	0.033 (.033, .033)	0.063 (.062, .064)	0.001 (.001, .001)
	1900-1910	1920-1930	0.131 (.122, .137)	0.037 (.037, .037)	0.095 (.087, .102)	-0.002 (-.003, 0)
	1920-1930	1940-1950	0.095 (.087, .104)	0.038 (.036, .04)	0.066 (.057, .075)	-0.009 (-.011, -.006)
	1940-1950	1960-1970	0.009 (-.001, .019)	0.028 (.027, .03)	-0.022 (-.033, -.011)	0.003 (0, .006)
Manual (0.521)	1860-1870	1880-1890	-0.002 (-.003, -.001)	0.012 (.012, .013)	-0.01 (-.011, -.009)	-0.005 (-.005, -.005)
	1880-1890	1900-1910	-0.024 (-.025, -.024)	-0.001 (-.001, -.001)	-0.014 (-.015, -.013)	-0.01 (-.01, -.009)
	1900-1910	1920-1930	-0.073 (-.081, -.066)	-0.014 (-.014, -.014)	-0.046 (-.053, -.038)	-0.014 (-.015, -.012)
	1920-1930	1940-1950	-0.087 (-.096, -.079)	-0.031 (-.033, -.03)	-0.063 (-.073, -.055)	0.008 (.006, .01)
	1940-1950	1960-1970	-0.009 (-.018, .002)	-0.027 (-.028, -.025)	0.02 (.011, .031)	-0.002 (-.005, 0)
Panel B: **Blacks**						
Non-Manual (0.038)	1860-1870	1880-1890	0.019 (.017, .021)	0.001 (.001, .002)	0.016 (.014, .018)	0.001 (.001, .001)
	1880-1890	1900-1910	0.048 (.045, .05)	0.008 (.008, .009)	0.035 (.032, .037)	0.005 (.004, .006)
	1900-1910	1920-1930	0.156 (.134, .179)	0.018 (.018, .019)	0.123 (.105, .144)	0.014 (.009, .02)
	1920-1930	1940-1950	0.213 (.185, .242)	0.044 (.034, .053)	0.159 (.129, .186)	0.01 (0, .023)
	1940-1950	1960-1970	0.083 (.049, .119)	0.065 (.056, .077)	0.03 (-.004, .064)	-0.012 (-.031, .003)
Manual (0.570)	1860-1870	1880-1890	0.112 (.107, .116)	0.015 (.015, .016)	0.095 (.091, .099)	0.002 (.001, .002)
	1880-1890	1900-1910	0.104 (.101, .108)	0.053 (.052, .053)	0.079 (.076, .082)	-0.027 (-.028, -.026)
	1900-1910	1920-1930	-0.055 (-.079, -.033)	0.025 (.024, .025)	-0.033 (-.053, -.013)	-0.046 (-.052, -.04)
	1920-1930	1940-1950	-0.2 (-.23, -.171)	-0.036 (-.046, -.026)	-0.15 (-.181, -.119)	-0.014 (-.028, -.004)
	1940-1950	1960-1970	-0.081 (-.117, -.048)	-0.063 (-.075, -.054)	-0.03 (-.061, .004)	0.012 (-.003, .03)

Notes: The table shows the results of the decomposition exercise for White (Panel A) and Black men (Panel B) across Non-Manual and Manual occupations, where each row represents changes in the occupational shares from one period to another; and how much each component contributes to the occupation-specific change in shares. We report the initial shares of each occupation in the first column in parentheses. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Column (1) shows that the share of "Non-Manual" occupations increases over time for both racial groups. The magnitude of change for Black men becomes larger than that of Whites between the 1900-1910 and 1920-1930 birth cohorts. In fact, it remains significantly larger across subsequent birth cohorts. A reciprocal pattern holds for "Manual" occupations, where we observe continuous decreases in shares. However, this share increases among Black men, particularly for the 1900-1910 birth cohort, before beginning to decline in all subsequent cohorts. Consistent with Figure 2, Table 1 shows significant changes in occupational shares between the 1920-1930 and 1940-1950 birth cohorts, where structural mobility (or transition effect) mainly explains the overall changes in occupational shares for both racial groups. For example, the shares explained by intergenerational transitions for "Non-Manual" ("Manual") occupations are roughly 75 percent (78 percent) and 78 percent (77 percent) for Black and White men, respectively.

Note that the observed trends do not persist in later periods. Changes in the occupational shares drop significantly for both racial groups, particularly for White men. Even for Black men, the magnitude of the progress achieved by the 1940-1950 birth cohort does not continue either in terms of increasing the share of "Non-Manual" or in terms of decreasing the share of "Manual" occupations relative to the previous period.[17]

5.2 Counterfactual Dynamics and Distributions

Building on the importance of the intergenerational transition channel, we conduct a series of counterfactual experiments to assess the role of each mobility regime in explaining racial inequality in the cross-sectional distributions.

We first characterize the historical evolution of the occupational distribution building on our formulation of the evolution of cross-sectional densities in Equation (1),

$$\mu_t = \mathbf{P}_{t-1}\mu_{t-1} = \mathbf{P}_{t-1}\mathbf{P}_{t-2}\mu_{t-2} = \mathbf{P}_{t-1}\mathbf{P}_{t-2}...\mathbf{P}_0\mu_0.$$

Then, the counterfactual $\mu_{t|\tau}$ (where $\tau = 0, 1, \cdots, t-2$) representing how the occupational distribution might have evolved if historical events and their consequential changes in

[17] Table B.3 shows results combining both racial groups, and we obtain similar results highlighting the importance of the change observed between the 1920-1930 and 1940-1950 birth cohorts; and the significant contribution of the intergenerational transition channel.

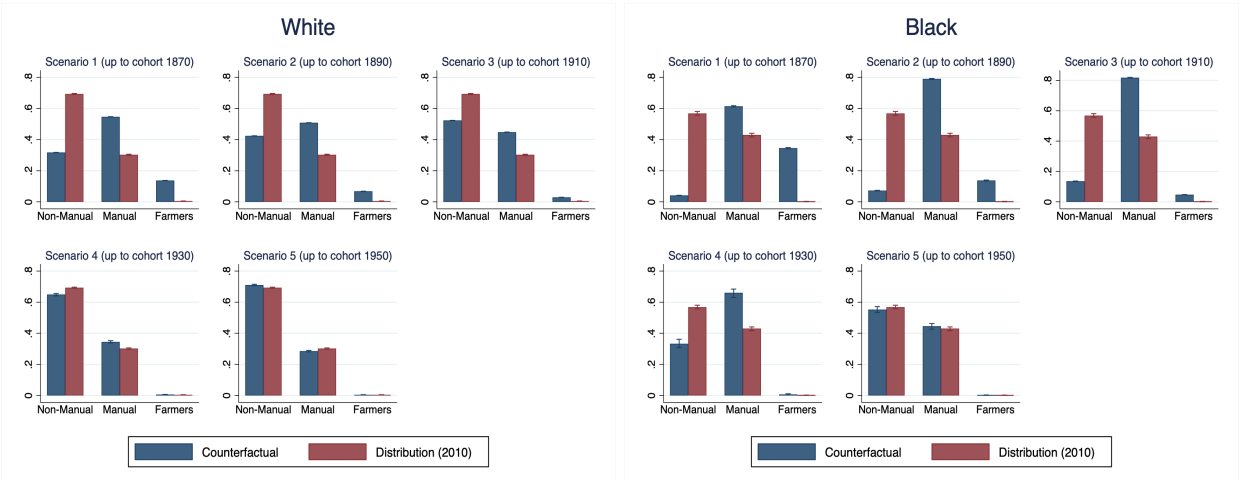
intergenerational mobility had not occurred are,

$$
\begin{aligned}
\mu_{t|0} &= \mathbf{P}_0\mathbf{P}_0 ... \mathbf{P}_0\mathbf{P}_0\mathbf{P}_0\mu_0 \\
\mu_{t|1} &= \mathbf{P}_1\mathbf{P}_1 ... \mathbf{P}_1\mathbf{P}_1\mathbf{P}_0\mu_0 \\
&\vdots \\
\mu_{t|t-2} &= \mathbf{P}_{t-2}\mathbf{P}_{t-2} ... \mathbf{P}_2\mathbf{P}_1\mathbf{P}_0\mu_0 \\
\mu_{t|t-1} &= \mathbf{P}_{t-1}\mathbf{P}_{t-2} ... \mathbf{P}_2\mathbf{P}_1\mathbf{P}_0\mu_0
\end{aligned}
\tag{3}
$$

where, by construction, $\mu_{t|t-1} = \mu_t$. Comparisons between the actual distribution μ_t and each counterfactual distribution $\mu_{t|\tau}$ (where $\tau = 0, 1, \cdots, t-2$) allow us to assess the importance of the mobility regime in period $t = \tau$ in explaining the actual cross-sectional distribution in period t.

Note that *changes* in the differences between the actual and counterfactual distributions over time, as we evaluate different periods $t = \tau$, capture the magnitude of changes in mobility regimes, or structural mobility, in their contributions to achieving μ_t. The Kitagawa-Oaxaca-Blinder decompositions highlight the magnitude of structural mobility in explaining cross-sectional changes over time. The counterfactual experiments additionally shed light on the role of structural mobility in explaining the observed cross-sectional distribution or the degrees of occupational segregation by race today.

Figure 3: Counterfactual Occupational Distributions



Notes: The graphs show the counterfactual occupational distributions for White (left) and Black men (right) in five different scenarios generated by sequentially updating the transition matrices over time. Our results are based on 3-category occupations. For example, in the top left panels, each group's current occupational distributions are contrasted with a counterfactual one where the transition matrix from the 1860-1870 birth cohorts is employed and remains unchanged over time. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure 3 presents the counterfactual occupational distributions for White (left) and Black men (right) in five scenarios, generated by sequentially updating the transition matrices over time. At the top left panel, each group's current occupational distributions are contrasted with a counterfactual distribution in which the transition matrix is assumed to be fixed at the level of the 1860-1870 birth cohort. In this scenario, both Black and White men exhibit a dominant group of farmers and manual workers, which is in stark contrast to the distribution observed for the 1960-1970 birth cohort. At the top middle panels, the transition matrix evolves up to the one from the 1880-1890 birth cohort. The results still suggest a substantial difference from the current distributions. The bottom middle panel incorporates the transition matrix from the 1940-1950 birth cohort and yields a great resemblance to the current distributions.

For White men, the gap between the counterfactual distributions and the distribution observed in 2010 gradually decreases as we update the matrices across different counterfactual scenarios. After including the transition process from the 1900-1910 birth cohorts, the share of "Non-Manual" occupations becomes the highest while the share of "Manual" occupations remains high. The share of "Non-Manual" occupations continues to increase as we update the transition matrices. Figures A.12 and A.16 (top panel) show results using detailed occupational definitions. The importance of the transition matrix from the 1900-1910 birth cohorts in increasing the shares of "Non-Manual" occupations is mainly driven by the middle-skill occupations in "Clerical" and "Sales" categories, not in "Professionals" and "Managers" that require higher levels of skills or have higher earnings. The inclusion of the transitions from the 1940-1950 birth cohorts leads to an occupational distribution that is similar to the current one, where the shares in "Professionals and Managers" significantly increase relative to other counterfactual scenarios.

For Black men, the gap between the counterfactual distributions and the current distribution persists and dramatically drops as we introduce the transition process from the 1940-1950 cohorts. The share of "Manual" occupations, in particular, remains a dominant category, even after including the 1910-1920 birth cohorts, which is in contrast with the patterns of Whites. Further analysis using detailed occupational definitions (Figures A.12 and A.16, bottom panel) shows that the overrepresentation of "Manual" occupations is driven by "Semi-Skilled and Unskilled Manual" occupations, whereas the lower share of "Non-Manual" occupations is explained by the lack of "Professionals and Managers," which significantly increases after the 1940-1950 birth cohorts.

Figure A.11 shows the level of occupational segregation by race for each counterfactual scenario, which we calculate using the corresponding counterfactual distributions in Figure 3 obtained for Black and White men, respectively. The dashed horizontal line indicates the

actual segregation level in 2010. We find that the level of segregation in all counterfactual scenarios strictly exceeds the actual level. The difference is most pronounced in scenario 3, where we allow the mobility process to evolve up to the birth cohorts of 1900-1910, during which the probability of maintaining or sorting into "Non-manual" jobs begins to increase only for White men, but not for Black men.

The contribution of the 1940-1950 birth cohorts in both racial groups significantly reduces differences in the cross-sectional distributions, and the youngest cohort further narrows the gap.[18] Our results using both the decompositions and counterfactual exercises collectively highlight the significance of structural mobility achieved by the 1940-1950 birth cohort, aligning with the substantial institutional changes (e.g., the GI Bill, the Civil Rights Act of 1964, the Higher Education Act of 1965, the Voting Rights Act of 1965) that promoted equality of opportunity across various aspects of American society, thereby affecting mobility opportunities.

6 Persistence of Black-White Inequality: Barriers and Memory

Analyses in the previous sections highlight the unique importance of changes in mobility experienced by the 1940–1950 birth cohort in shaping the current occupational distribution and reducing the racial gap. Despite important improvements, Black-White inequality in both the cross-sectional occupation distributions and intergenerational mobility persists, consistent with prior studies stressing the lack of Black-White convergence in economic status (Bound and Freeman, 1992; Collins and Wanamaker, 2022).

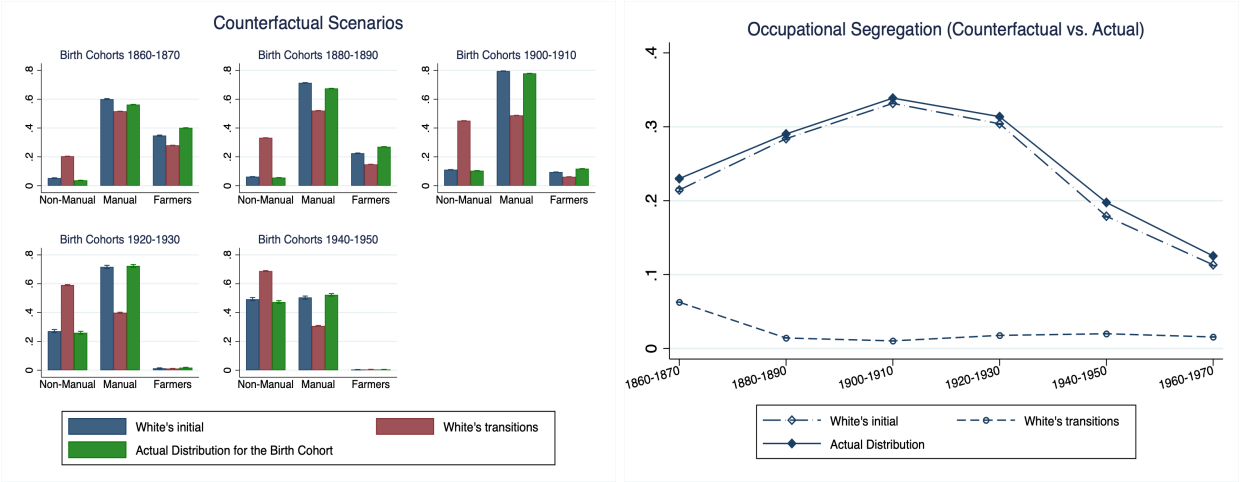
In this section, we investigate the role of mobility in explaining the degree of persistence of Black-White cross-sectional inequality and study properties of persistence embedded in the mobility process by measuring (i) mobility barriers and (ii) memory in mobility.

6.1 Persistence of Black-White Inequality

Our approach to assessing the role of mobility in explaining the degree of persistence of racial disparities in cross-sectional distributions involves a series of counterfactual experiments in which we allow Black men to experience either the *initial conditions* or the *mobility dynamics* of White men. The exercises result in comparing the occupational distribution of White men μ_t^W to the counterfactuals, $\mu_t^{B'} = \mathbf{P}_{t-1}^B \mathbf{P}_{t-2}^B ... \mathbf{P}_1^B \mathbf{P}_0^B \mu_0^W$ and $\mu_t^{B''} = \mathbf{P}_{t-1}^W \mathbf{P}_{t-2}^W ... \mathbf{P}_1^W \mathbf{P}_0^W \mu_0^B$, respectively.

[18] Figures A.15 and A.19 present results using 5- and 7-category occupations, respectively, where we find qualitatively similar results.

Figure 4: Counterfactual Occupational Distributions of Black Men



Notes: The left graphs contrast the actual occupational distributions of Black men and counterfactual ones where (i) both racial groups start with the same initial condition ($\mu_0^B = \mu_0^W$, in navy) but experience different mobility dynamics; (ii) both racial groups undergo the same mobility dynamics ($\mathbf{P}_t^B = \mathbf{P}_t^W$, in maroon) yet face different initial conditions. The right graph shows the degree of occupational segregation under each scenario. Our results are based on 3-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure 4 (left) shows the occupational distributions for both counterfactual exercises evaluated across time periods. The blue bars represent scenarios in which Black men begin with the initial conditions of White men; the red bars depict situations in which Black men experience the mobility dynamics of White men; and the green bars represent the actual occupational distribution of Black men in each period. Across all time periods, the share of "Non-Manual" occupations, when Black men undergo White men's transition matrix, exceeds the share obtained from the actual distribution. While smaller in magnitude, beginning at White men's initial conditions results in a slightly higher share of "Non-Manual" occupations than the actual ones. Results based on more detailed occupational definitions (both five and seven categories) are presented in Figures A.13 and A.17, which suggest that the higher shares in "Non-Manual" under these hypothetical scenarios are driven by both "Professional and Managerial" and "Clerical" and "Sales" occupations.

Figure 4 (right) shows changes in the degree of occupational segregation by race. The long- and short-dashed lines represent counterfactual scenarios with the same initial conditions and the same mobility dynamics, respectively. The solid line corresponds to the actual distribution. Comparing the long-dashed line with the solid line, we find a slight reduction in occupational segregation by race in the counterfactual scenario, where Black men experience the same initial conditions. In contrast, when Black men experience the same mobility dynamics as White men, the segregation index immediately drops near

zero in the second birth cohort group and persists in the subsequent cohorts. Thus, our findings suggest that racial differences in the evolution of mobility regimes are critical in explaining the persistent Black-White gap in cross-sectional distributions in 2010. These racial differences in the dynamics in part reflect how aggregate shocks have impacted racial groups differently, thereby highlighting the Black-White differences in structural mobility. In the following analyses, we make further progress by examining the properties of persistence embedded in each mobility regime.

6.2 Mobility as Movement: Measurement of Barriers

To study properties of persistence embedded in each mobility regime from the perspective of mobility as movement, we assess the sequence of transitions needed to achieve a particular status for the first time. Specifically, we characterize mobility barriers using the *mean first passage times* in Markov chains. Let $f_{ij}^{(n)}$ denote the probability that the first passage time from state i to j is equal to n, which satisfies, $f_{ij}^{(n)} = \sum_{k \neq j} p_{ik} f_{kj}^{(n-1)}$. The mean first passage times, b_{ij}, can be defined as

$$b_{ij} = E[f_{ij}^{(n)}] = \sum_{n=1}^{\infty} n f_{ij}^{(n)}. \tag{4}$$

Note that it can be easily verified that b_{ij} satisfies the following system of equations:

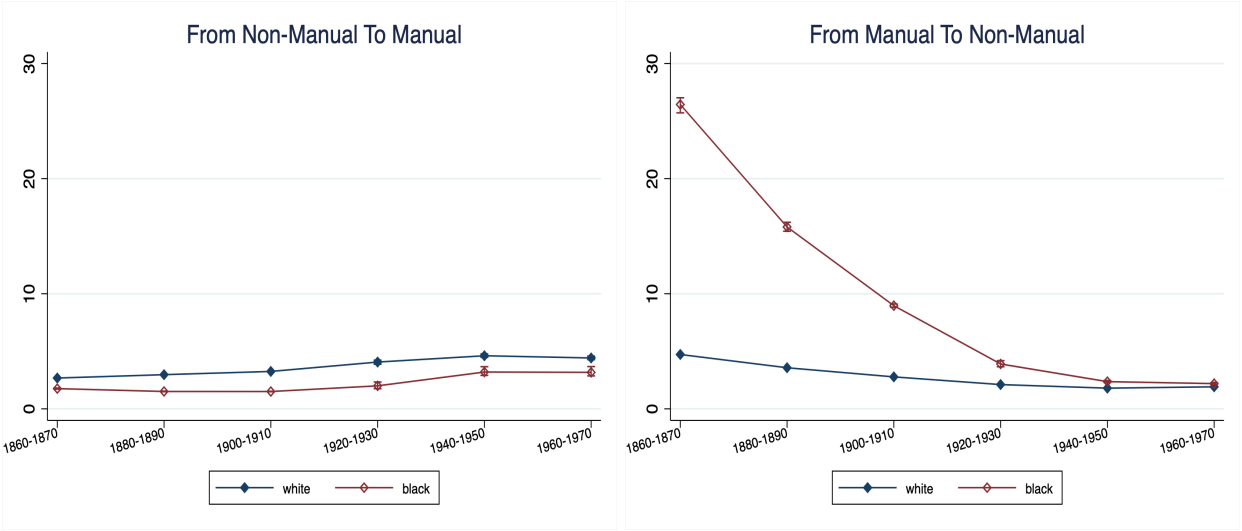
$$b_{ij} = 1 + \sum_{k \neq j} p_{ik} b_{kj} \tag{5}$$

If a chain begins at state i, state j can be directly reached from state i with probability $p_{ij} > 0$, and thus the first passage time is equal to 1. With probability p_{ik}, the chain first reaches the state $k \neq j$ and achieves the first passage time $(1 + b_{kj})$, since it has taken 1 period without reaching the state j, and it will take the same expected first passage time from state k to j starting the next period. Therefore, $b_{ij} = 1 \cdot p_{ij} + \sum_{k \neq j}(1 + b_{kj}) \cdot p_{ik}$. Expanding the summation and using $p_{ij} + \sum_{k \neq j} p_{ik} = 1$, we obtain $b_{ij} = 1 + \sum_{k \neq j} p_{ik} b_{kj}$.[19]

Figure 5 presents the mean first passage times from "Non-Manual" to "Manual" occupations (left) and from "Manual" to "Non-Manual" occupations (right), estimated separately for Black and White men. The mean first passage times from "Non-Manual" to "Manual" occupations remain largely stable over time for both racial groups. Across our sample

[19] Let $v_j \equiv b_{ij} | i \neq j = (b_{1j}, \cdots, b_{(i-1)j}, b_{(i+1)j}, \cdots b_{Nj})'$, and let P_{-j} denote the transition matrix with the j-th row and column removed ($(N-1) \times (N-1)$). The above system of equations can be rewritten as $v_j = 1 + P_{-j} v_j$. Rearranging, $v_j = (I_{N-1} - P_{-j})^{-1} \mathbb{1}_{N-1}$. We can then obtain the full set of b_{ij} from the transition matrix P.

Figure 5: Barriers to Mobility: Mean First Passage Times



Notes: The graphs show the mean first passage times from Non-Manual to Manual occupations (left) and from Manual to Non-Manual occupations (right) using 3-category occupations for Black and White men. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

of birth cohorts, the barriers for Black men, initially 2.7 generations and increasing to 4.4 generations, are lower compared to those of White men, which range from 1.8 to 3.2 generations. These results suggest that Black men face greater challenges in maintaining and transmitting high-status occupations to their offspring. Furthermore, the Black-White gap remains consistent over time. The estimates for White men continue to be greater than that of Black men by around one generation, even for the most recent birth cohort group.

The estimated mean first passage times from "Manual" to "Non-Manual" occupations reveal a striking difference between the two racial groups. The estimates for White men indicate a relatively low barrier from the outset, starting at around 4.7 generations. These estimates remain fairly stable over time, with a gradual downward trend, reaching approximately 1.9 generations for the most recent cohort. The results for Black men, on the other hand, exceed 20 generations for the initial 1860-1870 cohort, but the values drop to less than 10 generations for the 1900-1910 cohort and continue to decrease over time—the 1960-1970 birth cohort faces mean passage times of 2.2 generations. Recall that the corresponding changes in upward mobility for the first three birth cohort groups minimally increase from 3 to 8 percent (Figure 1); however, barriers to achieving high-status occupation, albeit significantly higher than that of White men, dramatically improve. The gap between the two groups shrinks over time, the mean passage times for the 1960-1970 cohort show negligible racial differences of around 0.3 generations.

We further explore these trends by using detailed occupational definitions to identify

specific occupation categories in which Black individuals experience significant changes in mobility opportunities. Figures A.20 and A.21 present results for 5- and 7-category occupations. We focus our discussion on mobility barriers faced by individuals from parents in "Semi-Skilled and Unskilled Manual" occupations in achieving high-status occupations such as "Professional and Semi-Professional" occupations and "Proprietors, Managers, and Officials."[20] Table B.4 shows that the mean first passage times for Black men reaching "Professional and Semi-Professional" occupations decreased significantly, from over 50 generations initially to 12.1, 6.2, and 5.4 generations for the most recent birth cohorts. A similar, though more pronounced, decline is observed in the transition to "Proprietors, Managers, and Officials" occupations, where the mean first passage times drop from over 90 to 43.1, 12.3, and 9.6 generations.

While these findings may reflect improvements in socioeconomic opportunities over time, they may also be influenced by the historical context, such as the growth of certain occupations during segregation. For example, African American proprietors notably thrived in Black communities between 1900 and 1930, a period Walker (2009) refers to as the "Golden Age of Black Business." It is important to note that, similar to Figure 5, these mobility barriers remain higher for Black men compared to White men throughout our sample period, even for our youngest birth cohort.

6.3 Mobility as Independence of Origin: Measurement of Memory of Mobility Regimes

Next, we investigate properties of persistence embedded in each mobility regime from the perspective of mobility as independence of origin, by assessing (i) *memory* of the mobility system, which refers to how long the influence of one generation lasts on future generations, and (ii) how quickly this influence dissipates over time.

As discussed in Section 2, we quantify the information retained from parents using the difference between the cross-sectional distribution and the steady state distribution, where individuals experience no parental influence in occupational sorting. More formally, we characterize *aggregate deviations* (AD) as the difference between the cross-sectional densities at time t ($\mu_0\mathbf{P}^t = \mu_t$) and the steady state ($\mu^*$),

$$AD(\mathbf{P}, \mu_0, t) = \|\mu_0\mathbf{P}^t - \mu^*\|. \tag{6}$$

Greater values of AD imply stronger memory of the initial conditions and the mobility process in the system. Examining $AD(\mathbf{P}, \mu_0, t)$ over time provides information on the

[20] Some occupations, such as "Clerical" and "Sales," have large mean first passage times due to their small shares in the occupational distributions (Figure A.1).

patterns and the rate of convergence toward the steady state.

The AD measure, however, does not capture heterogeneity in the persistence of memory among individuals. The chances for individuals to enter different occupations may vary substantially depending on their family background or for our focus, the occupation of their parents. Thus, we modify AD to evaluate *individual deviations* (ID) by parental occupation group,

$$ID(P, j, t) = \|e_j \mathbf{P}^t - \mu^*\|, \tag{7}$$

where the population-level vector of μ_0 in Equation (6) is replaced with a unit vector e_j, namely, a vector of zeros with a 1 in state (or occupation) j.

To aggregate the individual deviations in Equation (7), we integrate over the initial population density ($\mu_{e,0}$) and derive the total individual memory of the system to solve for the *aggregated individual deviations* (AID), which we characterize as taking a weighted average of the individual mobility curves:

$$AID(P, \mu_0, t) = \int \|e\mathbf{P}^t - \mu^*\|\mu_0. \tag{8}$$

For empirical analyses, we calculate the distances between data points ($\|\cdot\|$) using the L1 norm ($|x_1| + |x_2| + ... + |x_n|$).[21] The difference between the AD and AID measures captures the influence of mobility heterogeneity on the *memory* of inequality in the system.

We then define the *rate* at which memory dissipates, *aggregate mobility* (AM) and *aggregated individual mobility* (AIM), by taking the ratios of the distance to steady state between t and $t+1$,

$$AM(\mathbf{P}, \mu_0, t) = \frac{AD(\mathbf{P}, \mu_0, t+1)}{AD(\mathbf{P}, \mu_0, t)}, \quad AIM(P, \mu_0, t) = \frac{AID(\mathbf{P}, \mu_0, t+1)}{AID(\mathbf{P}, \mu_0, t)}, \tag{9}$$

where AM and AIM are less than one since the distance to steady state decreases in t. Note that *smaller* values of AM and AIM correspond to *faster* convergence and, therefore, imply *greater* mobility (as independence of origin). As t increases, AM converges to the second-largest eigenvalue of the transition matrix $|\lambda_2|$, which governs the asymptotic rate of convergence. Our measures allow us to study the intermediate dynamics, which can, for example, converge slowly in the short and accelerate in the medium run (Blume et al., 2024). As we construct period-specific transition matrices to examine mobility properties under each historical regime, our measures of AM and AIM are more relevant than the second-largest eigenvalue of the transition matrix $|\lambda_2|$ focusing on the asymptotic behavior.

In the interest of space and effective illustration of our results—for example, demon-

[21] See Blume et al. (2024) for more details.

strating heterogeneity in measures of memory by occupation groups—we present results focusing on 5-category occupations in the following analyses.

6.3.1 State of Equality in Opportunity: Steady State

Before examining the results for our measures of memory, we first discuss the steady state distributions. That is, we study whether the state of no parental influence on offspring's occupational sorting, or the state of equality of opportunity, describes "better" circumstances compared to the observed occupational distribution, for example, in terms of high- and low-skill occupation shares or the degree of segregation by race. This is important information as we interpret our results of memory measures and connect them with the discussion of racial inequality. Figure 6 compares the occupational distributions observed for each birth cohort group to their respective steady state distributions separately derived for Black and White men (μ^{B*} and μ^{W*}).

For White men (Figure 6, top panel), moving toward the steady state entails compositional shifts that increase the share of high-skill occupations. The share of "Professional and Managers" is always higher at the steady state than the actual, and the share of "Semi-Skilled and Unskilled Manual" is lower at the steady state across all periods except for the 1860-1870 and 1880-1890 birth cohorts. For Black men, in contrast, the share of "Professional and Managers" shows minimal differences comparing the steady state and the actual distributions up to the 1920-1930 birth cohort. The steady state distribution begins to show higher shares in these high-status occupations compared to the actual distribution for the 1940-1950 birth cohort, and this trend continues for the most recent birth cohort. The share of "Semi-Skilled and Unskilled Manual" is strictly higher at the steady state up to the 1900-1910 birth cohort and decreases for subsequent cohorts.

For Black men, reaching the steady state has similar implications as White men for later periods; however, for earlier periods, the steady state implies a shift toward a distribution with higher shares in low-skill and farming occupations. As we compare the Black-White gap in occupational distributions, we observe a higher level of occupational segregation by race at the steady state than the actual level for up to the 1900-1910 birth cohort, while the opposite holds for the 1940-1950 and 1960-1970 birth cohorts (Figure A.2). As demonstrated in previous exercises, opportunities to maintain or move into higher occupation status improved significantly for Black men compared to past cohorts, and the steady state distribution accordingly indicates an improvement in terms of occupational segregation by race.

Figure 6: Occupational Distribution at Steady States

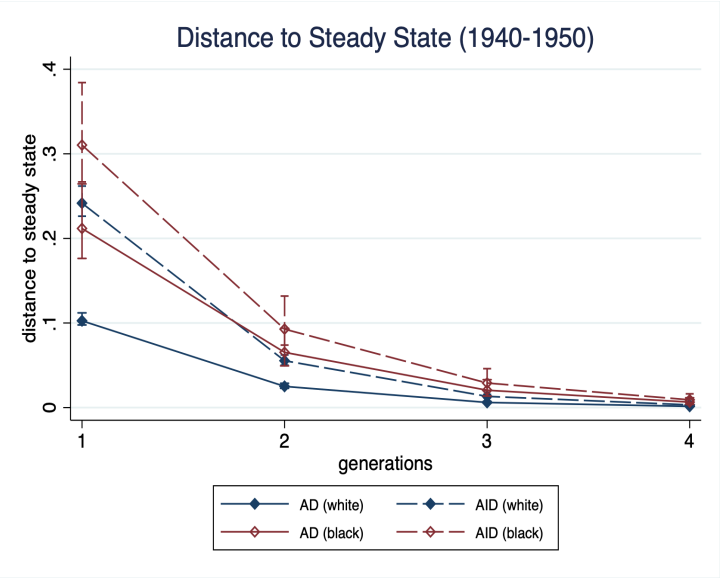


Notes: In each graph, the bars in navy show the occupational distributions observed in each period, which correspond to years when each birth cohort of interest reaches its prime age. The bars in maroon show the occupational distributions at steady states using the transition matrices of each birth cohort. Our results are based on 5-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

6.3.2 Memory: Distance to Steady State

We next discuss our results of memory estimated using aggregate deviations (AD) and aggregated individual deviations (AID). In the interest of space and a better illustration of our measures, we focus our discussion on the 1940-1950 birth cohort. Given its instrumental role in shaping the current occupational distribution and reducing the racial gap demonstrated in previous sections, it is useful to further understand the properties of memory embedded in the mobility regime of this birth cohort group.

Figure 7: Aggregate Deviations (1940-1950 Birth Cohort)



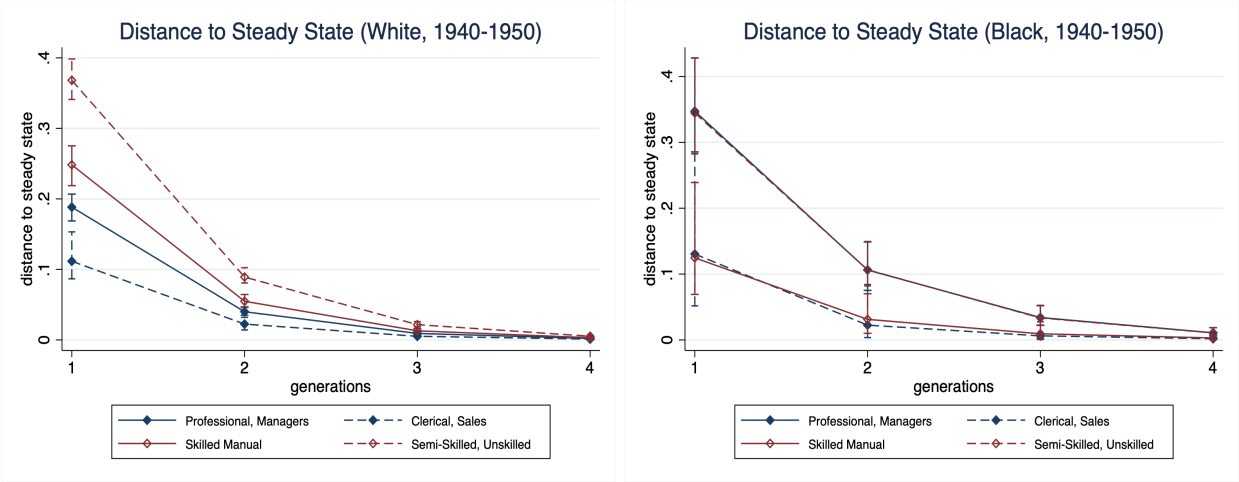
Notes: The graph shows AD (solid lines) and AID (dashed lines) for each racial group. Larger deviations to steady state correspond to greater memory. We use transition matrices for 5-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure 7 presents the results for AD (solid lines) and AID (dashed lines) estimated for each generation t where $t = 1, 2, 3, 4$. The level of AID is always greater than that of AD for any generation t. In Appendix D, we show that the inequality always holds by construction. There are two main takeaways. First, for both racial groups, AD and AID converge to the steady state after four generations. Thus, from $t = 5$ onward, any advantages or disadvantages that parents exert on offspring's occupational sorting disappear. Second, examining differences between racial groups, the levels of AD and AID are greater for Black men compared to White men at any given t. This suggests that Black men are more distant from steady state and exhibit greater memory of their family backgrounds in occupational sorting. As discussed using Figures 6 and A.2, for the 1940-1950 birth cohort, the steady state indicates a "better" distribution with lower degrees of occupational segregation

compared to the cross-sectional distributions. Hence, Black men face greater challenges reaching this better state of equal opportunity compared to their White counterparts.

We next discuss our results for individual deviations (ID), which unmask heterogeneity across parental occupational groups (j).[22] Figure 8 presents results, where we find varying patterns across occupation groups for both Black and White men.[23] For White men, the parental group that demonstrates the most influence on offspring occupational outcomes at $t = 1$ is the "Semi-Skilled and Unskilled Manual" occupational group. For Black men, the strongest memory at $t = 1$ is observed for both "Semi-Skilled and Unskilled Manual" and "Professional and Manager" occupations. The results indicate that the mobility regime of Black men is both rigid at the bottom and top of the system, whereas White men show stronger memory only for low-status occupations.

Figure 8: Individual Deviations (1940-1950 Birth Cohort)



Notes: The graphs show our measurements of individual deviations ID for White men (left) and Black men (right). Larger deviations from the steady state correspond to greater memory. We use transition matrices for 5-category occupations (excluding farmers). Bootstrapped 95 percent confidence intervals based on 200 draws are included.

6.3.3 Dissipation of Memory: Rate of Convergence to Steady State

We then study the rates at which AD and AID converge to steady state using AM and AIM, respectively, to examine how quickly memory of the mobility system dissipates over time. Here, we discuss results for all birth cohorts, which allows us to trace out the dynamics in these convergence rates and connect our findings with Black-White differences in mobility

[22] Appendix E uses variations of our individual deviation measures to study within- and between-group inequality.

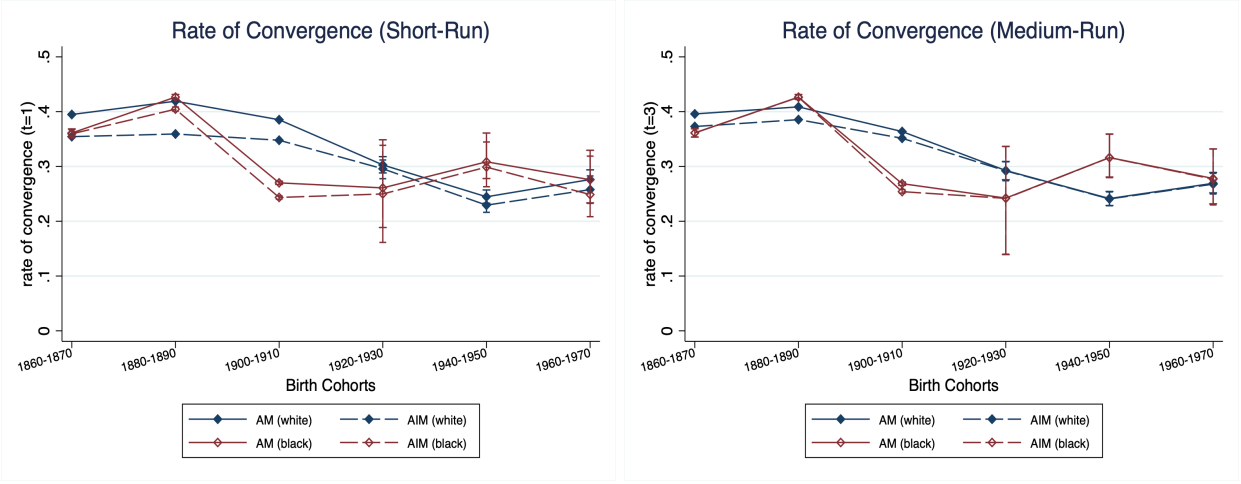
[23] For better illustration purposes, we omit the farmer category in the graph.

trends documented in other studies that focus on mobility as movement.

Figure 9 presents the estimated convergence rates in the short run (left, $t = 1$) and the medium run (right, $t = 3$). Recall that smaller values of AM and AIM correspond to faster convergences and, thus, greater mobility rates. The overall patterns of AM and AIM in the two graphs closely resemble each other, and their values converge in the medium run, particularly for the younger cohorts in our sample (1920-1930 to 1960-1970). For White men, we observe a downward trend in the estimates across birth cohort groups, with a slight uptick in the most recent cohort. For Black men, the estimates decline from the 1900-1910 birth cohort but increase from the 1940-1950 cohort onward.

Therefore, for White men, convergence rates increase steadily across birth cohorts. In contrast, Black men show relatively high convergence rates for the 1900-1910 and 1920-1930 cohorts, but these rates decline significantly for the 1940-1950 and 1960-1970 cohorts. When comparing across racial groups, White men exhibit faster convergence rates than Black men in the younger cohorts, whereas the pattern reverses in the older cohorts. Notably, the 1940-1950 birth cohort displays the lowest convergence rate for Black men, sharply contrasting with White men, who achieve their highest convergence rate within the sample.

Figure 9: Evolution of the Rate of Convergences (All Birth Cohorts)



Notes: The graphs show AM and AIM in the short-run (left) and those derived in the long-run (right). Smaller AM and AIM correspond to *faster* convergence, and, therefore, imply *greater* mobility. We use transition matrices for 5-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

It is important to understand these results in relation to our discussion of steady states, namely whether the probability of sorting across occupations independent of family background also accompanies better circumstances, for example, greater chances of

sorting into high-status occupations. Our sample of birth cohorts for White men shows an overall increase in convergence rates, and these higher mobility rates as independence of origin imply greater sorting probabilities into high-status occupations. As for Black men, the earlier cohorts show faster convergences toward the steady state, indicating worse circumstances with higher shares in low-status occupations, while more recent cohorts, facing a better distribution at steady state, converge rather slowly.[24] The results indicate an improvement in mobility as independence over time for White men but not Black men.

This finding importantly complements our results using mobility as movement and other existing studies that study historical trends in mobility. Similar to existing studies (Collins and Wanamaker, 2022; Jácome et al., 2021), our analysis of mobility as movement studying upward/downward mobility (Section 4.2) and bottlenecks (Section 6.2) finds the important role of the 1940-1950 birth cohort in improving mobility to a greater extent compared to previous cohorts, but also documents the persistence of the mobility gap between Black-White Americans. Our analysis of mobility as independence of parental origin reveals a new dimension of Black-White inequality. Specifically, the rate at which parental memory dissipates or parental occupations cease to influence occupational outcomes has improved only for White men. Notably, among Black men, such mobility rates for the 1940-1950 birth cohorts remain among the lowest in our sample, despite the mobility process suggesting a steady state distribution with higher shares in high-status occupations. This stands in stark contrast to the outcomes for their White counterparts.

6.3.4 Structural versus Exchange Mobility Redux

Finally, we use our measurements to study structural versus exchange mobility.[25] Structural mobility refers to shifts in occupational distributions across generations driven by aggregate changes in the economy, where individuals' mobility is influenced by external forces rather than personal efforts or choices. On the other hand, exchange mobility, also referred to as relative mobility, involves individuals moving up or down the occupational ladder compared to others, where one person's upward mobility results from another person's downward mobility. The concept has been widely used in the sociological literature to analyze whether society provides opportunities for individuals to improve their status through their own merit and effort (McClendon, 1977; Sobel, 1983; Sobel et al., 1985).

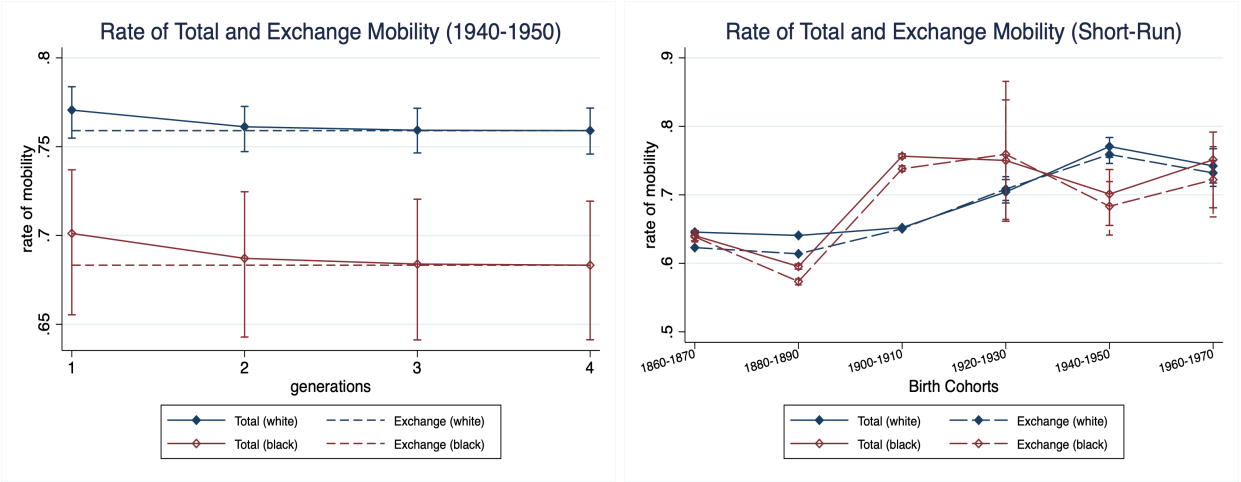
[24]The 1920-1930 birth cohort faces a "better" steady state and shows a point estimate that indicates fast convergence; however, not that the bootstrapped confidence intervals are quite wide.

[25]The conceptual distinction between structural versus exchange mobility dates back to the seminal work of Kahl (1957), where he identified "four causes of movement" in social mobility: changes due to technology, population dynamics, immigration, and the individual shifts that occur as some people fall in social standing, thereby creating opportunities for others to rise.

A society with a higher level of exchange mobility is considered more open and fluid as parental status is less constraining to children. However, note that our calculations do not speak to specific mechanisms.

The conceptual distinction between structural versus exchange mobility in our measurement builds on Berger and Snell (1957), contrasting (i) mobility that is produced in the process of reaching the steady state of a given Markov chain and (ii) mobility that occurs at the steady state or immobility that would be observed in the absence of this evolution. Specifically, we define the rate of *exchange mobility* as the rate of aggregated individual mobility near steady state, $AIM(P, \mu_0, t)$ when $t \to \infty$. The overall rate of mobility calculated using $AIM(P, \mu_0, t)$ examined at each time t, net of exchange mobility, therefore, gives the rate of *structural mobility*, $SM(P, \mu_0, t)$. By construction, the process of approaching steady state reduces structural mobility to zero. Blume et al. (2024) also measures these two objects but takes an alternative approach: exchange mobility is defined using an imbalance matrix, capturing the difference between the inflow and outflow of each occupation (or class). The imbalances disappear as the process reaches steady state (or as structural mobility becomes zero).

Figure 10: Structural versus Exchange Mobility



Notes: The left graph shows mobility rates for the 1940-1950 birth cohorts. For interpretation purposes, our plots are based on calculations using 1- $AIM(P, \mu_0, t)$, so that larger values indicate greater mobility rates. Solid lines represent aggregate mobility rates; dashed horizontal lines indicate the level of exchange mobility rates. The right graph shows the aggregate and exchange mobility examined at $t = 1$ for our sample of birth cohorts. The difference between the solid and dashed lines for each racial group captures the level of structural mobility rates. We use transition matrices for 5-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure 10 presents the results. For interpretative purposes, we present our results using 1-$AIM(P, \mu_0, t)$. Thus, larger values indicate higher mobility rates. Solid lines represent

total mobility rates, and dashed lines indicate exchange mobility rates. The difference between the two captures structural mobility rates, which become minimal as we iterate the mobility process over generations. The graph on the left presents results that focus on the 1940-1950 birth cohorts. For both racial groups, the importance of structural factors in explaining mobility patterns is limited, which accounts for less than 5 percent of the total mobility rates from $t = 1$ onward. When comparing across racial groups, Black men demonstrate higher levels of structural mobility than White men, while White men experience greater levels of exchange mobility than Black men.

The graph on the right compares the aggregate and exchange mobility rates at $t = 1$ for all birth cohorts in our sample. Again, we find limited importance for structural mobility—the difference between the solid and dashed lines—across all cohorts; however, these magnitudes are relatively larger for Black men. The overall mobility rate for White men, driven primarily by exchange mobility, shows an upward trend beginning with the 1900-1910 birth cohort, reaching its peak in the 1940-1950 cohort. In contrast, while Black men show a significant increase in exchange mobility in the 1900-1910 cohort compared to earlier generations, this upward trajectory does not persist in subsequent cohorts. In fact, the exchange mobility rate for the 1940-1950 cohort is lower than that of the 1900-1910 cohort. For younger birth cohorts, structural factors—though imprecisely estimated—appear to play a more significant role than for earlier generations.

Our findings on exchange mobility, focusing on mobility that occurs at the steady state, suggest a steady improvement for White men, but not Black men. Although estimates for the 1960–1970 birth cohort suggest a possible convergence in mobility rates between the two racial groups, the results lack sufficient statistical precision to confirm an upward trend among Black men or to substantiate convergence between Black and White men. Further analysis, incorporating more recent cohorts from 1980 onward—who are currently too young in the available data to have information on their primary occupations—presents important avenues for future research to better understand these long-run trends in exchange mobility within each race group, as well as differences in these measures between Black and White men.

7 Concluding Remarks

We study the evolution of Black-White inequality over a long time horizon focusing on the racial gap in occupational mobility. Our analyses using a Markov-Chains-based measurement approach, in combination with an extensive dataset that combines linked historical census data and contemporary large-scale survey data, produce a range of empirical

conclusions that confirm and augment existing studies on the Black-White gap in mobility.

We underscore the critical role of structural mobility measured using changes in the mobility regimes, particularly among the 1940-1950 birth cohort, in shaping the contemporary occupational distribution and contributing to a reduction in racial disparities. We also show that, despite these improvements, substantial racial disparities persist across cross-sectional distributions, largely due to differences in mobility dynamics. Our approach, which further investigates the properties of persistence within each mobility regime highlights new dimensions of Black-White inequality and reveals two key insights. First, mobility barriers faced by individuals from low-status occupational backgrounds in achieving high-status occupations remain substantially higher for Black men than White men. Second, the rate at which parental memory dissipates, or parental occupations cease to influence offspring outcomes has steadily improved for White men, but not necessarily for Black men. We show that the racial gap in these dissipation rates is attributed to the lack of exchange mobility. The role of structural mobility, measured using the mobility generated in the process of convergence toward steady state for each mobility regime, is limited.

Our work suggests the crucial role of anti-discrimination policies in addressing the unequal opportunities faced by Black Americans in attaining occupational status through personal effort and qualifications. Further assessment of the mechanisms that promote improvements in opportunities—such as the role of educational institutions, including the expansion of higher education through land-grant colleges—constitutes an important avenue of future work.

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Appendix

FOR ONLINE PUBLICATION

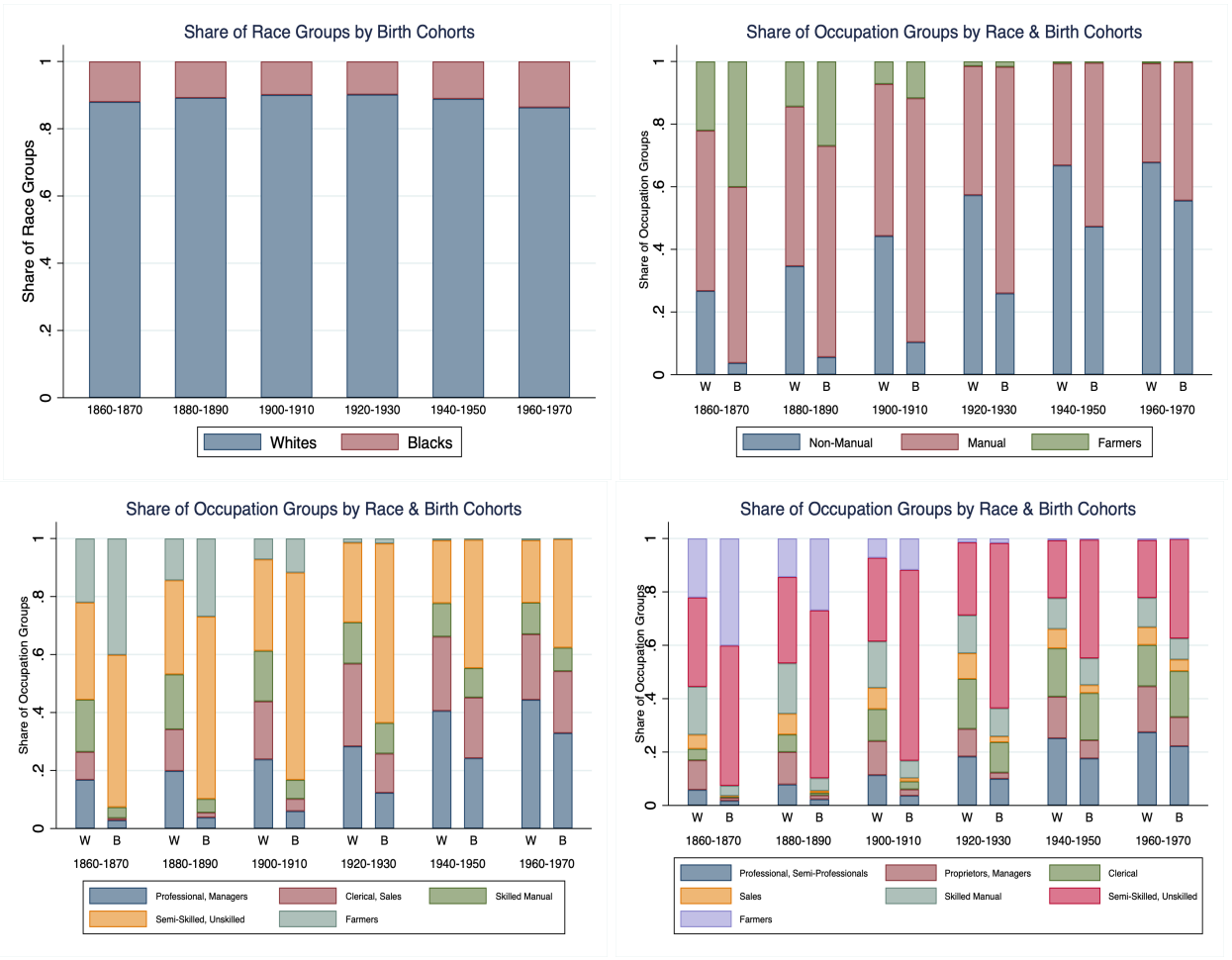
The Evolution of Black-White Differences in Occupational Mobility Across Post Civil War America

Steven Durlauf Gueyon Kim Dohyeon Lee Xi Song

Appendices

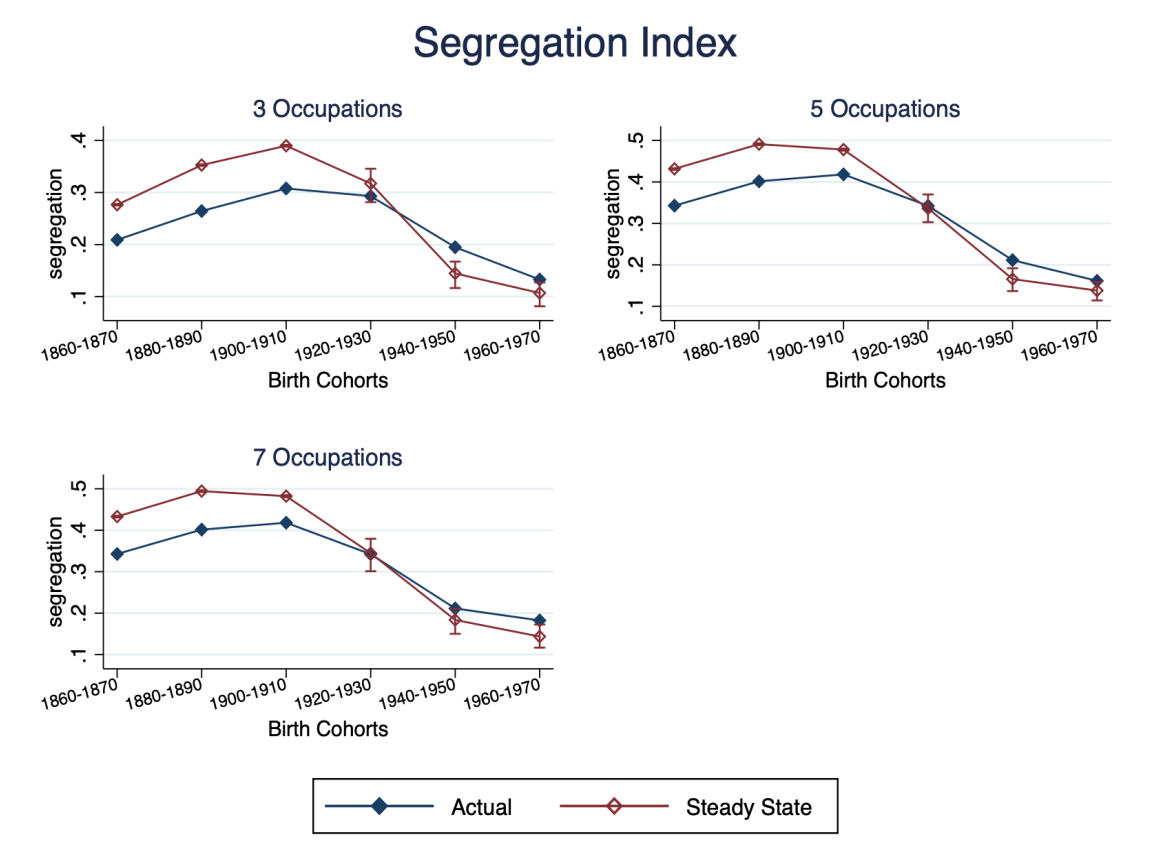
A Additional Figures

Figure A.1: Distribution of Race and Occupations



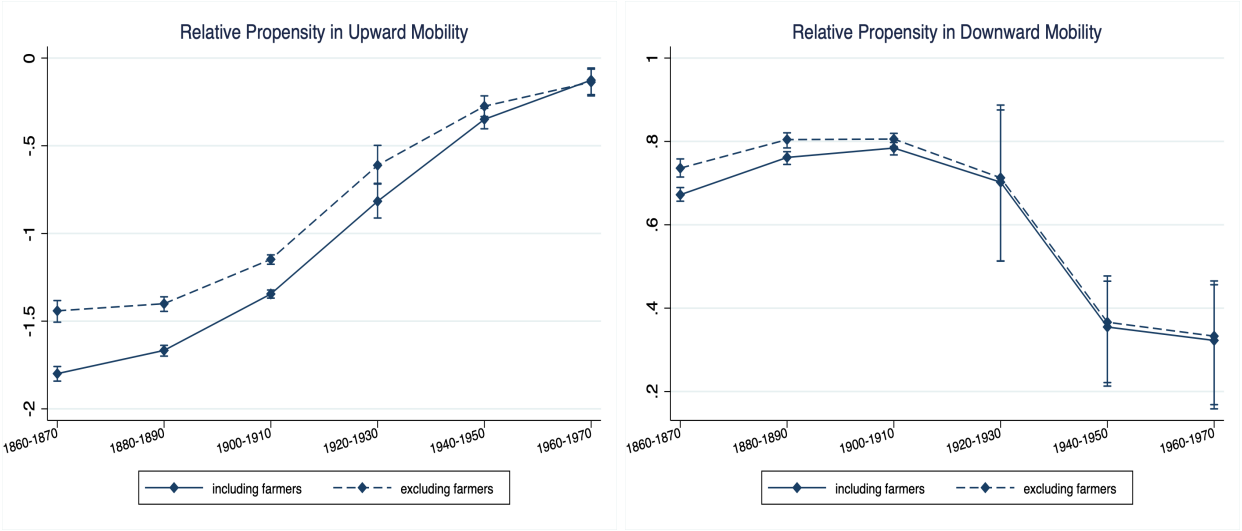
Notes: The graphs show the distribution of race (top, left) and the distribution of race and occupation (top right and bottom) for our sample of birth cohorts.

Figure A.2: Trends in Occupational Segregation by Race



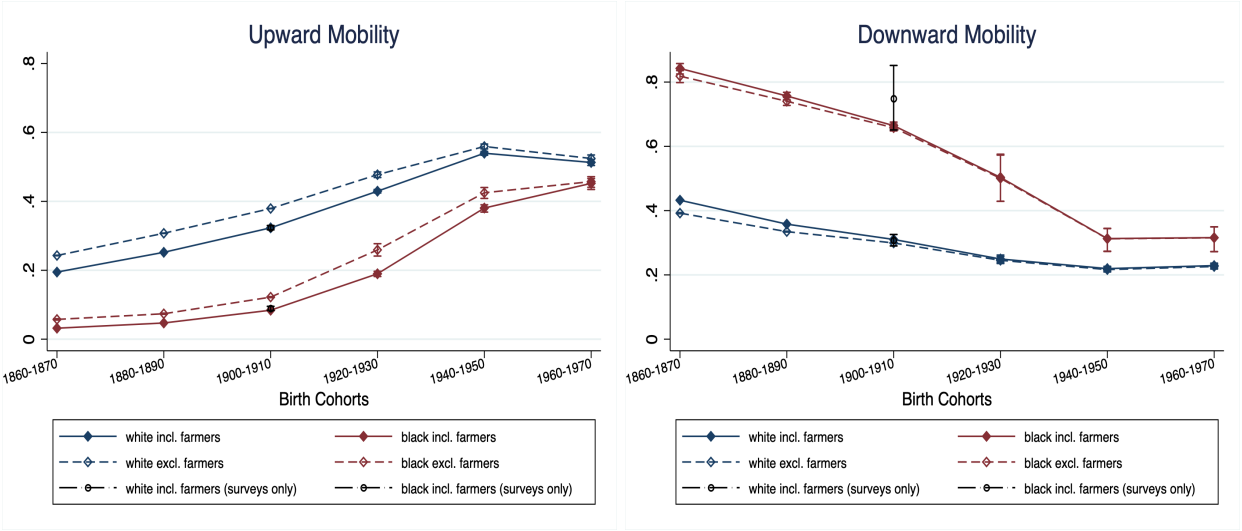
Notes: The graphs show trends in occupational segregation by race using (i) the actual distributions observed in each period—which correspond to years when each birth cohort of interest reaches its prime age; and (ii) the occupational distributions at steady states using the transition matrices of each birth cohort.

Figure A.3: Relative Propensities in Mobility (3 categories)



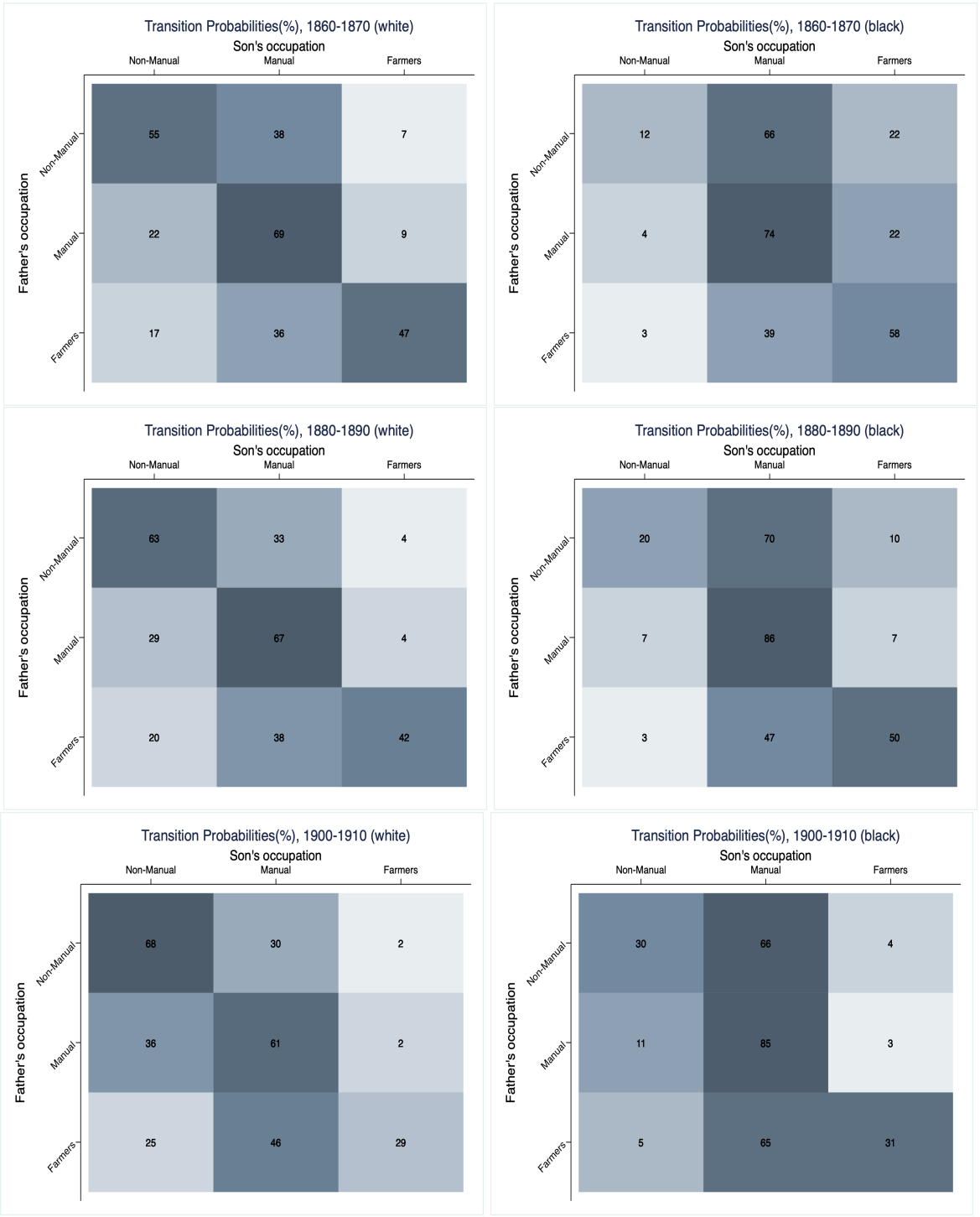
Notes: The graphs show trends in the Black-White log differences in transition probabilities ($log(p_b) - log(p_w)$) for upward (left) and downward (right) mobility. The solid graphs show trends in transitions from Farming or Manual to Non-Manual (left) and Non-Manual to Farming or Manual (right). The dashed graphs show trends in transitions from Manual to Non-Manual (left) and Non-Manual to Manual (right). Our results are based on 3-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.4: Mobility Patterns (3 categories) with MLP



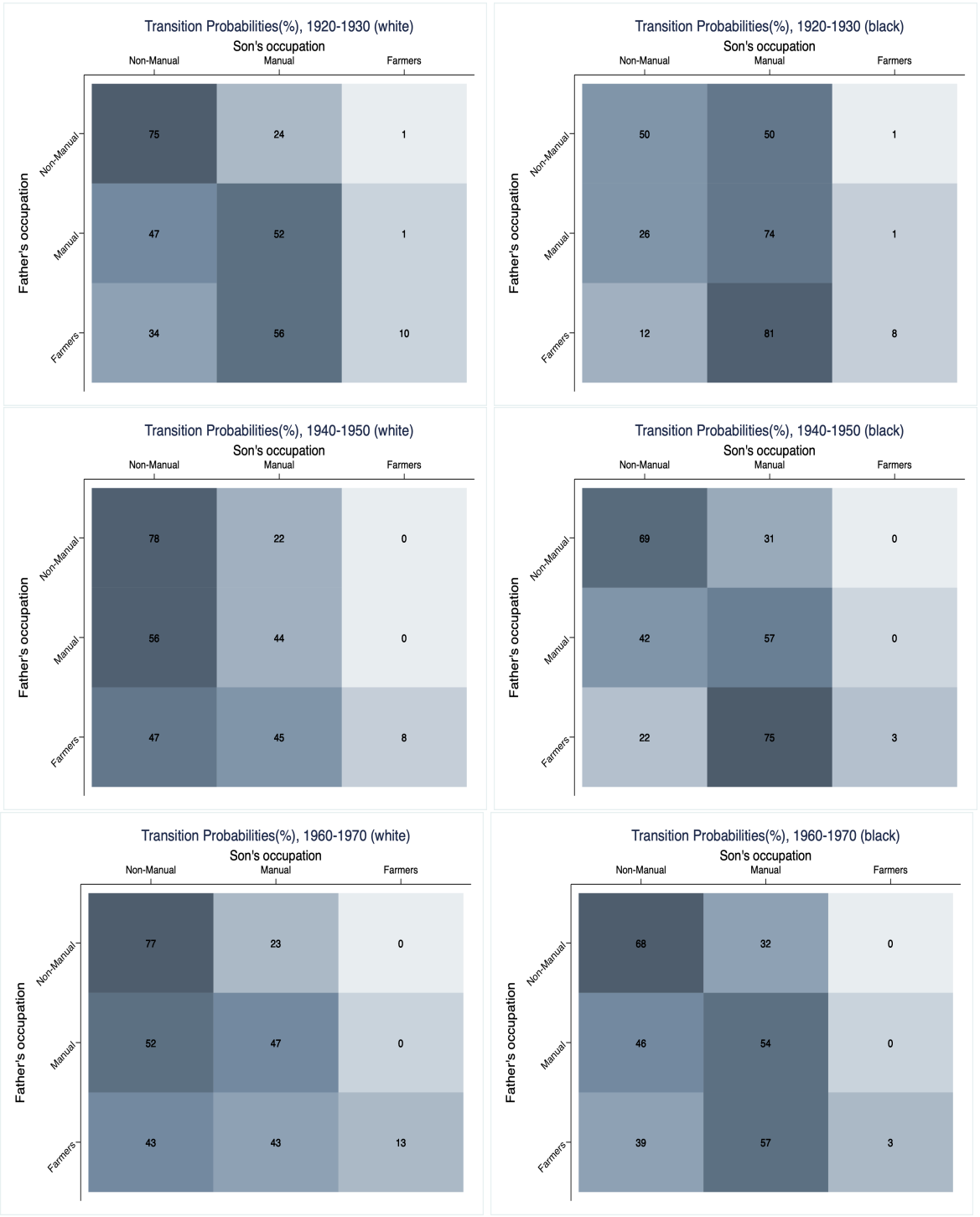
Notes: The graphs show upward (left) and downward (right) mobility patterns for White (in navy lines) and Black men (in maroon lines) using MLP for the historical sample. The solid graphs with solid diamond symbols show trends in transitions from Farming or Manual to Non-Manual (left) and Non-Manual to Farming or Manual (right). The dashed graphs with hollow diamond symbols show trends in transitions from Manual to Non-Manual (left) and Non-Manual to Manual (right). The long-dashed graphs with hollow circles use survey data and show trends in transitions from Farming or Manual to Non-Manual (left) and Non-Manual to Farming or Manual (right). Our results are based on 3-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.5: Transition Probabilities by Occupation Groups: 3 Categories



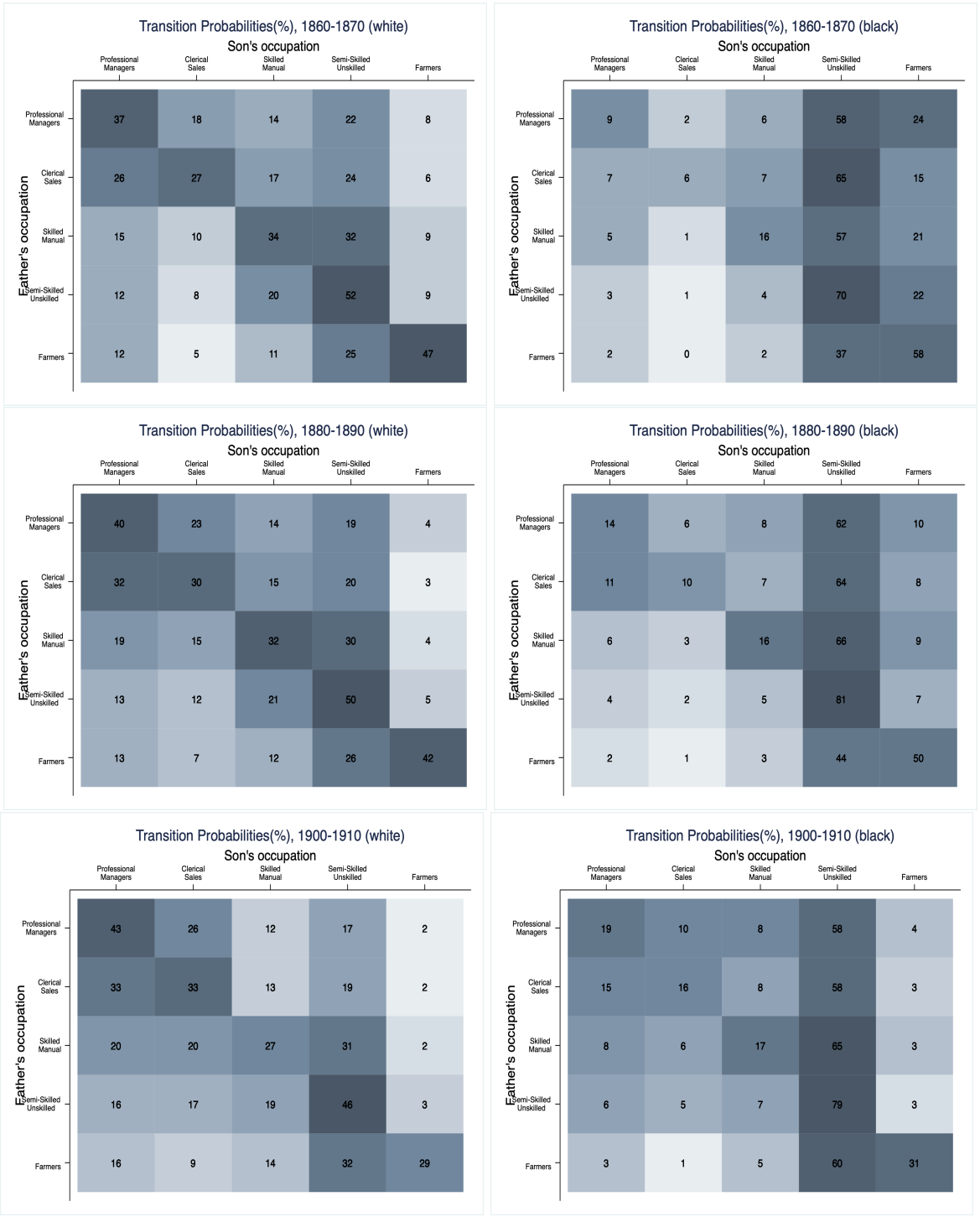
Notes: The graphs show the transition probabilities for the 1860-1910 birth cohorts using 3-category occupations: White population (left) and Black population (right).

Figure A.6: Transition Probabilities by Occupation Groups: 3 Categories



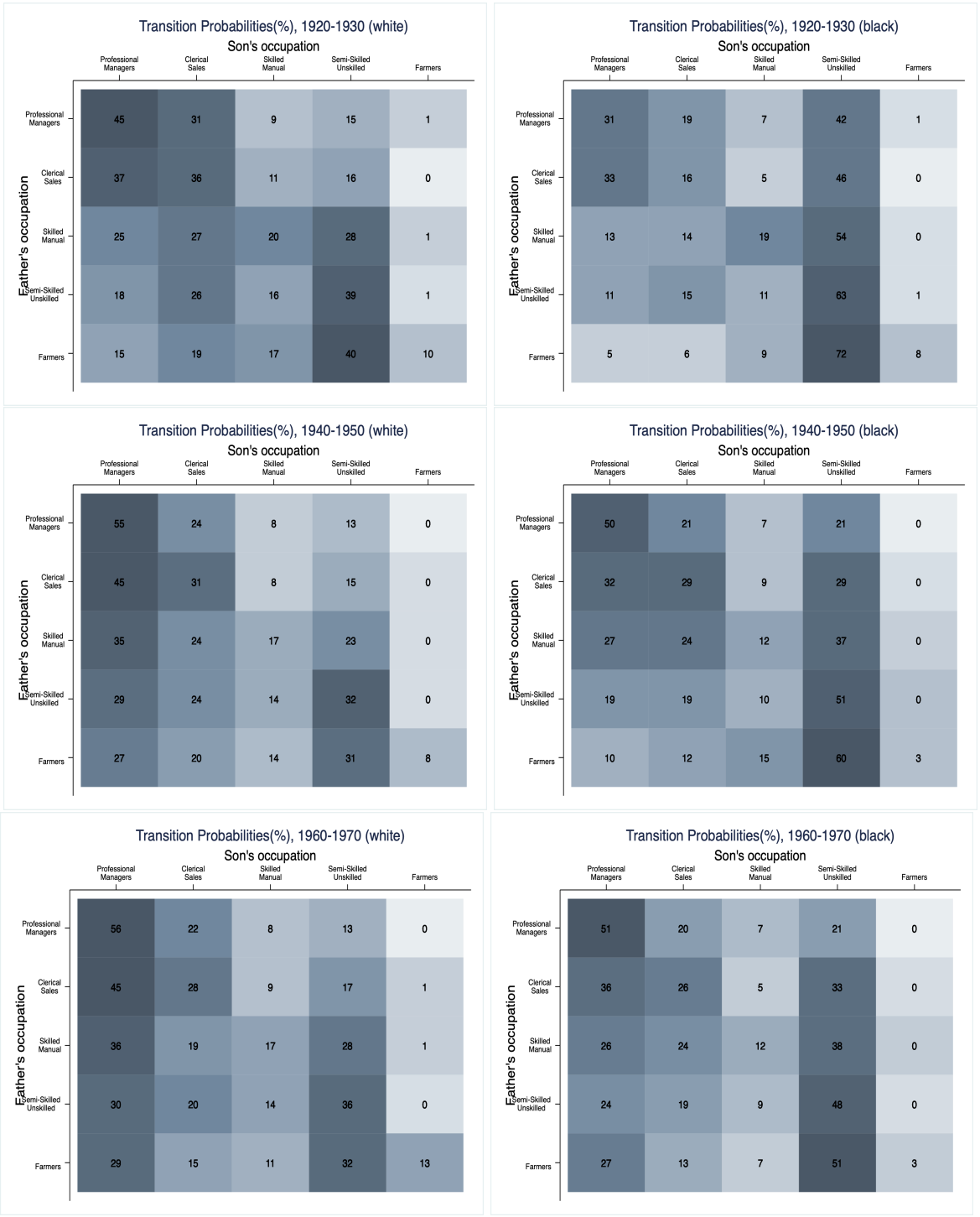
Notes: The graphs show the transition probabilities for the 1920-1970 birth cohorts using 3-category occupations: White population (left) and Black population (right).

Figure A.7: Transition Probabilities by Occupation Groups: 5 Categories



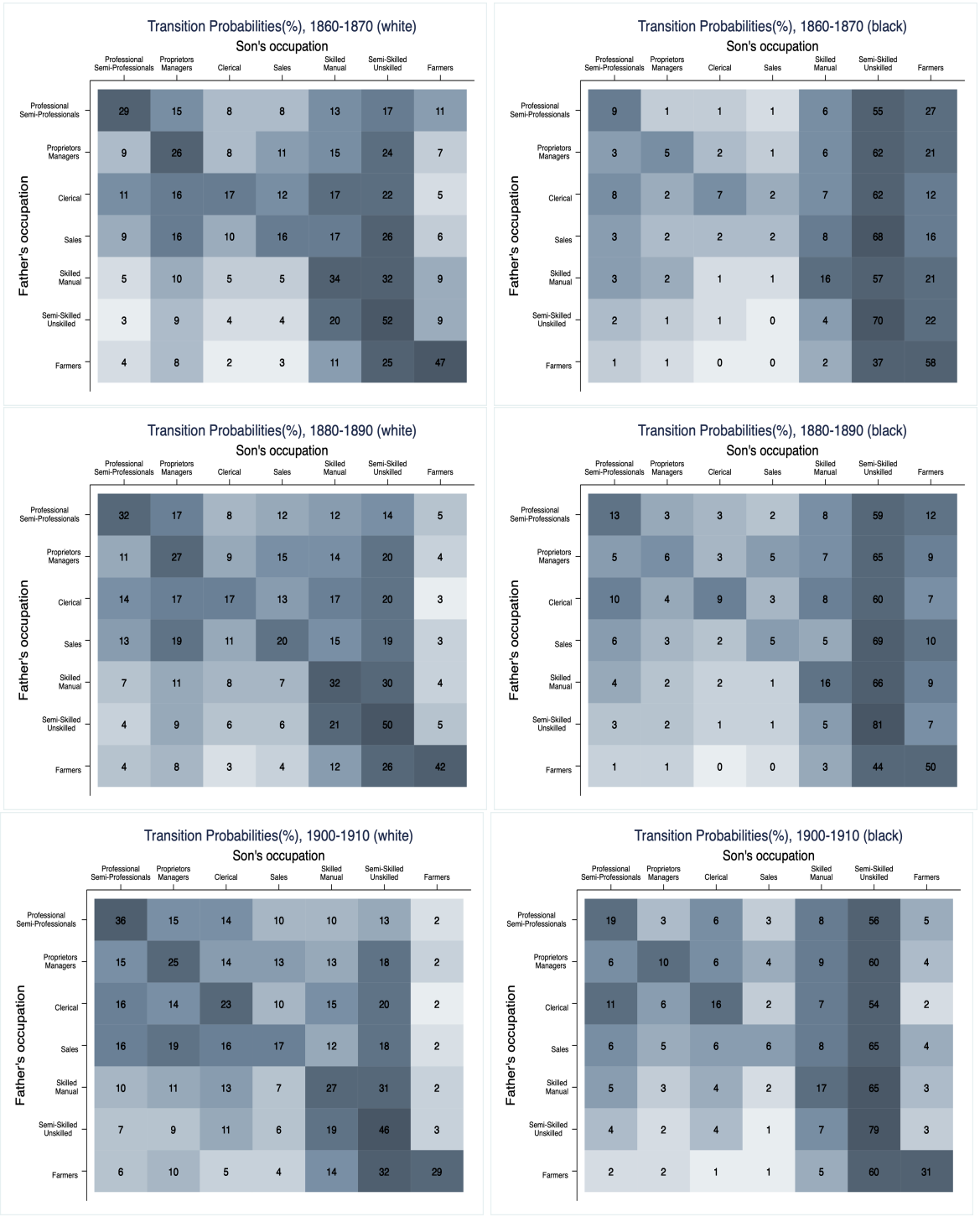
Notes: The graphs show the transition probabilities for the 1860-1910 birth cohorts using 5-category occupations: White population (left) and Black population (right).

Figure A.8: Transition Probabilities by Occupation Groups: 5 Categories



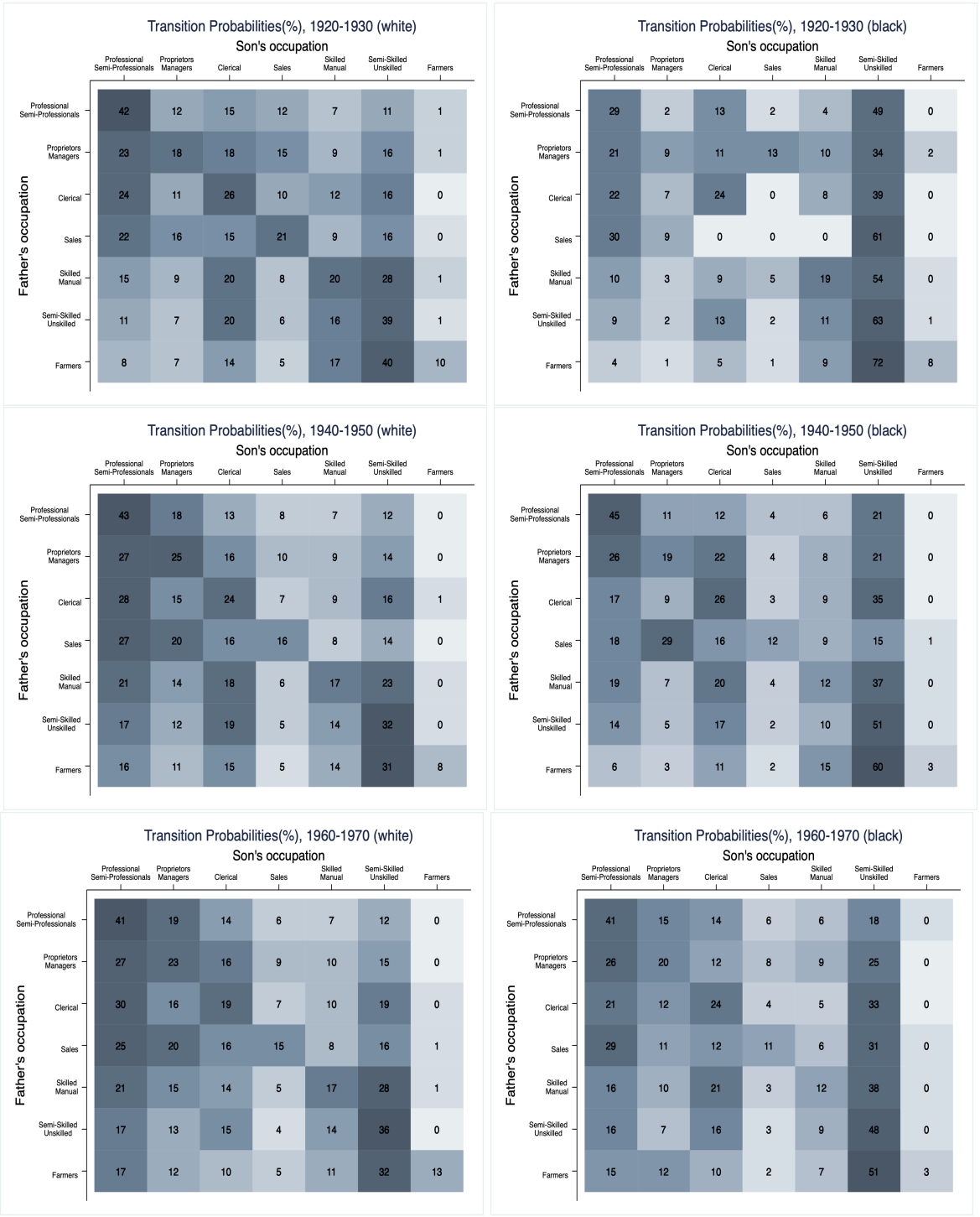
Notes: The graphs show the transition probabilities for the 1860-1910 birth cohorts using 7-category occupations: White population (left) and Black population (right).

Figure A.9: Transition Probabilities by Occupation Groups: 7 Categories



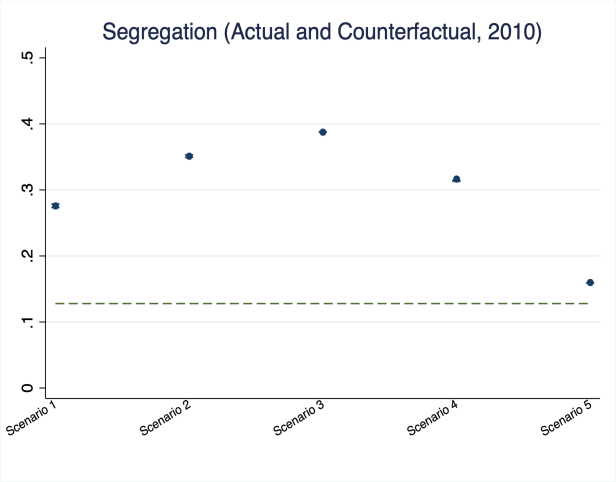
Notes: The graphs show the transition probabilities for 1880-1940 using 7-category occupations: White population (left) and Black population (right).

Figure A.10: Transition Probabilities by Occupation Groups: 7 Categories



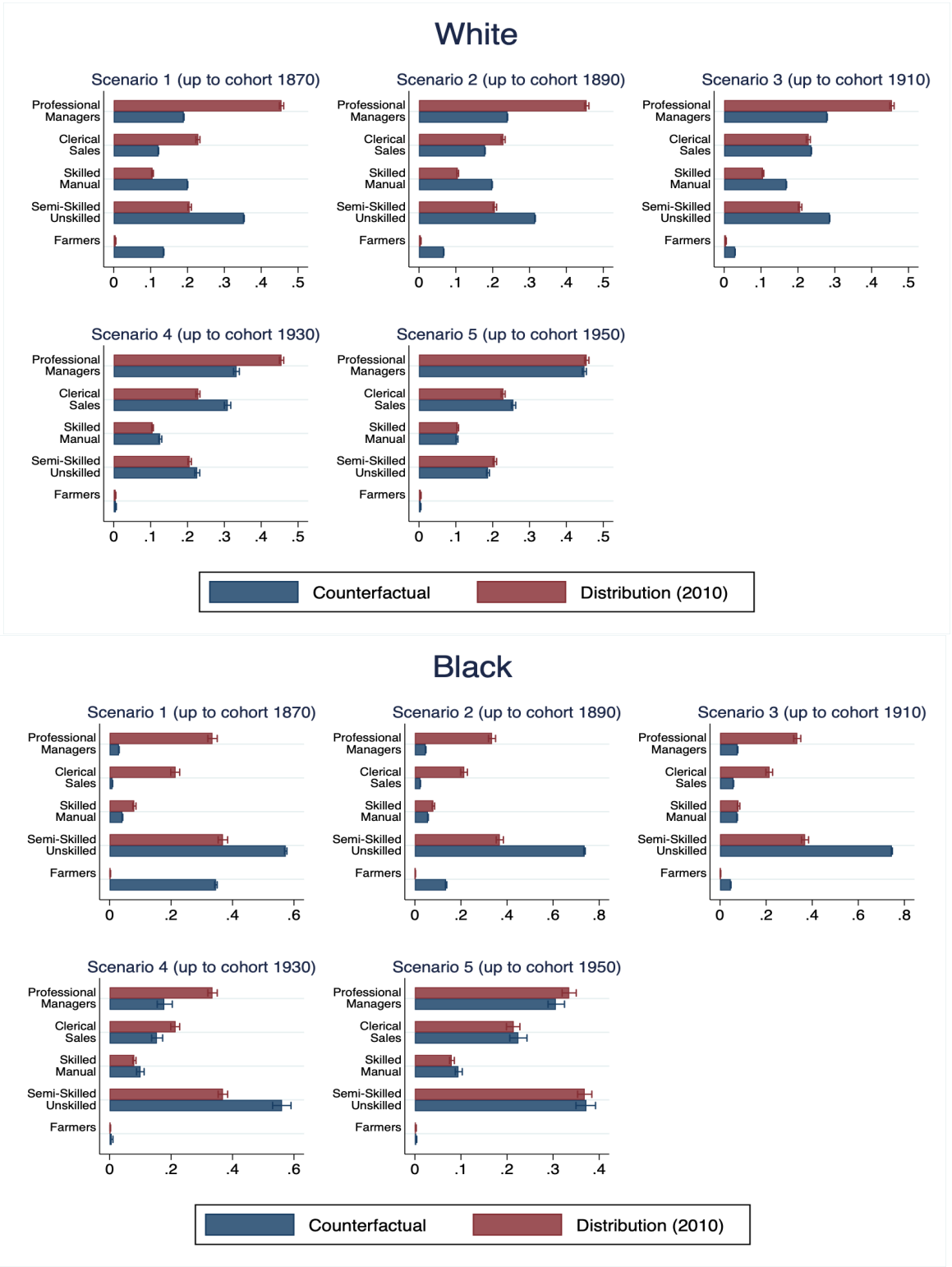
Notes: The graphs show the transition probabilities for the 1920-1970 birth cohorts using 7-category occupations: White population (left) and Black population (right).

Figure A.11: Segregation (Actual and Counterfactual, 2010): 3 categories



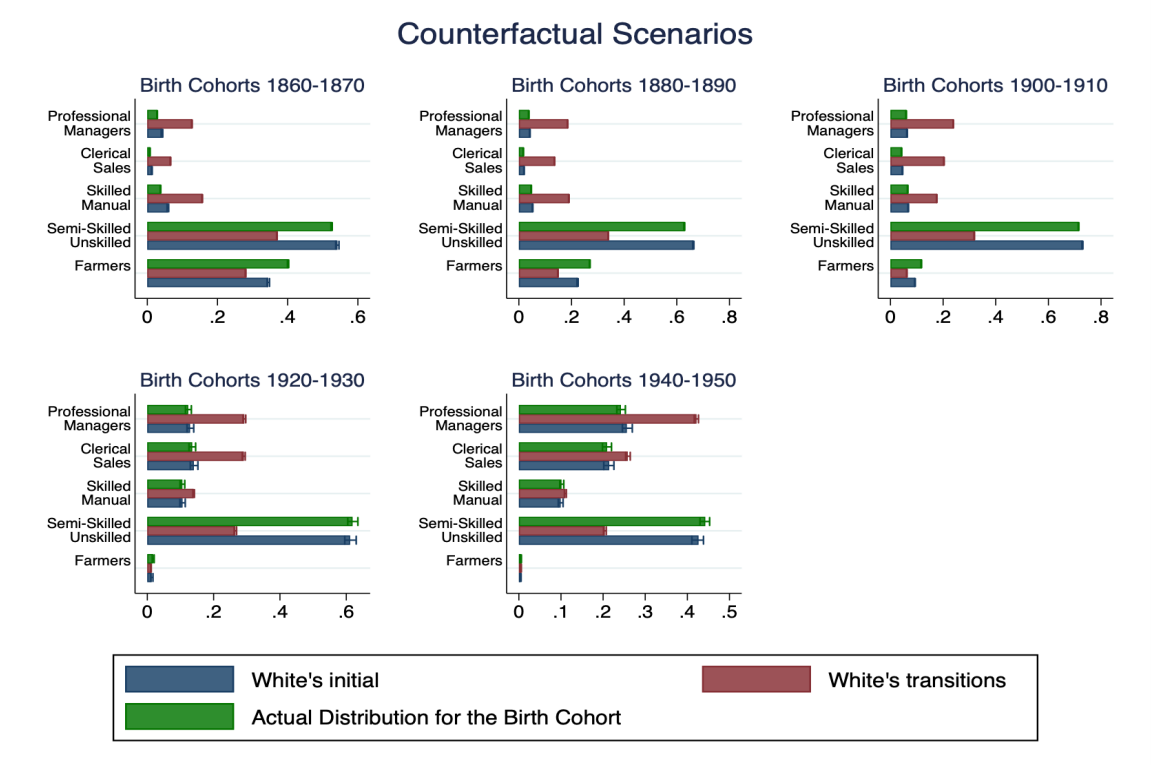
Notes: The graph shows the level of occupational segregation by race for each counterfactual scenario, which we calculate using the corresponding counterfactual distributions in Figure 3 separately obtained for Black and White men. The dashed horizontal line indicates the actual segregation level in 2010. Our results are based on 3-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.12: Counterfactual Occupational Distributions: 5 categories



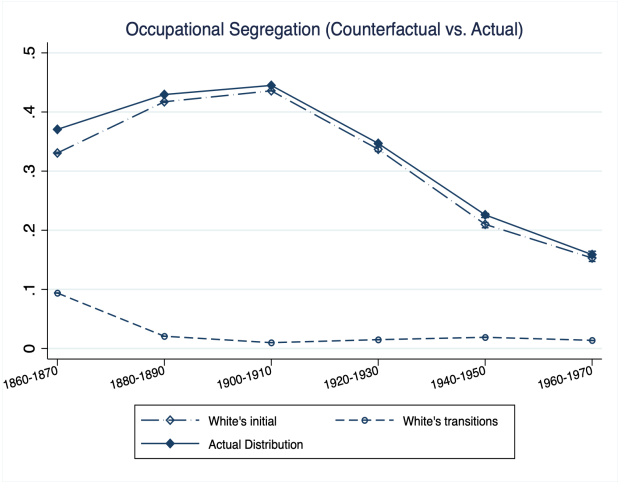
Notes: The graphs show the counterfactual occupational distributions for White (top) and Black men (bottom) in five different scenarios generated by sequentially updating the transition matrices over time. For example, in the top left panels, each group's current occupational distributions are contrasted with a counterfactual one where the transition matrix from the 1910 period—the 1860-1870 birth cohorts—is employed and remains unchanged over time. Our results are based on 5-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.13: Counterfactual Occupational Distributions (Black Men): 5 categories



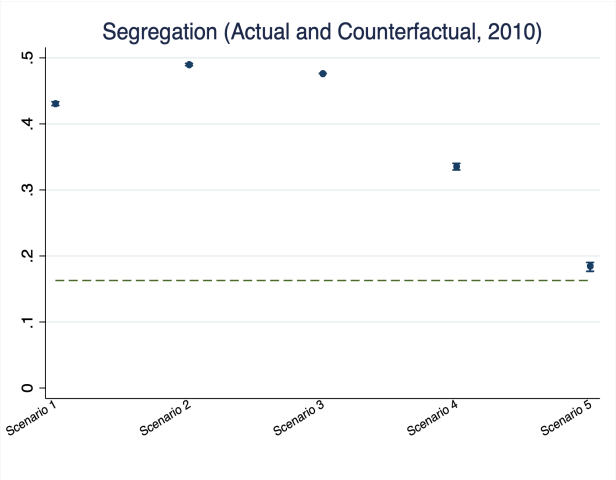
Notes: The graphs compare the actual occupational distributions of Black men and counterfactual ones where (i) both racial groups start with the same initial condition ($\mu_0^B = \mu_0^W$) but experience different mobility dynamics; (ii) both racial groups undergo the same mobility dynamics ($\mathbf{P}_t^B = \mathbf{P}_t^W$) yet face different initial conditions. Our results are based on 5-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.14: Counterfactual Occupational Distributions (Black Men): 5 categories



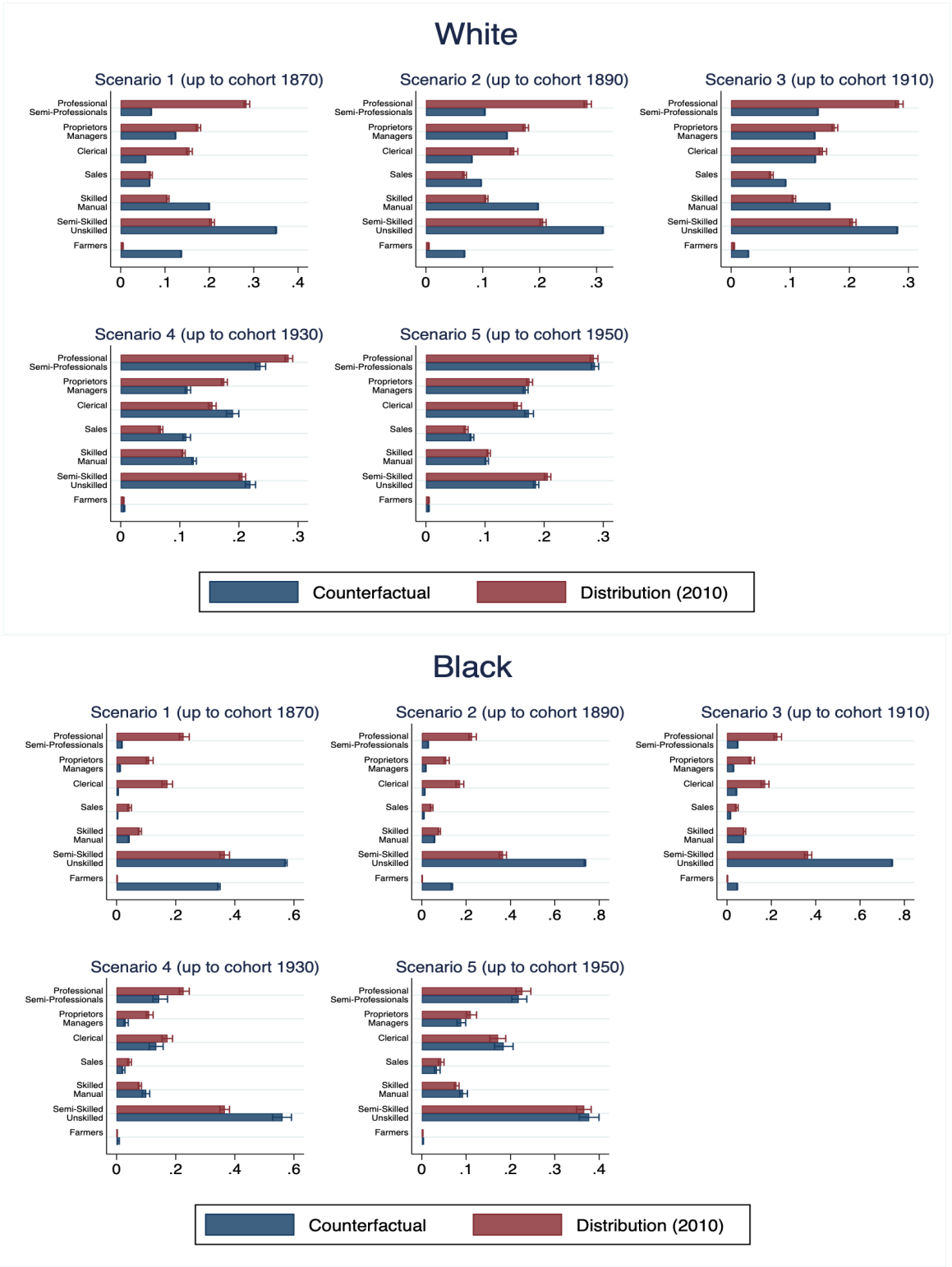
Notes: The graphs compare the degree of occupational segregation under each scenario: (i) both racial groups start with the same initial condition ($\mu_0^B = \mu_0^W$) but experience different mobility dynamics; (ii) both racial groups undergo the same mobility dynamics ($\mathbf{P}_t^B = \mathbf{P}_t^W$) yet face different initial conditions. Our results are based on 5-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.15: Segregation (Actual and Counterfactual, 2010): 5 categories



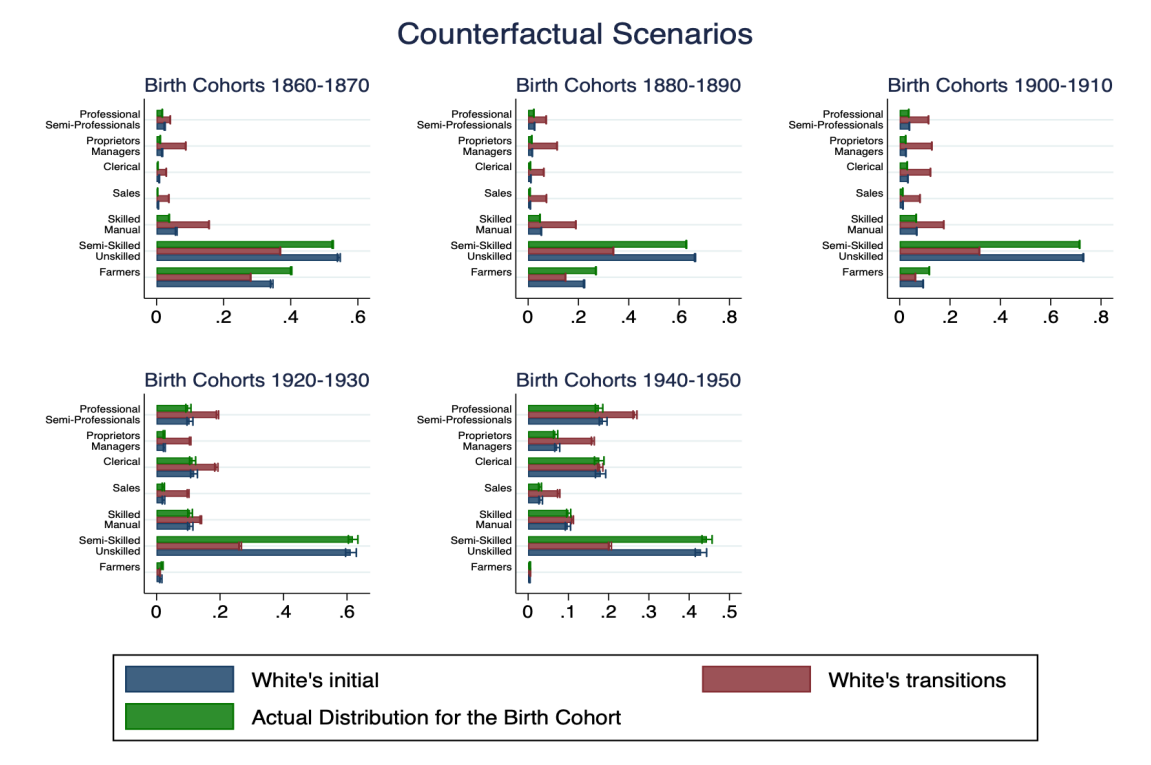
Notes: The graph shows the level of occupational segregation by race for each counterfactual scenario, which we calculate using the corresponding counterfactual distributions in Figure A.12 separately obtained for Black and White men. The dashed horizontal line indicates the actual segregation level in 2010. Our results are based on 5-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.16: Counterfactual Occupational Distributions: 7 categories



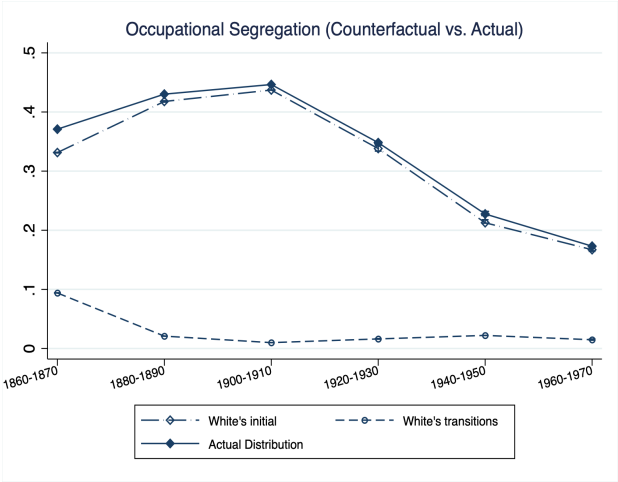
Notes: The graphs show the counterfactual occupational distributions for White (top) and Black men (bottom) in five different scenarios generated by sequentially updating the transition matrices over time. For example, in the top left panels, each group's current occupational distributions are contrasted with a counterfactual one where the transition matrix from the 1910 period—the 1860-1870 birth cohorts—is employed and remains unchanged over time. Our results are based on 7-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.17: Counterfactual Occupational Distributions (Black Men): 7 categories



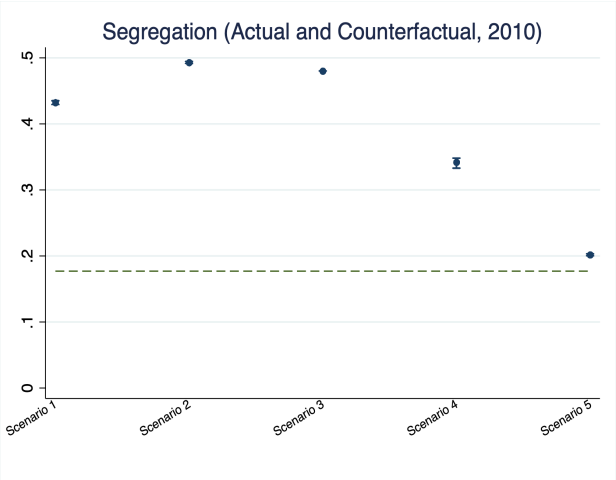
Notes: The graphs compare the actual occupational distributions of Black men and counterfactual ones where (i) both racial groups start with the same initial condition ($\mu_0^B = \mu_0^W$) but experience different mobility dynamics; (ii) both racial groups undergo the same mobility dynamics ($\mathbf{P}_t^B = \mathbf{P}_t^W$) yet face different initial conditions. Our results are based on 7-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.18: Counterfactual Occupational Distributions (Black Men): 7 categories



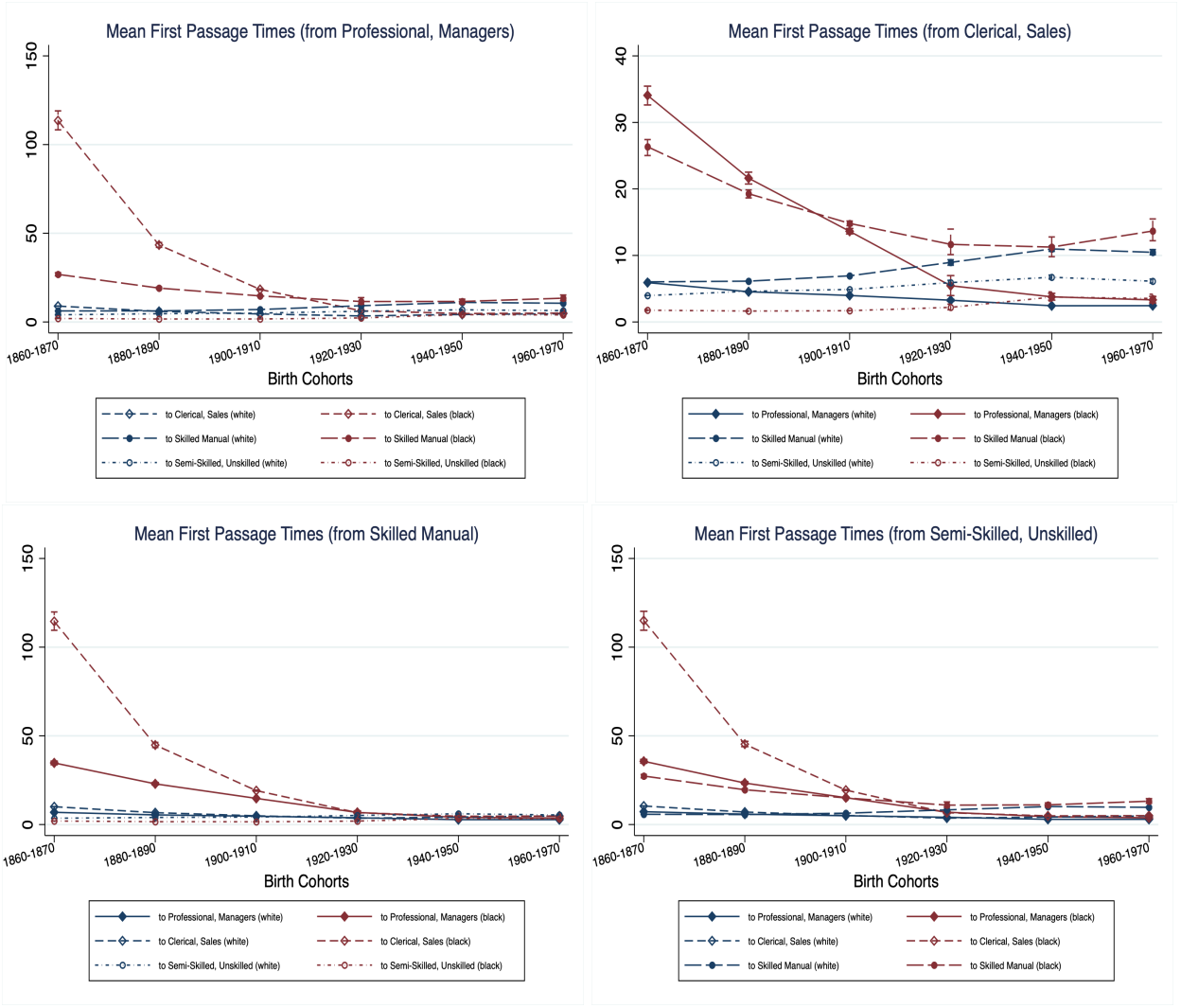
Notes: The graphs compare the degree of occupational segregation under each scenario: (i) both racial groups start with the same initial condition ($\mu_0^B = \mu_0^W$) but experience different mobility dynamics; (ii) both racial groups undergo the same mobility dynamics ($\mathbf{P}_t^B = \mathbf{P}_t^W$) yet face different initial conditions. Our results are based on 7-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.19: Segregation (Actual and Counterfactual, 2010): 7 categories



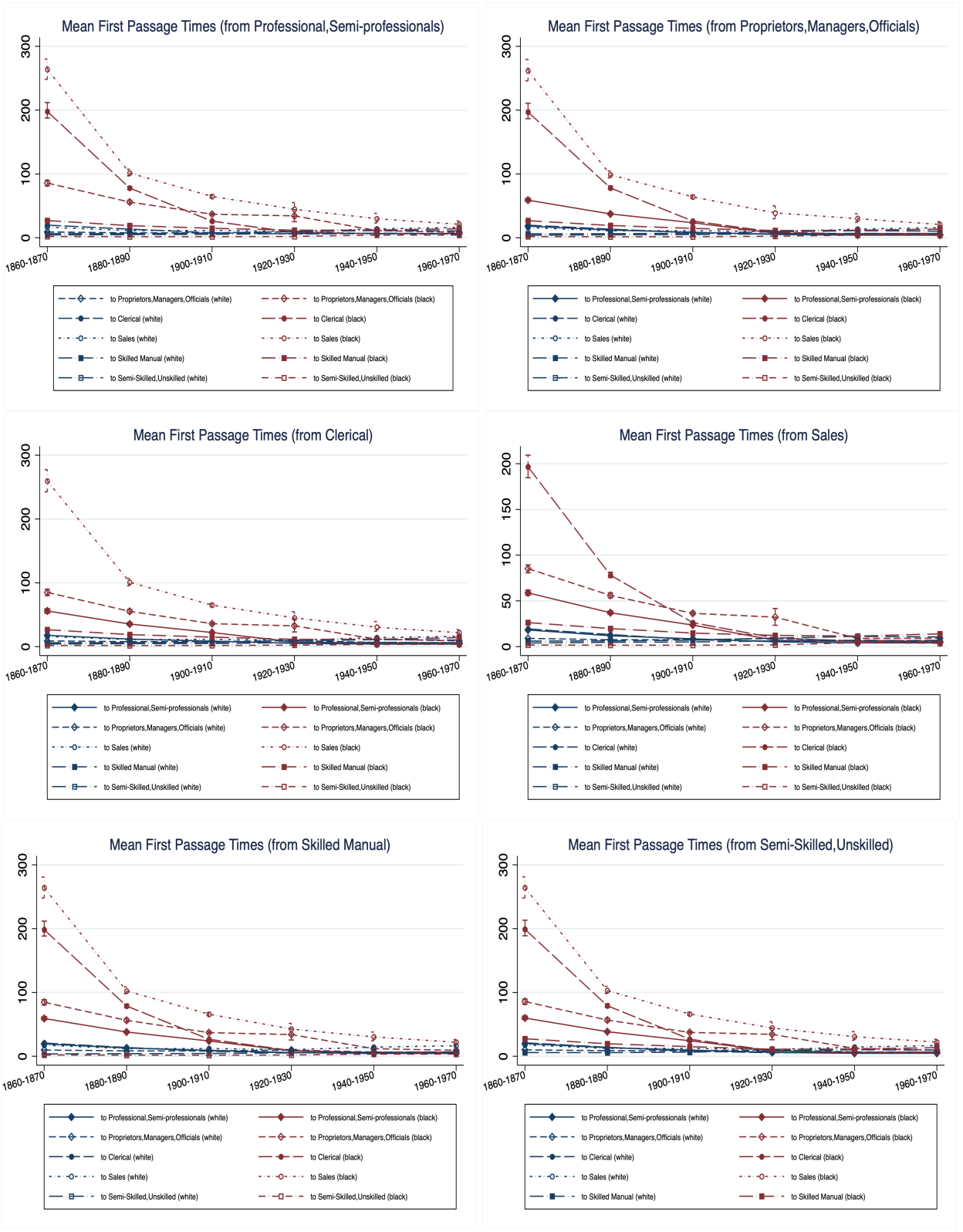
Notes: The graph shows the level of occupational segregation by race for each counterfactual scenario, which we calculate using the corresponding counterfactual distributions in Figure A.16 separately obtained for Black and White men. The dashed horizontal line indicates the actual segregation level in 2010. Our results are based on 7-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.20: Mean First Passage Times: 5 categories except Farmers



Notes: The graphs show the mean first passage times from Professional and Managerial occupations to others (top left); Clerical and Sales occupations to others (top right); Skilled Manual occupations to others (bottom left); Semi-Skilled and Unskilled Manual occupations to others (bottom right) estimated using period-specific transition matrices for Black and White men. Our results are based on 5-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure A.21: Mean First Passage Times: 7 categories except Farmers



Notes: The graphs show the mean first passage times from Professional and Semi-professional occupations to others (top left); Proprietors, Managers, Officials to others (top right); Clerical occupations to others (middle left); Sales occupations to others (middle right); Skilled Manual (bottom left); and Semi-Skilled and Unskilled Manual occupations to others (bottom right) estimated using period-specific transition matrices for Black and White men. Our results are based on 7-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

B Additional Tables

Table B.1: Occupational Groupings

Occupation Groups (3)	Occupation Groups (5)	Occupation Groups (7)	Census 1950 Occupation Codes (269)
White-Collar	Professional & Managerial	Professional, Semi-professionals	0-99
		Proprietors, Managers, Officials	200-290
	Clerical & Sales	Clerical	300-390
		Sales	400-490
Blue-Collar	Skilled Manual	Skilled Manual	500-594, 762, 773, 781, 782
	Semi-Skilled, Unskilled Manual	Semi-Skilled, Unskilled Manual	595, 600-690, 700-790, 810-840, 910-970
Farming	Farming	Farming	100, 123

Notes: The table shows the mapping of the 3-digit Census occupation codes to our categorization of occupations (3, 5, and 7).

Table B.2: Period and Birth Cohort Definitions

Period (Benchmark Year)	Birth Years (Data)	Birth Cohorts (Definition)
1910	1856-1875	1860-1870
1930	1876-1895	1880-1890
1950	1896-1915	1900-1910
1970	1916-1935	1920-1930
1990	1936-1955	1940-1950
2010	1956-1975	1960-1970

Notes: The table shows how our definitions of periods and birth cohorts of individuals correspond to one another. For each snapshot year we consider, we focus on those aged between 35 and 55 to back out the birth years of interest. Then, we assign decadal definitions of birth cohorts.

Table B.3: Kitagawa-Oaxaca-Blinder Decomposition of occupational distributions

Occupation (Initial Share)	Period (from)	Period (to)	(1) ΔOcc Shares	(2) ΔDistribution	(3) ΔTransitions	(4) ΔInteraction
Non-Manual (0.175)	1910	1930	0.081	0.017	0.058	0.005
	1930	1950	0.085	0.034	0.049	0.002
	1950	1970	0.107	0.040	0.073	-0.006
	1970	1990	0.131	0.038	0.098	-0.006
	1990	2010	0.014	0.032	-0.019	0.002
Manual (0.454)	1910	1930	0.005	0.009	0.001	-0.005
	1930	1950	-0.018	-0.002	-0.009	-0.007
	1950	1970	-0.052	-0.013	-0.031	-0.008
	1970	1990	-0.117	-0.027	-0.090	0.000
	1990	2010	-0.081	-0.063	-0.030	0.012

Notes: The table shows the results of the decomposition exercise across Non-Manual and Manual occupations, where each row represents (i) changes in the occupational shares from one period to another (Δ Occ Shares) and (ii) how much each component (ΔDistribution, ΔTransitions, and ΔInteraction) contributes to the occupation-specific change in shares. We use the 3-category occupation definition.

Table B.4: Mean First Passage Times: Semi-Skilled and Unskilled Manual

Birth Cohorts	Professional Semi-profs	Proprietors, Managers	Clerical	Sales	Skilled Manual	Farmers
Panel A: **Whites**						
1860-1870	17.56	9.07	20.17	18.15	5.46	10.98
1880-1890	12.43	8.24	13.31	11.37	5.38	25.72
1900-1910	9.61	8.78	7.92	12.14	6.44	59.09
1920-1930	6.94	12.21	5.33	11.6	8.21	197.95
1940-1950	4.61	6.72	6.1	14.32	10.23	239.87
1960-1970	4.63	6.39	6.67	16.68	9.63	251.36
Panel B: **Blacks**						
1860-1870	52.95	91.02	207.36	331.89	27.69	4.89
1880-1890	37.02	59.77	67.93	99.9	17.84	14.69
1900-1910	24.55	38.46	26.15	64.11	15.03	47.41
1920-1930	12.07	43.06	9.09	37.37	10.5	236.7
1940-1950	6.15	12.27	6.01	30.66	11.28	454.39
1960-1970	5.41	9.6	6.51	22.08	13.5	621.59

Notes: The table shows the mean first passage times from Semi-Skilled and Unskilled Manual to other occupations. We use the 7-category occupation definition.

C Data Sources

General Social Survey (GSS) is a large-scale, cross-sectional survey that has been implemented since 1972 by the National Opinion Research Center (NORC) at the University of Chicago. The survey was conducted annually in most years before 1994 and changed to a biennial basis thereafter. It is designed to be representative of all adults in US households aged 18 and older. The data have been widely used in studies on societal changes in individual attributes and attitudes and population composition. Our analysis relies on data from the years 1972 to 2018 and applies sample weight (wtssall) to account for the multistage sampling design. We keep oversamples of Black respondents in GSS 1982 and 1987. Respondents were asked to report their own occupation and education at the time of the survey and their father's occupation and education while they "were growing up." The data are publicly available and can be downloaded from the GSS website: `http://gss.norc.org/get-the-data/`.

Occupational Change in a Generation (OCG) I and II. OCG I is a large-scale survey of U.S. social mobility, implemented as a supplement to the March 1962 Current Population Survey (CPS). The target population of OCG I was U.S. males aged 20 to 64 in the civilian, noninstitutional population. We applied a sample weight using V24 to account for the multistage sampling design (see OCG I codebook Introduction p.3 for a description of the construction of sample weight). Occupational Changes in a Generation II (OCG II) was collected in 1973 as a supplement to the March 1973 Current Population Survey. It was designed as a strict replication of OCG I, but also incorporated some new questions about social background and career development. In both OCG I & II, Respondents were asked to report their own occupations at the time of the survey and their fathers' occupations when the respondent was 16 years old. Individuals were also asked to report their own education at the time of the survey and their fathers' education when the respondent was 16 years old. The data are publicly available and can be downloaded from the OCG website: `http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/6162`.

National Survey of Families and Households (NSFH) was a nationally representative household survey designed to provide information on family life. It was conducted in 3 waves: 1987–1988, 1992–1994, and 2001–2002. Households were randomly selected from 1,700 selection units that resulted from 17 enumeration districts within each of the 100 primary sampling units. For the first wave of data collection, a primary respondent at least 19 years of age was randomly selected from each household to participate

in a personal interview. We used data from waves 1 to 3 and applied sample weight (WEIGHT) to account for the multistage sampling design. Respondents were asked to report their own occupations in each wave and their fathers' occupations when the respondent was 16 years old. Respondents were also asked to report their own education and their fathers' education when the respondent was 16 years old in the 1987–1988 survey. The data are publicly available and can be downloaded from the NSFH website: `http://www.ssc.wisc.edu/nsfh/home2.htm`.

Panel Study of Income Dynamics (PSID) carried out at the Survey Research Center at the University of Michigan, is a longitudinal panel household survey in the US. The survey collects extensive economic, social, and health items on individuals and their household members over the life course and across generations. Begun in 1968, the PSID follows over 18,000 household members from roughly 5,000 US families. The study interviewed individuals annually until 1997 and biennially thereafter. All original 1968 PSID respondents and their offspring are considered to carry the PSID "gene" and thus are permanent PSID respondents. Their demographic and socioeconomic information, such as age and occupation, is gathered in each wave of the PSID survey and can be linked across years. The PSID project also provides a "Family Identification Mapping System" (FIMS) tool designed to link family members across generations. The data consist of 2 distinct samples: SRC (Survey Research Center) is a nationally representative household sample based on a stratified, multistage selection of the civilian noninstitutional population of the US; SEO (Survey of Economic Opportunity) is a national sample of low-income families with household heads under age 60 in 1968. Occupation is collected for household heads and their spouses in all PSID waves. We first harmonized all the occupation variables by converting them to the 1950 Census scheme and then chose individuals' occupations measured in the year closest to age 40 as the lifetime occupation. That is, if occupation at age 40 was unavailable, we then looked for occupation at ages 41, 39, 42, 38, and so forth. For individuals whose fathers were not PSID respondents and thus were not directly observed, we relied on the question that asked household heads to report the father's occupation in waves 1997–2019. If the father's occupation was reported multiple times, we chose the mode of the data values. The level of education was asked for household heads in all PSID waves. For individuals whose fathers were not PSID respondents and thus were not directly observed, we relied on the question that asked household heads to report the father's education. We chose the highest level of education for individuals and their fathers across waves. The data are publicly available and can be downloaded from the PSID website: `https://simba.isr.umich.edu/data/data.aspx`.

National Longitudinal Survey of Youth 1979 (NLSY79) was another longitudinal cohort study conducted by the Bureau of Labor Statistics under the United States Department of Labor. The project followed the lives of a nationally representative sample of 12,686 respondents born between 1957 and 1964. The respondents were aged 14—22 when first interviewed in 1979 and revisited annually until 1994 and biennially thereafter. We used data from 1979 to 2012 and applied sample weight (R0216100) to account for the multistage sampling design. Respondents were asked to report their occupations in each survey year and their fathers' (or stepfathers') longest jobs in 1978 during the first wave. Individuals were also asked to report their own education in each survey year and their fathers' (or stepfathers') education in 1979. We relied on respondents' highest education across survey years. The data are publicly available and can be downloaded from the NLS website: `http://www.nlsinfo.org/investigator/pages/login.jsp`.

National Longitudinal Survey of Young Men (NLS–YM) was another dataset among the several longitudinal cohort studies conducted by the Bureau of Labor Statistics under the United States Department of Labor between 1966 and 1981. The project began with a nationally representative sample of 5,225 American males aged 14 to 24 in 1966 and was discontinued in 1981 when the respondents were 29 to 39, at the time of their last interview. Respondents were surveyed annually between 1966 and 1971, and in the subsequent years of 1973, 1975, 1976, 1978, 1980, and 1981. The data have been used to study the education and labor market experiences of men during their early careers, such as their educational attainment and expectations, school-to-work transitions, labor market attachment, and activities related to crime, delinquency, and school discipline. We used data from the years 1966 to 1981 (12 rounds) and applied the sample weight (R0000200) to account for the multistage sampling design. Respondents were asked to report their current or the last occupations and those of their fathers in each survey year between 1966 and 1969. To make the data comparable with other datasets used in the analysis, we relied on respondents' occupations reported in the last wave of the survey and their fathers' occupations reported in 1966. If the father's information was missing in the first wave, occupation in the next available year was used. Respondents were asked to report their highest levels of education in each survey year and those of their fathers in 1966. We relied on respondents' highest education ever reported across survey years. The data are publicly available and can be downloaded from the NLS website: `http://www.nlsinfo.org/investigator/pages/login.jsp`.

National Longitudinal Survey of Older Men (NLS-OM) is one of a set of longitudinal cohort studies conducted by the Bureau of Labor Statistics under the United States Department of Labor from 1966 to 1990. The project began with a nationally representative sample of 5,020 American men aged 45 to 59 in 1966 and was discontinued when respondents were 69 to 83 at the time of their last interviews in 1990. Respondents were surveyed annually between 1966 and 1969, and in the subsequent years of 1971, 1973, 1975, 1976, 1978, 1980, 1981, 1983, and 1990. The final interview was conducted with both living older male respondents and widows or other family members of deceased respondents. The data have mainly been used to study labor market activities of middle-aged men and men close to retirement, such as their work and unemployment experiences, retirement planning, work and health insurance, and job evaluation and satisfaction. We used data from the years 1966 to 1976 (8 rounds) and applied the sample weight variable R0000200 to account for the multistage sampling design. Respondents were asked to report their own occupations in each survey year, and in the year 1966, they were asked about their fathers' occupations when the respondents were 15 years old. Respondents who did not live with their fathers at age 15 were asked to report household heads' occupations. The mobility analysis relies on respondents' occupations reported in the year 1966. If this information was missing, occupation in the next available year was used. The data are publicly available and can be downloaded from the NLS website: `http://www.nlsinfo.org/investigator/pages/login.jsp`.

Survey of Income and Program Participation (SIPP), conducted by the United States Census Bureau, is a longitudinal panel survey that is designed to provide income of individuals and households and their participation in income transfer programs. Other topics include education, occupation, family dynamics, health insurance, childcare, and food security. The SIPP survey design is a continuous series of national panels, with the sample size ranging from approximately 14,000 to 52,000 interviewed households. The original goal was to have all panels participate for a 32-month period (8 waves), with each panel randomly divided into one of 4 rotation groups. Each rotation group is interviewed in a separate month. Four rotation groups constitute one wave of interviewing. At each interview, respondents provide information covering the 4 months since the previous interview. The first interview began in October 1983 for the 1984 panel. Subsequent panels began interviews in February of each year. We used data from survey years 1986, 1987, and 1988 because the information about fathers' occupations and education was collected only in a topical module in wave 2 during these years. We applied the sample weight (FNLWGT_5) to account for the multistage sampling design and kept respondents aged 25

to 64. Respondents were asked to report their own occupations during each survey year as well as their fathers' occupations when the respondent was 16 years old. Respondents were also asked to report their own education during each survey year as well as their fathers' education when the respondent was 16 years old. The data are publicly available and can be downloaded from the SIPP website: `http://www.census.gov/sipp/`.

Americans View Their Mental Health was sponsored by the US Congress Joint Commission on Mental Illness and Health, and the first survey was conducted in 1957 by the Survey Research Center at the University of Michigan. A sample of Americans were interviewed on marriage, parenthood, employment, and general social relationships. The second survey was implemented in 1976 with the sponsorship of the National Institute of Mental Health. All the variables used in our project are taken from the publicly available data set (Americans View Their Mental Health, 1957 and 1976: Selected Variables (ICPSR 7949)). The dataset includes variables for respondents' occupation (V133) and respondents' father's occupation (V256) from the 1976 survey round. Both variables code occupation in the 1970 US Census Classification System. We recode the 1970 Census occupation codes into the 1950 Census occupation codes using the IPUMS crosswalk. Race and ethnicity variable in the dataset (V244) classifies respondents into three groups (White, Black, and others). We use the same grouping and only recode the group numbers (1 for White, 2 for Black, and 3 for others).

National Survey of Black Americans is a series of surveys conducted in 4 waves (1979-1980, 1987-1988, 1988-1989, and 1992). The survey's target population is Black US citizens 18 years of age or older. Our project uses Wave-1 variables from a publicly available data set (National Survey of Black Americans, Waves 1-4, 1979-1980, 1987-1988, 1988-1989, 1992 (ICPSR 6668)). Respondent's occupation variable (V307) classifies respondents' occupation into the 1970 Census 3-digit codes. We recoded this variable into the 1950 Census occupation codes using the IPUMS crosswalk. The data set also includes variables for the occupation of the respondents' father (V1471) and mother (V1477). The parents' occupation variables assign two-digit codes and have substantially fewer categories than the 1970 US Census occupation classification. We mapped these variables to a new occupation variable (occ_b) that we constructed by collapsing the 1950 Census occupation code.

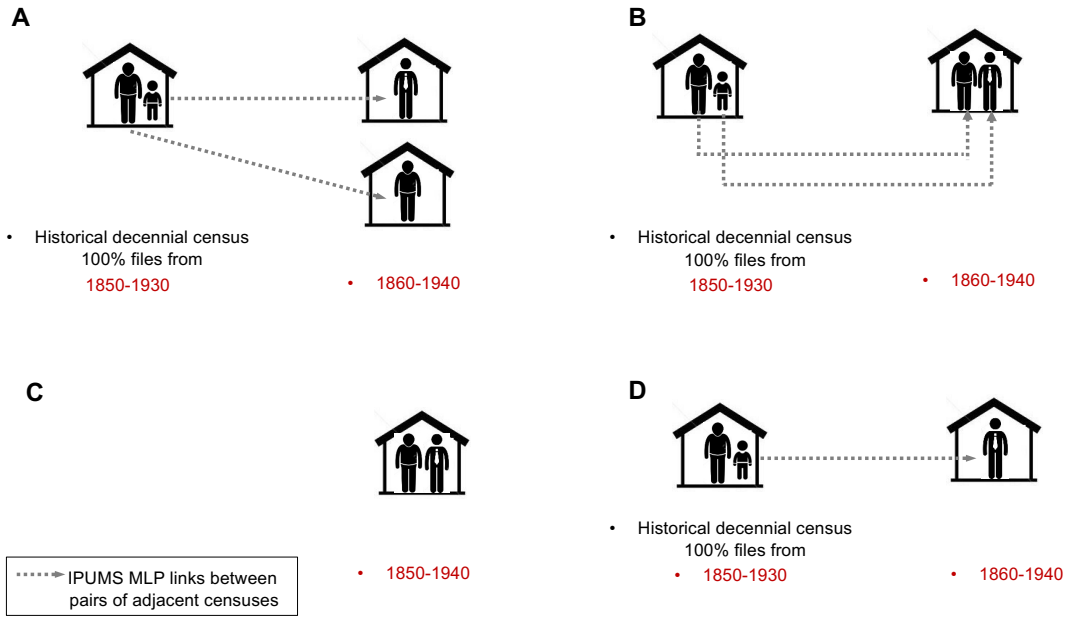


Figure C.1: Father–Son Pair Construction in Historical Samples, 1850-1940

Data sources: IPUMS 1850-1940 linked full-count Censuses (MLP); Census Linking Project 1850-1940 linked full-count Censuses (CLP). IPUMS full-count 1940 Census.
Note: This plot shows four linking scenarios in our sample using historical U.S. full-count Censuses. In Scenario (A), parents and offspring lived in the same household in one of the Census years during 1850-1930 when the offspring was a child, and they were observed in different households in a later census when the offspring became an adult. In Scenario (B), parents and offspring lived in the same household during the offspring's childhood and adulthood. In Scenario C, parents and offspring lived in the same household when the offspring was an adult, and no childhood records were available. In Scenario D, parents and offspring lived in the same household in one of the Census years during 1850-1930 when the offspring was a child, and only the child can be linked to a later census.

D Theory and Proofs

D.1 Mixing Analysis: Example

To illustrate our measures of mixing calculations (AD, AID), this section provides a simple example. Let $P_\alpha = \alpha I + (1-\alpha)\frac{ii'}{N}$, where I is the identity matrix with dimension N, i is an N-dimensional column vector consisting of 1's, and $\alpha \in [0,1)$. Note that $\frac{ii'}{N}$ is the transition matrix that makes the next period's distribution equal to i', since $\mu_0 \cdot \frac{ii'}{N} = (\mu_0 i)\cdot \frac{i'}{N} = \frac{i'}{N}$, where the last equation uses $\sum_k \mu_{0,k} = 1$ for any distribution μ_0. In other words, P_α is a combination of maintaining the original distribution with probability α and fully randomizing with probability $(1-\alpha)$.

Claim: $P_\alpha \cdot P_\beta = P_{\alpha\beta}$

Proof:

$$\begin{aligned} P_\alpha \cdot P_\beta &= \left(\alpha I + (1-\alpha)\frac{ii'}{N}\right)\left(\beta I + (1-\beta)\frac{ii'}{N}\right) \\ &= \alpha\beta I + \left(\alpha(1-\beta) + \beta(1-\alpha) + (1-\alpha)(1-\beta)\right)\frac{ii'}{N} \\ &= \alpha\beta I + (1-\alpha\beta)\frac{ii'}{N} \end{aligned}$$

where the second equation uses the fact that $\frac{ii'}{N}\cdot\frac{ii'}{N} = \frac{1}{N}\cdot i \cdot (\frac{i'i}{N})\cdot i' = \frac{1}{N} ii'$.

A corollary of this is that $P_\alpha^t = P_{(\alpha^t)}$. That is, $P_\alpha^t = \alpha^t I + (1-\alpha^t)\frac{ii'}{N}$. Also, $\lim_{t\to\infty} P_\alpha^t = \frac{ii'}{N}$, which implies that the steady state distribution is $\mu^* = \frac{i'}{N}$.[26]

Now to characterize the measures related to mixing using this $P = P_\alpha$,

$$\begin{aligned} (AD) &= \|\mu_0 P^t - \mu^*\| \\ &= \|\alpha^t \mu_0 + (1-\alpha^t)\frac{i'}{N} - \frac{i'}{N}\| \\ &= \alpha^t \|\mu_0 - \frac{i'}{N}\| \end{aligned}$$

[26] Note that $\alpha \neq 1$ is important because $\alpha = 1$ will result in $\mu^* = \mu_0 \neq \frac{i'}{N}$. This is because $\lim_{t\to\infty}\lim_{\alpha\to 1}\alpha^t = 0$, but $\lim_{\alpha\to 1}\lim_{t\to\infty}\alpha^t = 1$, resulting in a discontinuity at $\alpha = 1$.

$$
\begin{aligned}
(AID) &= \sum_k m_k \| e_k P^t - \frac{i'}{N} \| \\
&= \sum_k m_k \alpha^t \| e_k - \frac{i'}{N} \| \\
&= \alpha^t \| e_1 - \frac{i'}{N} \|
\end{aligned}
$$

where the last equation is due to the symmetry across k, and $\sum_k m_k = 1$. Note that (AM) depends on μ_0 but (AIM) doesn't,[27] and they both converge to zero at rate α. Finally,

$$
(AID) - (AD) = \alpha^t \left(\| e_1 - \frac{i'}{N} \| - \| \mu_0 - \frac{i'}{N} \| \right) \geq 0
$$

D.2 Mixing Analysis: Bounds

Let $\mu_0 = (m_1, \cdots, m_N)$ where m_j's are scalar, and $P^t = (r_1; \cdots; r_N)$ where r_j's are row vectors for which the sum of N elements is equal to 1. Let e_j denote the row vector with j-th element equal to 1 and 0 otherwise. Then the following equations hold:

$$
e_j P^t = r_j
$$

$$
\mu_0 = \sum_k m_k e_k
$$

$$
\mu_0 P^t = \sum_k m_k e_k P^t = \sum_k m_k r_k
$$

Then

$$
AD = \| \mu_0 P^t - \mu^* \| = \left\| \sum_k m_k r_k - \mu^* \right\| \in [0, M]
$$

$$
ID = \| e_j P^t - \mu^* \| = \| r_j - \mu^* \| \in [0, M]
$$

$$
AID = \sum_k m_k \| e_k P^t - \mu^* \| = \sum_k m_k \| r_k - \mu^* \| \in [0, M]
$$

where M is the upper bound of the norm, e.g., $\|(1,0,0) - (0,1,0)\| = \ say, \ 2$.

[27] That (AIM) does not depend on μ_0 is an artifact of the symmetry assumed in this example in terms of P, and is clearly not a general property.

Examining the difference between AID and AD,

$$
\begin{aligned}
AID - AD = & \\
&= \sum_k m_k \| \underbrace{r_k - \mu^*}_{v_k} \| - \left\| \sum_k m_k r_k - \mu^* \right\| \\
&= \sum_k m_k \|v_k\| - \left\| \sum_k m_k v_k \right\| \\
&\geq 0 \ \text{ by triangular inequality (Minkowski)}
\end{aligned}
$$

For the bound in the other direction,

$$
\begin{aligned}
AID - AD &= \sum_j m_j \left(\|r_j - \mu^*\| - \left\| \sum_k m_k r_k - \mu^* \right\| \right) \\
&\leq \sum_j m_j \left\| r_j - \sum_k m_k r_k \right\| \ \text{ by triangular inequality (Minkowski)} \\
&= \sum_j m_j \left\| \sum_k m_k (r_j - r_k) \right\| \\
&\leq \sum_{j,k} m_j m_k \|r_j - r_k\| \ \text{ by triangular inequality (Minkowski)} \\
&= \sum_{j \neq k} m_j m_k \|r_j - r_k\| \ \ (\because \|r_j - r_j\| = 0) \\
&\leq \sum_{j \neq k} m_j m_k \cdot M \ \ (\text{M is the upper bound of the norm, e.g., 2}) \\
&= M \Bigg(\underbrace{(\sum_j m_j)^2}_{=1} - \underbrace{\sum_j m_j^2}_{\geq \frac{1}{N}(\sum_j m_j)^2 \ \text{by Cauchy-Schwarz inequality}} \Bigg) \\
&\leq (1 - \frac{1}{N}) M = (1 - \frac{1}{N}) \cdot 2
\end{aligned}
$$

E Additional Exercises: Within and Between Racial Group Inequality

We examine within- and between-group inequality using various deviation measures in mixing analysis defined in Equation (7). Specifically, for each racial group, we calculate the difference in the occupational distributions of descendants, comparing individuals who have parents in two distinct occupations,

$$ID^{wn}(P, j, k, t) = \|e_j \mathbf{P}^t - e_k \mathbf{P}^t\|. \tag{10}$$

The measure evaluated at $t = 1$ reveals differences in the predicted occupational distribution among *offspring* within the same racial group. Examining the differences between high- and low-status occupations, for example, captures the within-group variance in the opportunities to sort across occupations faced by offspring.

We also examine the between-group inequality by comparing individuals from different racial groups who have parents in the same occupations,

$$ID^{bn}(P_W, P_B, j, t) = \|e_j \mathbf{P}_W^t - e_j \mathbf{P}_B^t\|. \tag{11}$$

For example, investigating the between-group variance for "Professional, Managers" parents provides insights into how the opportunities to maintain or move into different occupations for the offspring generation differ by race.

Figure C.2: Within and Between Group Convergences (Short-Run)



Notes: The graphs show the within-race-group deviations between "Professional and Managers" and "Semi-Skilled and Unskilled" groups (left); and the between-race-group deviations for "Professional and Managers" and "Semi-Skilled and Unskilled" groups separately (right). We use transition matrices for 5-category occupations. Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Figure C.2 (left) shows the within-group differences for families of high- and low-status occupations in occupations, namely "Professional and Managers" and "Semi-Skilled and Unskilled." We find that the trends are similar to the dynamics of the rate of convergences shown in Figure 9 using AIM, which reflect within-group heterogeneity in mobility across families. For Black Americans, the within-race difference continues to increase, though we observe a decrease for the most recent cohort. The opposite holds for White men. Our results echo recent findings studying within-variance between the two racial groups, which highlight similar contrasting trends between Black and White Americans for younger cohorts (Chetty et al., 2023).

Figure C.2 (right) separately shows the between-group differences in their job opportunities for families of "Professional and Managers" and "Semi-Skilled and Unskilled" groups. We show that the trend closely follows the dynamics in the degree of occupational segregation (Figure A.2), which is initially high but dramatically falls for the 1940-1950 and 1960-1970 birth cohorts. Our measurements further highlight that, while the between-group difference falls by a greater magnitude for the high-status compared to the low-status group over time, the downward trend does not continue, but rather slightly increases for the 1960-1970 birth cohort. Black-White convergences have improved significantly, driven by the 1940-1950 birth cohort, but recent trends still show a non-negligible Black-White gap in their opportunities for offspring to sort into high-status occupations or to move away from low-status ones (Collins and Wanamaker, 2022).