# Class Mobility in the Era of Rising Inequality: A Synthetic Dynasty Analysis

Preliminary Draft - Do Not Circulate

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**Abstract**

Widely regarded as a barometer for equality of opportunity, intergenerational mobility has attracted renewed attention amid concerns that it may have declined in the wake of rising economic inequality since the 1970s. Although earlier research documents stability, or even modest increases, in mobility among cohorts who grew up or entered the labor market before this period, evidence for more recent cohorts is limited and highly inconsistent. This ambiguity is compounded by the nearly universal reliance on parametric models that impose restrictive assumptions on the pattern of change in mobility over time. We address these limitations by introducing a nonparametric approach to analyzing class mobility based on the "synthetic dynasties" represented in Markov chains. This approach yields several new measures of mobility, including (i) steady-state mobility, defined as movement across classes in the Markov steady sate, where the marginal distribution of occupations is invariant, and (ii) intergenerational memory, which captures the rate at which the influence of class origins on destinations dissipates across generations. Applying these methods to data from the U.S., we find that both steady-state mobility and intergenerational memory have remained stable across cohorts born since 1945. This stability, however, masks offsetting class-specific trends. Among those from the upper and lower classes, movement has declined and memory has increased slightly. In contrast, among the middle classes, movement has risen and memory has weakened.

**Keywords:** class, occupations, mobility, inequality, trends, Markov chains

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# 1 Introduction

Intergenerational mobility refers to the extent to which individuals' social positions differ from—or resemble—those of their parents. It is widely regarded as a key indicator of societal openness, equality of opportunity, and whether meritocratic principles shape economic outcomes (Blau and Duncan, 1967; Erikson and Goldthorpe, 1992; Featherman and Hauser, 1978). Both scholarly and public interest in mobility stems largely from its connection to these ideals, and nowhere has this interest been more pronounced than in the U.S., where national mythology has cast the country as a "land of opportunity," promising abundant possibilities for advancement regardless of class background. In recent decades, however, concerns about the prospect of declining mobility have increased (DeParle, 2012; Haldane, 2025; Krueger, 2012; Putnam, 2015), as economic growth has slowed and inequality has widened since the 1970s. These trends—sluggish growth coupled with a steep rise in income and wealth inequality—have renewed interest in mobility and reignited debates over whether American society is straying from its professed commitment to equality of opportunity (DiPrete, 2020; Mitnik et al., 2016).

Trends in mobility have long been the subject of vibrant theoretical debate, and recent concerns have drawn fresh attention to competing perspectives on how mobility evolves over time. A contemporary perspective argues that rising inequality reduces mobility by deepening disparities in resources between upper- and lower-class families, which further polarize parental investments in children. These disparities reinforce class differences in the acquisition of human, social, and cultural capital, thereby increasing the capacity of more advantaged families to transmit their social position across generations (Andrews and Leigh, 2009; Mitnik et al., 2016). In contrast, the modernization perspective anticipates a steady increase in mobility as societies develop economically (Featherman and Hauser, 1978; Lipset and Bendix, 1959). In particular, as modernization expands access to education and increases the importance of skills and credentials for occupational attainment, it is thought to weaken the influence of family background and foster greater mobility over time (Hout, 1988; Pfeffer and Hertel, 2015). A third perspective, articulated in the Featherman-Jones-Hauser (FJH) hypothesis, contends that the association between class origins and destinations remains largely stable in market-based societies with nuclear family systems, and that any fluctuations in overall mobility mainly reflect structural shifts in the distribution of occupations (Erikson and Goldthorpe, 1992; Featherman et al., 1975; Ildefonso and Sun, 2025).

Prior research on mobility trends in the United States provides mixed support for these competing perspectives, particularly during the recent period of rising inequality.

For cohorts born before the 1970s, a large body of evidence indicates that the influence of class origins on destinations either remained stable or declined modestly over much of the twentieth century (e.g., Featherman and Hauser 1978; Featherman et al. 1975; Grusky and Hauser 1984; Hauser et al. 1975; Hout 1988). However, research covering more recent cohorts—those who grew up or entered the labor market during the era of growing inequality—is both more limited and more inconsistent. Among studies of occupational mobility, some report continued stability in origin-destination associations (Song et al., 2020), others suggest a modest decline in the influence of parental background (Beller and Hout, 2006; Pfeffer and Hertel, 2015), and still others point to signs of increasing persistence across generations (Beller, 2009; Mitnik et al., 2016). Research on income mobility during this period is similarly inconclusive: while some studies report little change (Chetty et al., 2014; Lee and Solon, 2009), others suggest a decline in mobility for cohorts entering the labor force after 1980 (Aaronson and Mazumder, 2008; Davis and Mazumder, 2024). In sum, the evaluation of recent tends in intergenerational mobility—whether measured using occupational classes or income—remains "plagued with inconsistent findings" (Torche 2015:56).

Some of these inconsistencies may stem from limitations in how recent trends have been analyzed. Most studies focus on income-based measures of mobility, which are sensitive to volatility over the life course and may be less effective than occupation-based measures at capturing individuals' positions within a complex, multidimensional system of social stratification (Connelly et al., 2016; Nybom and Stuhler, 2016). Prior studies of occupational mobility, while more robust to life-course volatility, have largely relied on samples of recent cohorts that are quite sparse (e.g., Mitnik et al. 2016; Pfeffer and Hertel 2015), limiting their ability to detect change during the period of rising inequality. Moreover, the most influential analyses of trends in occupational mobility were conducted before this period and draw on data that exclude recent cohorts entirely (e.g., Erikson and Goldthorpe 1992; Featherman and Hauser 1978; Hout 1988). Finally, nearly all studies of occupational mobility employ parametric log-linear models. Although widely used and analytically powerful, these models typically rest on restrictive functional form assumptions about the evolution of mobility over time. When these assumptions are violated, they can obscure meaningful changes and introduce bias (Bucca and Urbina, 2021; Zhou, 2015), complicating efforts to assess whether, and how, mobility has shifted in recent decades.

In this study, we analyze cohort trends in occupational class mobility in the United States during the era of rising inequality. To this end, we draw on the most recent data available, apply nonparametric smoothing techniques to improve the precision of

estimates for recent cohorts, and use a new class of mobility measures based on the "synthetic dynasties" represented in Markov chains. These measures adapt the logic of synthetic cohort analysis and stable population models—widely used in demography (Wachter, 2014)—to study class mobility. Rather than tracking actual family lineages over multiple generations, we use cross-sectional data on parent-child pairs to simulate the long-run trajectories of hypothetical dynasties initiated by individuals in a given birth cohort. This approach allows us to characterize a cohort's mobility not only in terms of single-generation transitions from parental origins to child destinations, but also through the extent to which class origins would continue to influence subsequent, synthetic generations formed as if patterns of occupational inheritance were to remain stable indefinitely.

Our approach yields several novel and complementary measures of mobility. First, we distinguish between *overall mobility* and *steady-state mobility*. Overall mobility is defined conventionally as the total amount of movement across classes observed among parent-child pairs in a given cohort. It reflects both shifts in the occupational distribution and the influence of parental origins on child destinations. It is also commonly decomposed into two components: structural mobility, which reflects movements necessitated by changes in the marginal distribution of occupations, and exchange mobility, which captures residual movements (Featherman and Hauser, 1978; Jones, 1985).

Steady-state mobility, by contrast, measures the amount of movement between classes in the steady state of a Markov chain, where the marginal distribution of occupations becomes invariant across generations and thus structural mobility ceases to exist. In other words, steady-state mobility reflects the movement that would persist among descendants of synthetic dynasties once the occupational structure has stabilized. These movements are driven solely by the association—or lack thereof—between parent origins and child destinations.

Second, we analyze a measure of *intergenerational memory*, defined as the distance between the observed transition probabilities among parent-child pairs and the limiting transition probabilities of a Markov chain (Blume et al., 2025), where the influence of class origins on the occupational attainments of descendants has dissipated entirely. In essence, memory captures how quickly the influence of class origins would fade out over successive generations of a synthetic dynasty. By this measure, a society is considered highly mobile when origins lose their influence quickly, such that descendants from different class backgrounds rapidly converge to a state in which they have equal chances of attaining any destination.

These measures extend a long tradition of using Markov chains to study the inter-

generational transmission of social status (Boudon, 1973; Dardanoni, 1993; Van de Gaer et al., 2001), and they offer several advantages over more conventional approaches to measuring mobility. In particular, they provide simple, interpretable summary indices that can also be disaggregated to reveal more granular, class-specific patterns. They are fully nonparametric, imposing no assumptions about the functional form of origin-destination associations. And they align closely with different theoretical conceptions of social mobility, offering a coherent framework for distinguishing among types of mobility and tracing how they have changed over time.

Applying these methods to data from the 1972-2024 General Social Survey (GSS), we find that overall mobility in the United States, which refers to the total amount of movement observed across classes, has remained remarkably stable across cohorts born between 1945 and 1985. In addition, the influence of class origins on destinations—as captured by our measures of steady-state mobility and intergenerational memory—also appears largely unchanged over this period. These general patterns are consistent across alternative sample definitions, a range of different class typologies, and multiple approaches to measurement.

Beneath this apparent stability, however, lies a more complex set of underlying dynamics. The stable level of overall mobility results from offsetting trends in its component parts: structural mobility has declined steadily, reflecting a slowdown in occupational upgrading, while exchange mobility has increased. Similarly, the flat trends in steady-state mobility and intergenerational memory conceal notable variation across class origins. Among those from the upper and lower classes, movement has declined and memory has increased, albeit slightly. Conversely, among those from middle-class origins, movement has risen while memory has weakened.

The present study makes several contributions to research on class mobility. Empirically, it provides the most up-to-date and comprehensive estimates of American trends in intergenerational mobility during the era of rising inequality. Theoretically, these estimates help adjudicate among competing accounts of how mobility evolves over time, offering limited evidence for modernization theory, mixed support for the inequality perspective, and partial alignment with the FJH hypothesis. Methodologically, we introduce novel measures of class mobility that are easy to interpret and do not rely on restrictive parametric assumptions.

In the sections that follow, we begin by reviewing different theoretical perspectives and prior research on trends in mobility. Next, we introduce Markov models of class mobility and describe our synthetic dynasty measures based thereon. We then outline the data and methods used to estimate these measures, present their trends across co-

horts, and conclude by considering the broader implications of our findings for theory and future research.

## 2 Trends in Class Mobility: Continuity or Change?

Different theoretical perspectives offer contrasting predictions about trends in class mobility over time. The modernization perspective—also known as the liberal theory of industrialization—anticipates steadily rising mobility as societies develop and expand access to education. The FJH hypothesis, by contrast, contends that the influence of class origins on destinations remains largely stable across generations, despite changes in the economy and institutions. A third, historically contingent perspective emphasizes the role of economic change, suggesting that recent increases in income and wealth inequality may be disrupting patterns of mobility that were once relatively stable.

Modernization theory views rising class mobility as a natural consequence of economic development and the institutional changes that accompany it (Featherman and Hauser, 1978; Lipset and Bendix, 1959; Treiman, 1970). As societies industrialize, they are thought to transition from "particularistic" forms of social stratification—where opportunities are allocated primarily on the basis of kinship and ascribed status—to more meritocratic systems, in which occupational attainment depends increasingly on individual achievement and formal qualifications (Featherman and Hauser 1978:12). This process is only expected to intensify in the post-industrial era, as service- and information-based economies place an even greater premium on education and human capital (Bell, 1976; Featherman and Hauser, 1978).

Expansion of the formal education system plays an especially important role in promoting mobility, according to the modernization perspective. Social mobility is thought to increase not only because of a decline in the direct influence of class origins on destinations, but also through changes in population composition brought about by expanded access to education (Beller and Hout, 2006; Hout, 1988). Even if class-based disparities in educational attainment persist following expansion (Bailey and Dynarski, 2011; Raftery and Hout, 1993), a growing share of the population nonetheless attains higher levels of schooling, particularly college degrees. Because the association of class origins with destinations tends to be weaker among those with higher levels of schooling, educational expansion promotes greater mobility by shifting more people into subpopulations where social origins seem to exert less influence. In this way, post-secondary expansion may generate steady increases in social mobility at the population level (Breen, 2010; Hout, 1988; Pfeffer and Hertel, 2015).

In contrast to modernization theory, the FJH hypothesis rejects the possibility that class mobility follows an upward, developmentally driven trajectory. Rather than anticipating mobility to increase steadily with economic development, this perspective posits that the association between class origins and destinations—what FJH referred to as the "intrinsic pattern of generational mobility" and measured using odds ratios in log-linear models—remains relatively stable over time in societies with market economies and a nuclear family system (Featherman et al., 1975). While overall rates of mobility may rise or fall, these fluctuations are thought to reflect changes in the occupational structure, driven by technological change, shifting labor demand, or educational expansion, and not by any systematic strengthening or weakening of the association between class origins and destinations. The FJH hypothesis thus distinguishes between a "genotypic" pattern of mobility, referring to stable origin-destination associations, and a "phenotypic" pattern based on observed mobility rates, which vary in response to shifts in the distribution of occupations over time (Featherman et al. 1975:339-340).

Empirical research on the United States largely supports the modernization or FJH perspectives for cohorts born before the 1970s. Studies of occupational mobility throughout much of the twentieth century generally find that the influence of class origins on destinations—the "genotypic pattern of mobility"—either remained stable or declined modestly during this period (Featherman and Hauser, 1978; Featherman et al., 1975; Grusky and Hauser, 1984; Hauser et al., 1975; Hout, 1988). Similar patterns also appear in Europe, where early studies pointed to "trendless fluctuation" in origin-destination associations across cohorts (Erikson and Goldthorpe, 1992) and later reanalyses suggested that these associations had actually weakened in some countries (Breen, 2004). However, most evaluations of the modernization and FJH perspectives are based on data that predate the contemporary period of rising inequality.

Since the 1970s, income and wealth inequality in the United States have increased sharply (Killewald et al., 2017; Morris and Western, 1999; Saez and Zucman, 2020). Much of this increase has been driven by disproportionate gains at the top of the distribution. For example, the share of national income held by the top 1% of families has roughly doubled, climbing from under 10% in the late 1970s to around 20% today (Saez and Zucman, 2020). The recent shifts in economic inequality map closely onto occupational class boundaries (Mouw and Kalleberg, 2010; Wodtke, 2017; Zhou and Wodtke, 2019), with professional and managerial workers increasingly pulling away from the rest of the labor force. The emergence of this high-inequality regime marks a potentially new phase in the long-term dynamics of class reproduction (Andrews and Leigh, 2009; DiPrete, 2020; Mitnik et al., 2016).

Specifically, a contemporary perspective argues that rising inequality may reduce intergenerational mobility by exacerbating disparities in the resources that families invest their children (Andrews and Leigh, 2009; Mitnik et al., 2016). As affluent families consolidate income and wealth, they may become increasingly effective at transmitting their advantages to the next generation, while families with fewer resources find it harder to facilitate upward mobility for their children. A growing body of evidence suggests that upper-class parents now invest more heavily in their children's human, social, and cultural capital—through high-quality childcare and extracurricular activities, enrollment in private or well-resourced public schools, residence in affluent neighborhoods, and access to selective colleges and universities (Bailey and Dynarski, 2011; Kornrich and Furstenberg, 2013; Putnam, 2015; Schneider et al., 2018). Moreover, parental investments may extend beyond adolescence, as affluent parents are also better positioned to support their children during adulthood—for example, by financing graduate and professional degrees or subsidizing prolonged job searches (Mitnik et al., 2016). All of these investments are thought to increase the likelihood of class reproduction, particularly among those at the top of the occupational hierarchy.

According to this perspective, then, class mobility should decline following the rise in economic inequality, with a lag determined by the timing and nature of parental investments in their children. If these investments are concentrated in childhood and adolescence, shifts in mobility may only become apparent once cohorts raised during the era of growing inequality reach adulthood. However, if parental support during adulthood plays an important role, changes could emerge more quickly. In either case, the effects are likely to appear as stronger associations between class origins and destinations among cohorts who grew up or entered the labor market after the 1970s. Because the largest gains in income and wealth have accrued to those in professional and managerial occupations, the consequences of rising inequality for mobility may be more evident among their children. In this scenario, rising inequality would not necessarily produce a uniform increase in the strength of origin-destination associations but would instead engender a growing capacity for the upper class to secure desirable positions for their children, effectively hardening class boundaries at the top of the occupational hierarchy (Mitnik et al., 2016).

Research on the relationship between inequality and mobility has produced mixed and often contradictory findings. Cross-national comparisons consistently show that countries with higher levels of income inequality tend to exhibit lower levels of income mobility (Andrews and Leigh, 2009; Blanden, 2013; Corak, 2013)—an empirical pattern that Krueger (2012) termed "The Great Gatsby Curve." However, this inverse re-

lationship is weaker, or altogether absent, when occupational class rather than income is used to measure parental origins and child destinations (Bukodi and Goldthorpe, 2018; DiPrete, 2020; Torche, 2015). Moreover, within the U.S., research examining the association between income inequality and mobility across states also finds little evidence of a consistent relationship (Bloome, 2015).

A second line of evidence comes from trend analyses, which examine whether mobility has declined with rising inequality since the 1970s. Findings from this literature are inconsistent as well. Among studies of income mobility, some report little change over time (Chetty et al., 2014; Lee and Solon, 2009), while others document a decline in mobility for more recent cohorts (Aaronson and Mazumder, 2008; Davis and Mazumder, 2024). Research on occupational mobility during this period is less extensive but similarly divided. Some studies report that the association between parental origins and child destinations has remained largely unchanged (Song et al., 2020). Others find evidence of growing persistence across generations (Beller, 2009; Mitnik et al., 2016). And still others suggest a decline in the influence of parental origins (Beller and Hout, 2006; Pfeffer and Hertel, 2015). Taken together, these findings do not support a clear or consistent conclusion. Whether class mobility has changed, and in what direction, during the era of rising inequality thus remains an unsettled question.

One reason this question remains unresolved is that the most reliable data on the occupations of children and their parents contain only sparse samples of cohorts who grew up or entered the labor market after the 1970s. To compensate, prior studies have typically grouped cohorts into broad, arbitrarily defined bins in an effort to boost statistical power, yet even then, the ability to detect change is distorted. In addition, nearly all studies of trends in class mobility rely on parametric log-linear models, such as the "unidiff" or log-multiplicative layer effect model (Erikson and Goldthorpe, 1992; Xie, 1992). Despite their many advantages, these models impose strong assumptions about the nature of change over time. For example, the "unidiff" model assumes that the pattern of association between class origins and destinations remains the same across cohorts, allowing only the strength of these relationships to vary according to a single parameter. These constraints can obscure meaningful changes in mobility for specific classes and may introduce bias into estimates of overall trends (Bucca and Urbina, 2021; Zhou, 2015).

The present study aims to overcome these limitations and provide new evidence on trends in class mobility during the era of rising inequality. To assemble larger samples of recent cohorts, we leverage the most recent data available on the occupations of children and their parents. We then employ nonparametric smoothing techniques to reduce

random variation in the cohort-specific mobility tables and further enhance precision. Finally, we use these smoothed tables to estimate a new set of mobility measures that avoid parametric assumptions about how mobility changes over time.

# 3 Methods

## 3.1 Data

To study the dynamics of class mobility in the United States, we use data from the 1972 to 2024 waves of the General Social Survey (GSS; Davern et al. 2025). The GSS is a repeated cross-sectional survey that collects demographic, employment, and occupational information from nationally representative samples of non-institutionalized American adults. Surveys were conducted annually from 1972 to 1994—except in 1979, 1981, and 1992—and biennially thereafter. The GSS is well-suited for this analysis because it is one of the few long-running surveys that records information both respondents' occupations and those of their fathers, enabling comparisons across cohorts spanning multiple decades.

Our analytic sample consists of all GSS respondents who were born between 1945 and 1985, who were 25 to 55 years old at the time of their interview, and who reported complete information on both their own and their father's occupations. This yields a total of $n = 22,549$ respondents spanning birth cohorts that grew up or entered the labor market during the era of rising inequality in the United States. Sample sizes vary by cohort, ranging from 245 to 788 respondents. The birth-year and age-at-interview restrictions serve to maximize the size of our samples across cohorts while simultaneously limiting the potential for life-cycle bias in our trend estimates by ensuring that occupational destinations are observed at broadly comparable stages of respondents' working lives. Parallel analyses using alternative age restrictions (e.g., 25 to 65, 30 to 65, or 30 to 55) all produced similar results. Including respondents born after 1985 added only a small number of cases and merely introduced noise at the end of the time series. Results from these ancillary analyses are reported in Appendix D.

## 3.2 Occupational Classes

In each wave of the GSS, respondents are asked, *"What kind of work do you normally do?"*. They are also asked retrospectively, *"What kind of work did [your father] usually do while you were growing up?"* Responses to both questions were coded using the 2010 Census

Table 1: A Five-class Version of the EGP Typology

| Class | Description | Illustrative Occupations | EGP Labels |
|---|---|---|---|
| 1 | Higher-grade professionals, administrators, and managers | Accountants, postsecondary teachers, lawyers | I |
| 2 | Lower-grade professionals, administrators, and managers | Primary school teachers, registered nurses, managers (all other) | II |
| 3 | Higher-grade routine non-manual workers, technicians, and supervisors | Secretaries, office supervisors, bookkeepers | V + IIIa |
| 4 | Higher-grade manual workers, lower-grade technicians, and farmers | Carpenters, auto technicians, electricians | VI + IVc |
| 5 | Lower-grade routine non-manual and manual workers | Retail sales supervisors, nursing aides, truck drivers | VII + IIIb |

*Notes:* The illustrative occupations for each class include the three most common occupational titles among sample members in the 2022 wave of the GSS. The self-employed (EGP Classes IVa and IVb) are allocated across all five of our classes based only on their occupation.

Occupational Classification (COC) system, which we use to assign sample members to class origins based on their father's occupation and to class destinations based on their own occupation. These father-child, origin-destination pairs constitute the empirical basis for our analysis of mobility.

To translate detailed COC codes into occupational classes, we adopt a five-class version of the Erikson-Goldthorpe-Portocarero (EGP) typology (Erikson et al., 1979). Widely used in prior studies of intergenerational mobility, the EGP typology groups occupations according to their employment relations, skill requirements, and work conditions. We focus on a five-class version of the typology to preserve clear distinctions in skills, conditions, relationships at work while avoiding overly fine categories that would lead to excessive sparsity. The resulting classes—summarized in Table 1—include: (1) higher-grade professionals and managers; (2) lower-grade professionals and managers; (3) higher-grade routine non-manual workers, technicians, and supervisors; (4) higher-grade manual workers, lower-grade technicians, and farmers; and (5) lower-grade rou-

tine non-manual and manual workers. Figure 1 displays the number of observations in each of these classes, separately by birth cohort.

Although the EGP typology is widely used, the details of its implementation vary across studies. We implement our classification using the crosswalk developed by Morgan (2017), which maps 2010 COC codes to EGP classes. To assess the robustness of our key findings, we also conducted a series of parallel analyses based on several alternative implementations. These included versions of the typology that (i) omit farmers and the self-employed; (ii) follow the classification decisions adopted by Erikson and Goldthorpe (2010), Goldthorpe and Jackson (2007), and Pfeffer and Hertel (2015); and (iii) expand the typology to seven classes following Morgan (2017). These alternatives differ mainly in their treatment of farmers, the self-employed, technicians, and routine non-manual workers. As reported in Appendix D, our trend estimates are highly consistent across different approaches to measuring occupational class.

### 3.3 Smoothing

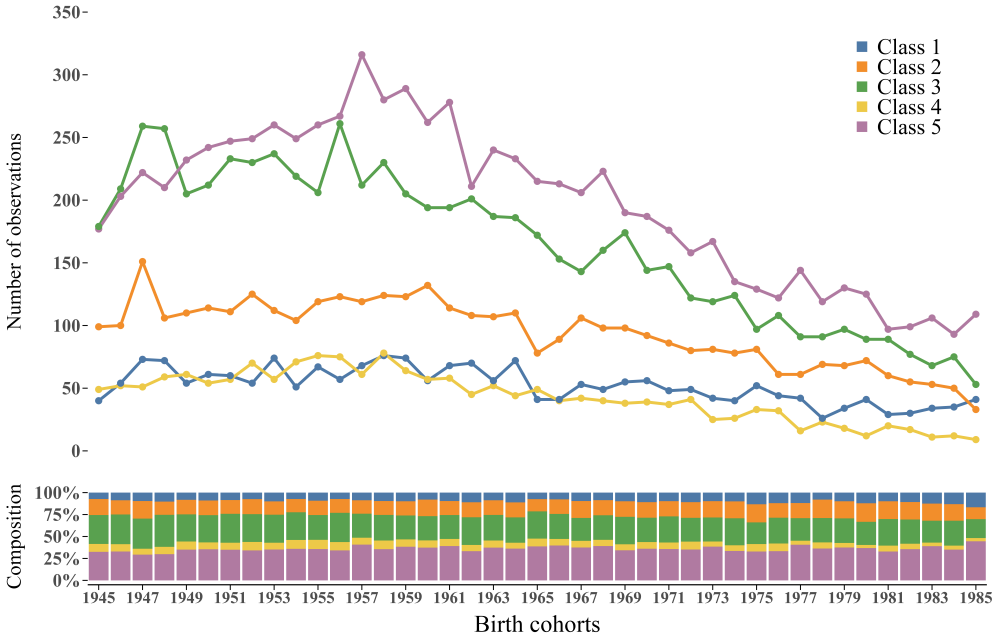
To reduce the influence of random sampling variability and improve the precision of our trend estimates, particularly for more recent cohorts for whom we have comparatively fewer observations, we smooth all the mobility tables used in our analysis using thin-plate splines (Wood, 2003). Specifically, we smooth these tables using the following model:

$$\log\left(n_{ijt}\right) = \alpha_{ij} + f_{ij}(t) + \epsilon_{ijt}, \tag{1}$$

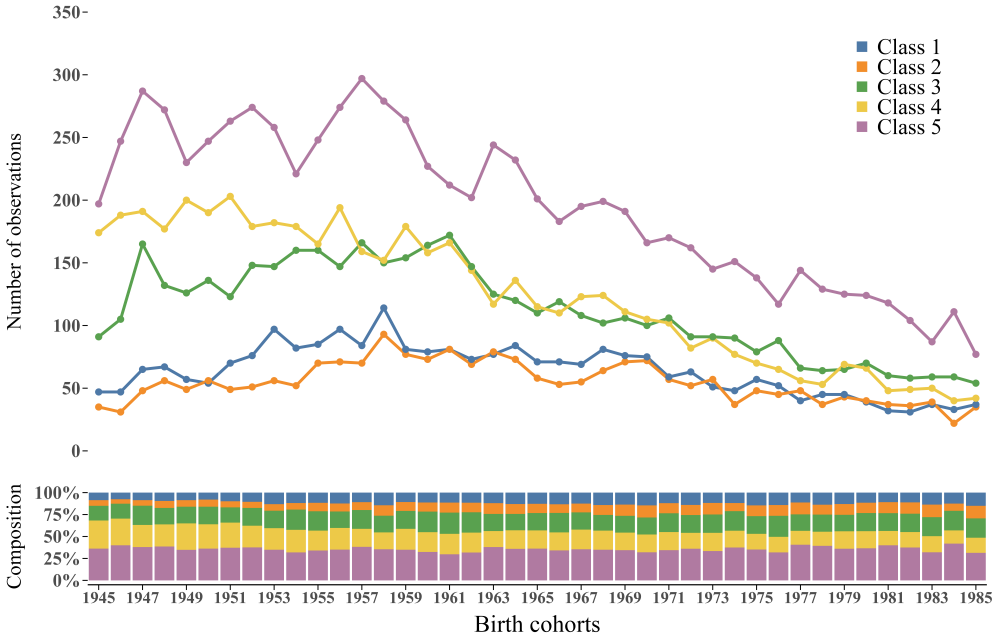
where $n_{ijt}$ denotes the number of respondents from origin class $i$ in destination class $j$ who belong to birth cohort $t$, $\alpha_{ij}$ denotes a set of origin-by-destination fixed effects, and $f_{ij}(t)$ denotes a smooth function of time (i.e., cohort) that is allowed to differ for each group of respondents defined jointly by their class origin and destination. The functions $f_{ij}(\cdot)$ are a series of thin-plate splines, which allow us to flexibly smooth over random variation in the cell counts of the mobility tables across cohorts.

The model is estimated by solving a penalized likelihood problem (Wood, 2003). With this approach, the likelihood function is modified by adding a penalty term for the complexity, or "wiggliness," of the splines. This penalty has the form of an integrated second derivative, multiplied by a smoothing parameter. Specifically, it can be expressed as $\lambda \int f''_{ij}(t)^2\, dt$, where higher values of the smoothing parameter $\lambda$ promote smoother fits and greater resistance to departures from a simple linear trend. The value of this parameter can be selected via cross-validation or restricted maximum likelihood (REML). We use REML, as it has been shown to yield superior performance in most settings

Figure 1: Sample sizes by class origin, destination, and birth cohort




(a) Class Destinations of Children




(b) Class Origins based on Fathers

*Notes:* These figures illustrate the evolution of class distributions among fathers and their children in our analytic sample. Class 1 refers to higher-grade professionals and managers; Class 2 refers to lower-grade professionals and managers; Class 3 refers to higher-grade routine non-manual workers, technicians, and supervisors; Class 4 refers to higher-grade manual workers, lower-grade technicians, and farmers; and Class 5 refers to lower-grade routine non-manual and manual workers.

(Wood, 2011).

After fitting the model in Equation 1, we use it generate a set of predicted counts, denoted by $\hat{n}_{ijt}$, that populate the mobility tables we use in all subsequent analyses. Essentially, this procedure smooths both the cell counts and the marginal totals of each cohort-specific mobility table, using a non-parametric model that does not impose any meaningful constraints on how the tables differ across cohorts.

## 3.4 Analyses

In our analysis, to study the intergenerational transmission of occupational class we employ Markov chain–based mobility measures. The categorical nature of occupational classifications makes Markov transition matrices a particularly suitable tool for capturing the structure and dynamics of intergenerational mobility. Markov chain models have a long history of being used to study the intergenerational transmission of social status in the sociology literature (see, for example, Boudon (1973); Dardanoni (1993); Van de Gaer et al. (2001); and Song (2021) for comprehensive reviews).

### 3.4.1 Markov Chains and Synthetic Dynasties

Suppose there are $n$ occupational classes. We define the transition matrix $P$ as an $n \times n$ matrix, where each element $P_{ij}$ represents the probability of transitioning from class $i$ in the parent generation to class $j$ in the child generation. We assume that $P$ is time-invariant, reflecting a stationary (homogeneous) Markov process governing the intergenerational transmission of occupational class. Given a parental distribution of occupational classes $\mu^p$ and a transition matrix $P$, the distribution of occupational classes in the child generation can be obtained as $\mu^c = \mu^p \cdot P$. More generally, under a stationary Markov chain, the distribution of occupational classes at any generation $t$ can be derived either recursively from the distribution in the previous generation via $\mu^t = \mu^{t-1} \cdot P$, or from an initial distribution $\mu^0$ using the t-step transition matrix: $\mu^t = \mu^0 \cdot P^t$. The former approach is used to define mobility within the movement concept, while the latter serves as the basis for deriving measures of memory.

If the transition matrix $P$ is primitive,[1] then as $t \to \infty$, the cross-sectional distribution of occupational classes converges to a unique invariant – or steady state – distribution, $\mu^t \to \mu^\infty$. At the same time, the transition matrix converges to the limiting matrix,$P^t \to P^\infty$, where each row of $P^\infty$ is equal to $\mu^\infty$. These limiting properties of the Markov

[1]Formally, this means there exists a positive integer $k$ such that $P^k$ is a strictly positive matrix.

chain play a central role in the construction of both movement and memory measures employed in this study.

In this paper, we examine two distinct notions of mobility: mobility as movement and mobility as detachment from family class origins ("memory" concept). The first concept refers to intergenerational mobility as the probability that a child's occupational class differs from that of their father. The second concept captures the degree to which a child's occupational class is independent of their father's class – that is, the extent to which the influence of parental class diminishes across generations.

### 3.4.2 Movement measures

Within the movement concept, a society is considered highly mobile if children do not follow their parents' occupational class. Conversely, a perfectly immobile society is one in which each individual remains in the same occupational class as their parents – a case of the identity matrix as the transition matrix. Therefore, more generally, movement mobility indices are designed to capture shifts in the probability mass in the transition matrix away from the main diagonal, reflecting a higher degree of mobility through greater intergenerational movement across classes.

In this paper, we employ a set of movement-based mobility measures, originally proposed in the sociology literature to decompose overall mobility into exchange and structural components. This framework, rooted in the work of Broom and Jones (1969) and Featherman et al. (1975), has been further developed by subsequent studies in sociology (Matras, 1961; McClendon, 1977; Sobel, 1983; Sobel et al., 1985). We build on the extension of this framework by Butaeva et al. (2025), who highlight the importance of the steady-state mobility.

To analyze mobility as movement, we adopt a recursive approach to modeling the distribution of occupational classes within a Markov chain framework, as previously described. Specifically, we examine the dynamics of class distributions defined by the recursive relation $\mu^t = \mu^{t-1} \cdot P$, and its evolution toward the steady state, where the distribution converges to the invariant distribution $\mu^\infty$, satisfying $\mu^\infty = \mu^\infty \cdot P$. The latter equation is particularly useful for illustrating the classic definition of exchange mobility – namely, the extent of movement across classes that occurs in the absence of changes in the marginal distributions (Berger and Snell, 1957).

Building on the above, we define an overall mobility index as the expected fraction of dynasties that experience a change in occupational class from generation $t$ to generation

$t+1$:

$$OM^t(P, \mu^t, t) = 1 - \sum_i \mu_i^t \cdot P_{ii}. \tag{2}$$

We further decompose overall mobility into two components: exchange mobility and structural mobility. Structural mobility refers to the part of mobility that results from changes in the marginal distribution of dynasties across occupational classes at time $t$:

$$SM^t(P, \mu^t, t) = \|\mu^t - \mu^t \cdot P\|_{TV} = \frac{1}{2} \cdot \sum_i |\mu_i^t - \mu_i^{t+1}|. \tag{3}$$

Exchange mobility is defined residually as a part of mobility that occurs without altering the cross-sectional distribution of occupational classes at $t$:

$$EM^t(P, \mu^t, t) = OM(P, \mu^t, t) - SM(P, \mu^t, t). \tag{4}$$

Structural mobility vanishes in the long run, as the marginal distributions converge to the steady-state distribution $\mu^\infty$ as $t \to \infty$. At the steady state, the overall mobility is equal to the exchange mobility. Following Butaeva et al. (2025), we define this measure as steady-state exchange mobility:

$$SSM(P, \mu^\infty) = 1 - \sum_i \mu_i^\infty \cdot P_{ii}. \tag{5}$$

We treat $SSM$ as our preferred measure of intergenerational mobility within the movement framework, as it captures the extent of transitions in the Markov chain in the absence of structural mobility, namely, at the steady state – where the cross-sectional distribution of occupational classes has stabilized.

We will further decompose overall mobility $OM$ into upward and downward mobility by estimating eq. (2) separately for individuals who attain a higher occupational class than their parents – defining upward mobility – and for those who fall to a lower class – defining downward mobility.

To examine class-specific heterogeneity in mobility dynamics, we employ a well-established measure from the Markov chain literature – the mean time to exit from each initial class (Kemeny et al., 1969):

$$MTE_i(P) = (1 - P_{ii}) \cdot \sum_{t=1}^{\infty} t \cdot P_{ii}^{t-1} \tag{6}$$

The $MTE$ estimates how many generations, on average, it takes for descendants to exit from each social class.

We also employ the mean first passage time (MFPT) metric to characterize transitions between specific pairs of classes (Grinstead and Snell, 1997). MFPT estimates the expected number of steps required to reach class $j$ starting from class $i$:

$$MFPT_{ij}(P) = 1 + \sum_{k \neq j} P_{ik} \cdot MFPT_{kj} \tag{7}$$

### 3.4.3 Memory Measures

Within the memory concept, a society is considered highly mobile if, within a relatively short period of time, the distribution of chances to end up in any occupational class for descendants – referred to here and henceforth as the "lottery" – becomes similar across all initial parental classes. In other words, such a society is expected to reach equality of opportunity quickly. Conversely, a low-mobility society is one in which it takes for a while for individuals from different parental classes to face similar lotteries over occupational outcomes.

Consistent with standard modeling approaches, equality of opportunity can be represented by a transition matrix in which all rows are identical. Accordingly, for our analysis of memory-based mobility, we examine the evolution of the class distribution in the Markov chain under the process $\mu^t = \mu^0 \cdot P^t$, which converges to the steady-state distribution as $t \to \infty$. In this setting, the limiting transition matrix $P^\infty$ , as previously discussed, consists of identical rows and thus reflects a state of equality of opportunity. This allows us to investigate the speed at which the Markov chain approaches this equilibrium, providing a natural measure of memory in the intergenerational mobility process.

Specifically, in this paper we employ two memory-based mobility measures developed in Blume et al. (2025).[1] First, we consider class-specific mobility measures, referred to as individual memory curves:

$$IM_i(P, t, \mu^\infty) = \| \, e_i \cdot P^t - \mu^\infty \, \|_{TV} = \frac{1}{2} \cdot \sum_{k=1}^{n} |P_{ik}^t - \mu_k^\infty|, \tag{8}$$

where $e_i$ is a vector with weight 1 in class $i$ and zeros in other classes. This measure captures the evolution of the class-specific deviation of the current "lottery" towards the the steady state "lottery". By plotting these individual memory curves for different

[1] Classic approaches to assessing the speed of convergence in Markov chains – also discussed in Blume et al. (2025) – include the analysis of the eigenvalues of the transition matrix (Conlisk and Sommers, 1979; Shorrocks, 1978; Sommers and Conlisk, 1979; Theil, 1972), as well as the examination of the maximum distance between its rows, known as the Dobrushin contraction coefficient (Dobrushin, 1956).

initial classes $i$, we can illustrate how the rate of memory decay varies depending on the ancestor's occupational origin. A smaller value indicates that a class retains less memory of its origin, moving closer to a structure that resembles independence.

Second, by averaging the individual memory curves weighted by the initial class distribution, we obtain a measure of aggregate class-specific memory at time $t$:

$$AIM^t(P, \mu^0, t) = \sum_i \left\| e_i \cdot P^t - \mu^\infty \right\| \cdot \mu_i^0 \tag{9}$$

This measure captures the expected deviation from the invariant distribution at time $t$, calculated for a dynasty randomly drawn from the population in period $t = 0$. In other words, it reflects the rate at which average memory – aggregated over different initial class origins – fades over time.

For all estimates reported, we employ the standard bootstrap bias-corrected estimator (Cameron and Trivedi, 2005, p. 365) and construct 95% basic (reverse percentile) bootstrap confidence intervals (Davison and Hinkley, 1997, p. 194).

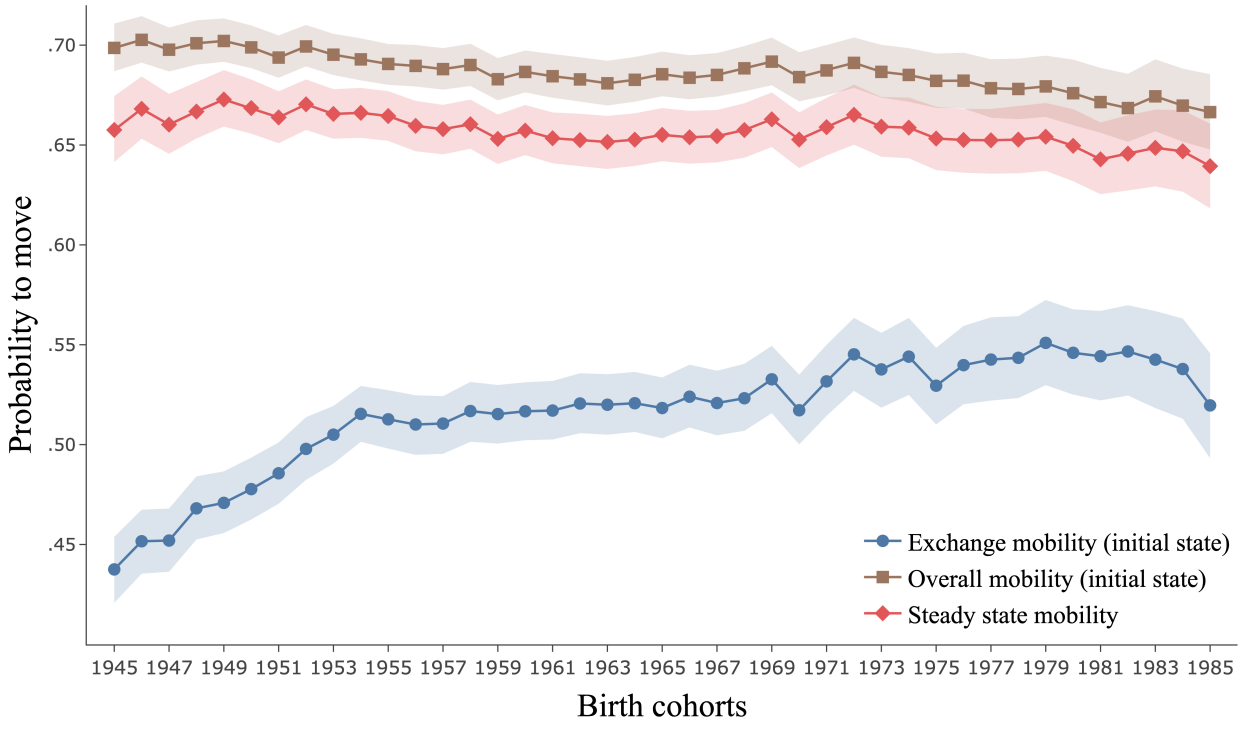
# 4 Results

## 4.1 Movement measures

### 4.1.1 Overall mobility and exchange mobility

From Figure 2, it can be sen that between 1945 and 1980 birth cohorts, the United States experienced a steady increase in the current (initial state) exchange mobility, rising from approximately 45% to 55%. Exchange mobility refers to the probability that individuals will move out of their father's occupational class, holding constant the overall occupational distribution in the economy. This measure isolates mobility attributable to conditional transition patterns rather than structural changes in the labor market. In contrast, overall mobility – defined as the probability of moving – remained relatively stable across cohorts, fluctuating narrowly around 69%. This suggests that the aggregate likelihood of occupational movement — driven jointly by changes in marginal occupational distributions and conditional transition probabilities — was largely invariant over time. Similarly, steady state mobility, in which structural mobility is by construction absent and overall mobility is equal to exchange mobility, remained flat at approximately 66% from the 1945 to the 1980 birth cohorts. This stability indicates a consistent level of intergenerational fluidity when marginal occupational distributions are held constant. The vertical distance between initial overall mobility and exchange mobility on Figure 2

Figure 2: Overall and exchange mobility



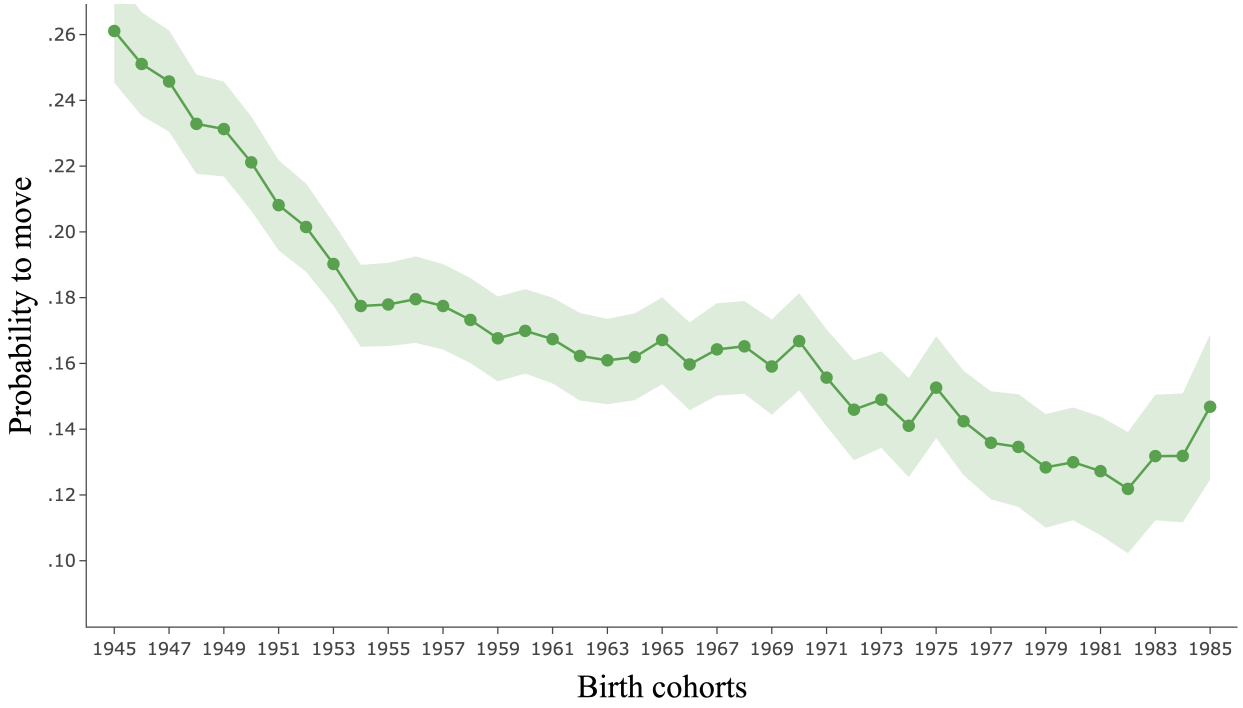

*Notes:* This figure illustrates the evolution of current overall mobility $OM^1$ from eq. (2), current exchange mobility $EM^1$ from (4), and steady state mobility $SSM$ from (5). We use standard bootstrap bias-corrected estimator. Shaded areas represent 95% reverse percentile CIs, derived from 2,000 bootstrap samples.

captures the contribution of structural mobility – mobility arising from shifts in the distribution of occupational opportunities rather than changes in relative mobility across classes.

### 4.1.2 Structural mobility

The stability of overall mobility at the initial state reflects an offsetting relationship between structural and exchange mobility. Structural mobility – driven by shifts in the marginal occupational distribution – declined from 26% for the 1945 birth cohort to 12% for the 1980 cohort, counterbalancing the corresponding increase in exchange mobility over the same period (Figure 3). This inverse relationship between structural and exchange components helps explain the relatively flat trend in overall intergenerational mobility across cohorts.

Figure 3: Structural mobility

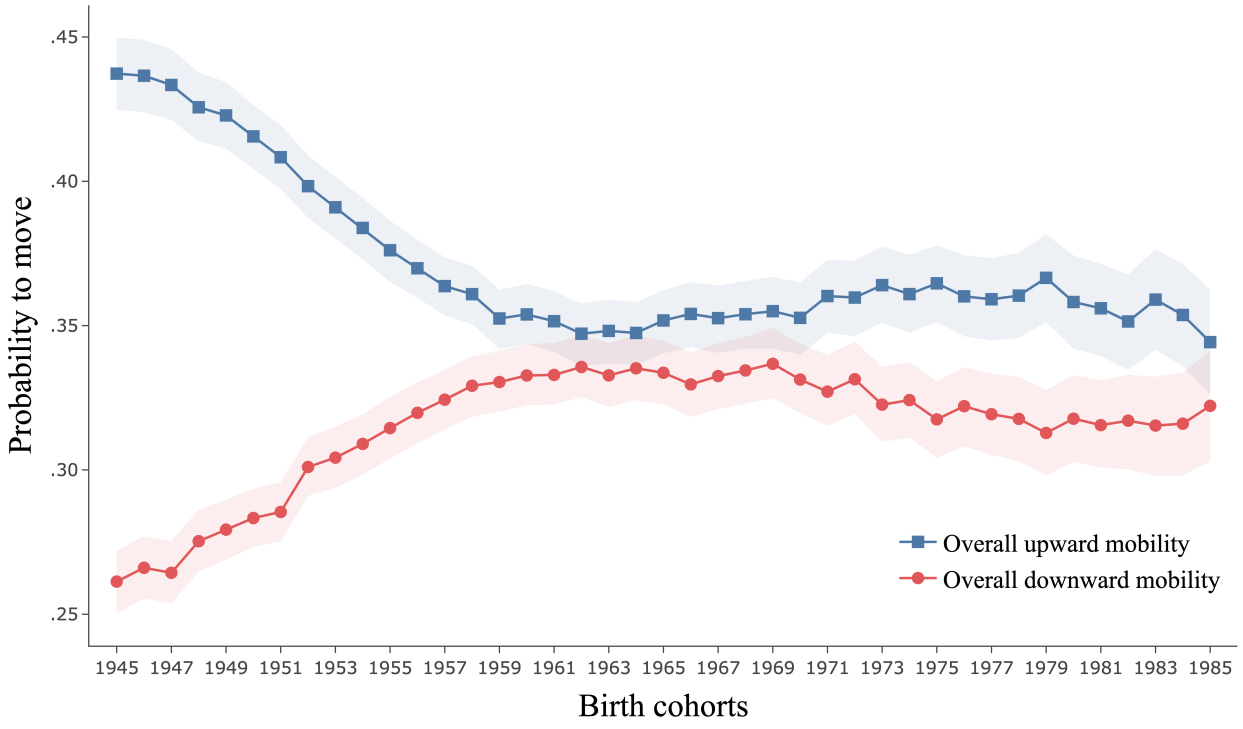



*Notes:* This figure illustrates the evolution of current structural mobility $SM^1$ from eq. (3). We use standard bootstrap bias-corrected estimator. Shaded areas represent 95% reverse percentile CIs, derived from 2,000 bootstrap samples.

### 4.1.3 Upward and downward mobility

We further decompose overall mobility into upward and downward components to assess whether children tend to move into occupational classes that are higher or lower than those of their fathers. Given that overall mobility remains relatively stable across cohorts, this pattern suggests that upward and downward mobility trends largely offset one another. From the 1945 to 1986 birth cohorts, upward mobility generally exceeded downward mobility. However, between the 1945 and 1960 cohorts, upward mobility declined steadily from 43% to 35%, while downward mobility increased from 26% to 33%. These opposing trends stabilized around the 1969 cohort. Starting with the early 1970s cohorts, upward mobility began to rise gradually, reaching 35% by the 1982 cohort, while downward mobility declined to approximately 30%.

Figure 4: Overall upward and downward mobility



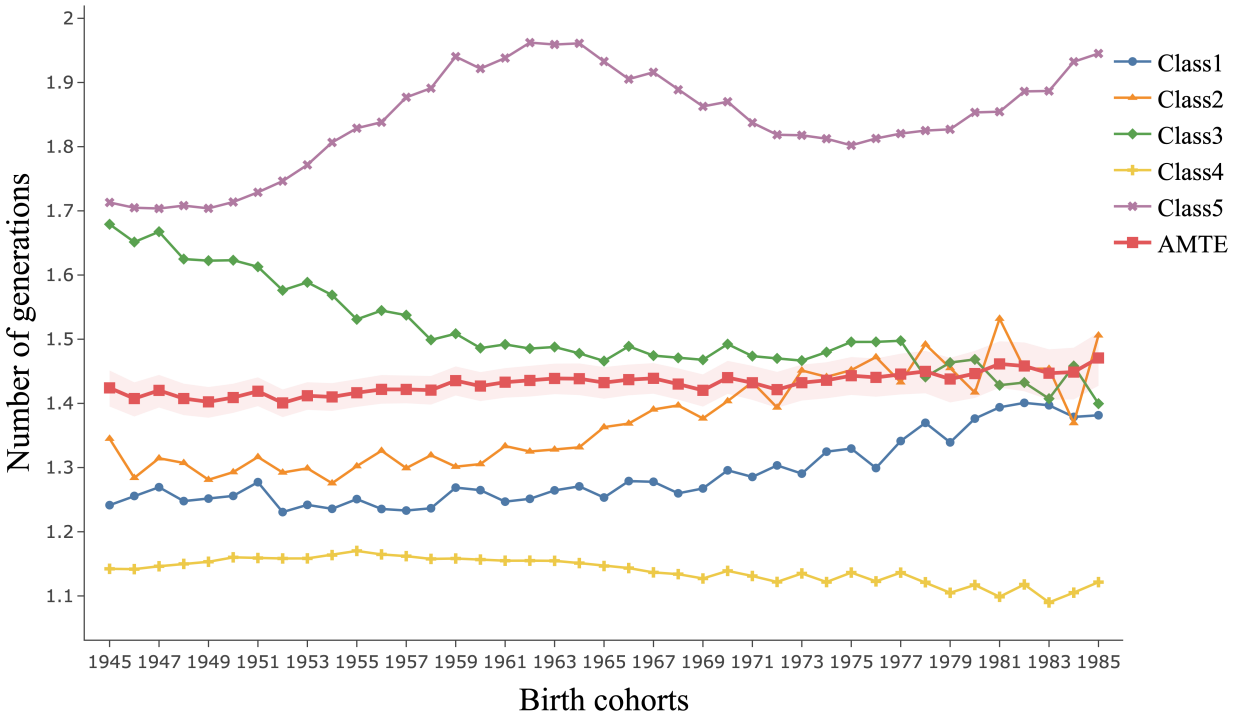

*Notes:* This figure illustrates the evolution of current overall upward and downward mobility. We use standard bootstrap bias-corrected estimator. Shaded areas represent 95% reverse percentile CIs, derived from 2,000 bootstrap samples.

#### 4.1.4 Class heterogeneity: MTE and MFPT

The Mean Time to Exit ($MTE$) captures the average number of generations required for members of a certain class origin (defined by the occupational class of their fathers') to transition into a class different from their origins. Since the $MTE$ is entirely determined by the conditional probability that children remain in the same class as their fathers, a stable – or nearly flat – average $MTE$ ($AMTE$) across cohorts indicates a consistent concentration of probability mass along the diagonal of the transition matrix, which is also consistent to the nearly flat pattern of overall mobility described above (Figure 5).

That said, the consistent probability mass along the diagonal of the transition matrix does not preclude the existence of class heterogeneity and may, once again, reflect off-setting dynamics across birth cohorts and occupational classes. For instance, Classes 1 (higher professional) and 2 (lower professional) exhibit a slow but steady increase in size prior to 1975, followed by a period of fluctuation during which they gradually converge. In contrast, Classes 3 (higher routine non-manual workers, high-grade technicians, and

Figure 5: Mean time to exit from each class



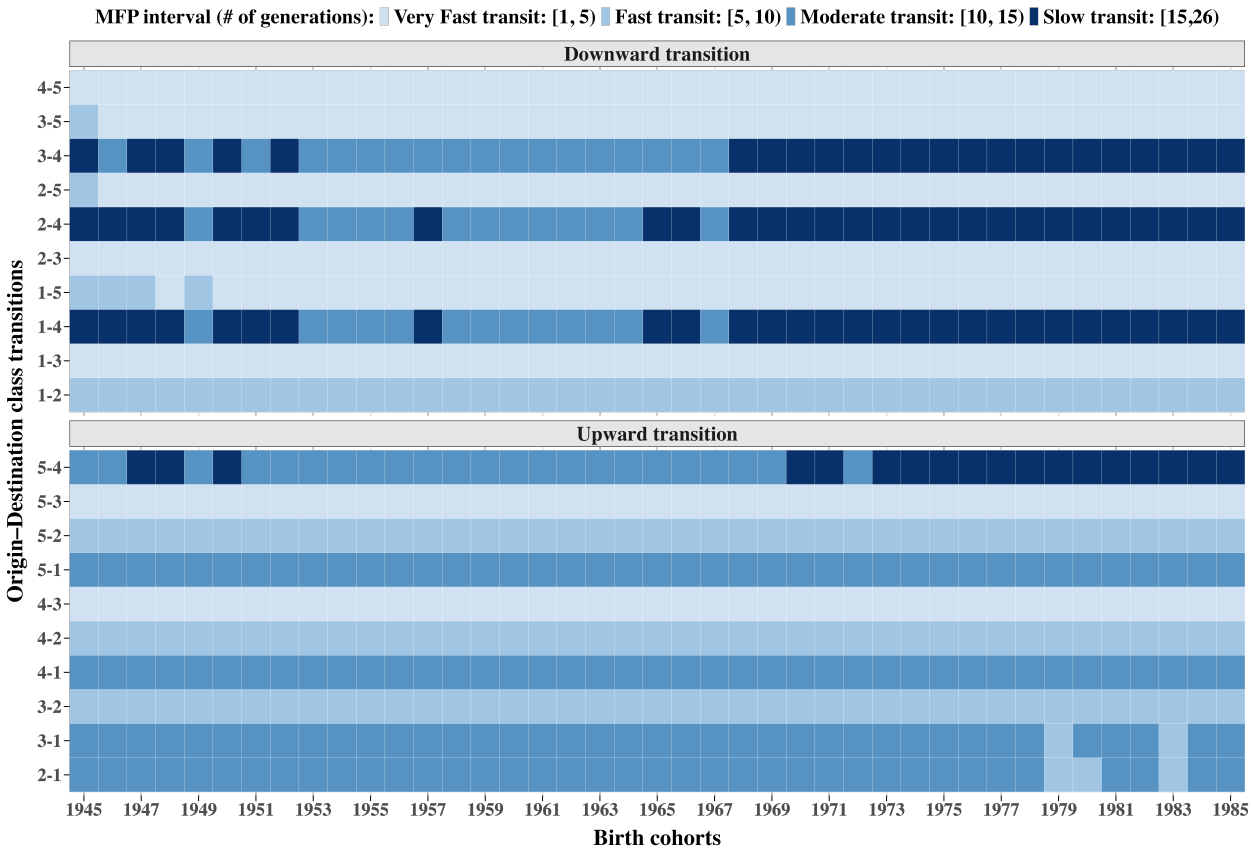

*Notes:* This figure illustrates the evolution of the mean time to exit *MTE* from each class, as defined in eq. (6), along with its weighted average *AMTE*, where weights are based on the distribution of classes among fathers. Class 1 refers to Higher Professionals; Class 2 to Lower Professionals; Class 3 includes Higher Routine Non-Manual workers, High-Grade Technicians, and Supervisors; Class 4 comprises Farmers, Higher Skilled Manual workers, and Lower-Grade Technicians; and Class 5 includes Lower Routine Non-Manual and Lower Skilled Manual workers. We use standard bootstrap bias-corrected estimator. Shaded areas represent 95% reverse percentile CIs, derived from 2,000 bootstrap samples.

supervisors) and 4 (farmers, higher skilled manual workers, and lower-grade technicians) both experience a steady decline over time, with the reduction in Class 3 being particularly pronounced. Class 5 (lower routine non-manual and lower skilled manual workers) undergoes a noticeable expansion before 1964, followed by a decline until 1975 – effectively offsetting the upward trend in Classes 1 and 2 – before increasing again, albeit with greater fluctuation, in the later years.

In terms of absolute magnitude, Class 5 generally exhibits a higher mean time to exit, indicating that individuals born into this class tend to remain longer in their father's occupational class before transitioning out. In contrast, Class 4 shows a shorter *MTE*, likely due to structural changes – particularly the declining prevalence of farmers, who constitute the majority of this class, in later cohorts. The rising *MTEs* observed for Class 1 and Class 2 suggest an increasing tendency for individuals born into these

higher – status classes to maintain their father's occupational class, reflecting a potential intensification of occupational persistence at the top of the hierarchy.

Figure 6: Mean first passage time




*Notes:* This figure illustrates the evolution of the mean first passage time $MFPT$ from eq. (7). Class 1 refers to Higher Professionals; Class 2 to Lower Professionals; Class 3 includes Higher Routine Non-Manual workers, High-Grade Technicians, and Supervisors; Class 4 comprises Farmers, Higher Skilled Manual workers, and Lower-Grade Technicians; and Class 5 includes Lower Routine Non-Manual and Lower Skilled Manual workers. We use standard bootstrap bias-corrected estimator. Shaded areas represent 95% reverse percentile CIs, derived from 2,000 bootstrap samples.

The results on Mean First Passage Time ($MFPT$) complement the class-specific mobility estimates from the $MTE$ framework by capturing how the direction of mobility varies by class origin. As shown in Figure 6, reaching Class 4 takes the longest time (more than ten generations) regardless of the starting class. For several birth cohorts around the 1950s, and for all cohorts after the 1970s, this duration extends beyond fifteen generations. This trend is driven by the declining representation of Class 4 among children in our data, which falls especially notably after the 1970 birth cohort (see Figure 1). This pattern reflects the near disappearance of farming occupations from the occupational

structure.

Figure 6 also reveals that the fastest downward mobility – occurring in fewer than five generations – is from any class to Class 5 (the lowest skill-level class), as well as from the higher classes (Classes 1 and 2) to Class 3. In contrast, downward mobility from the highest class (Class 1) to the second-highest (Class 2) takes longer, ranging from five to ten generations. This pattern remains relatively stable across all birth cohorts considered.

Among the upward mobility patterns, aside from the longest time required to reach Class 4 from Class 5 (as discussed above), the most difficult upward transition is reaching the top class (Class 1) from any lower class, which takes between ten and fifteen generations. The second most difficult transition is from any class below Class 2 to Class 2, requiring five to ten generations. In contrast, the easiest upward movement occurs from Classes 4 and 5 to Class 3. As with downward mobility, these patterns of upward mobility remain relatively stable across all birth cohorts considered.

Overall, the MFPT analysis reveals that the lowest class (Class 5) is the easiest to reach through downward mobility, requiring fewer than five generations from any starting class. The middle class (Class 3) is similarly accessible, with the shortest transition times from both higher and lower classes. In contrast, the most difficult class to reach through upward mobility – aside from the increasingly rare Class 4 – is the top-skilled Class 1, which takes between ten and fifteen generations to attain from any lower class.

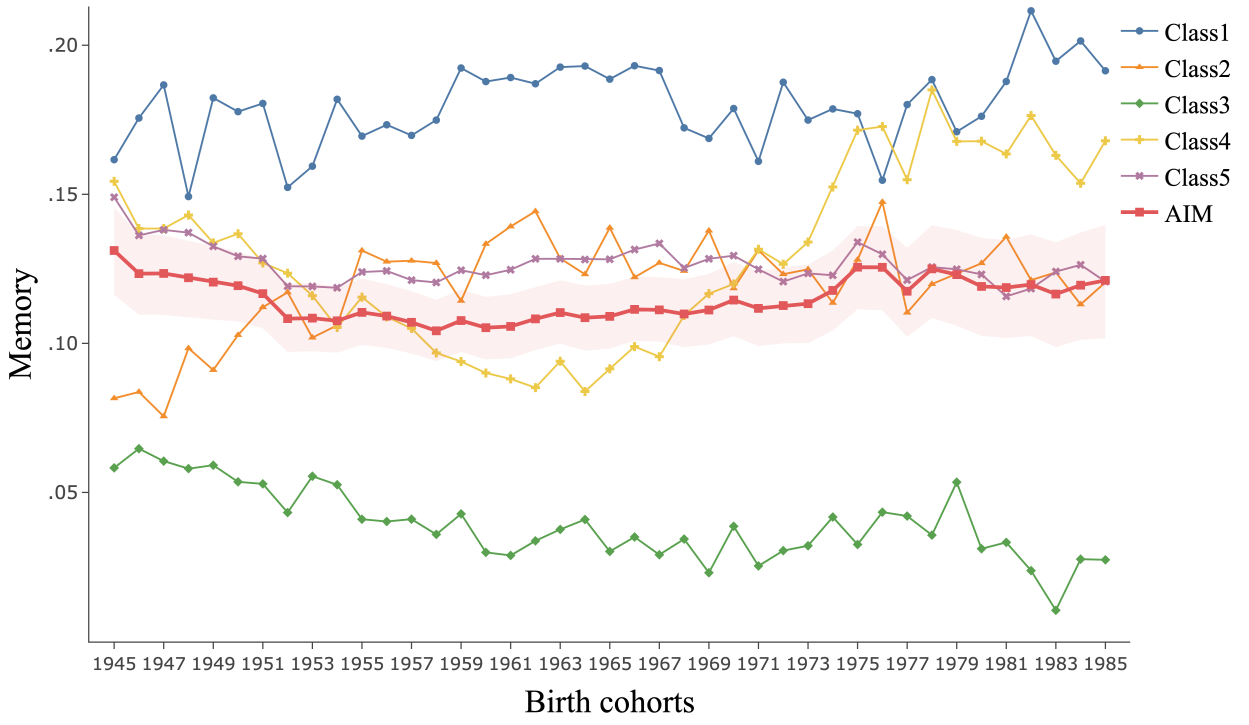
## 4.2 Memory measures

To recall, memory measures are designed to capture how quickly children's occupational class becomes "independent" of their parents' occupational class. In Markov chain theory, this idea is related to the concept of mixing time – the number of steps required for the process to converge to its stationary distribution. As we already described, at the steady state, the influence of the initial state (i.e., the parent's occupational class) vanishes, and the conditional probabilities of transitioning into each occupational class become identical across origin classes: each row of the transition matrix converges to the same distribution ($\mu^{\infty}$), implying that an individual's origin no longer affects their occupational outcomes. These limiting probabilities $\mu^{\infty}$ reflect the occupational structure of society at the steady state.

In this paper, we build on this framework to ask: given the observed transition probability matrix for individuals born in a specific cohort, and assuming that their subsequent generations evolve under the same transition dynamics, how long would it take for the influence of one's father's occupational class to fully dissipate for that cohort? Do

some cohorts converge to the steady state more quickly than others? Do certain origin occupational classes approach the steady state faster than others?

Figure 7: Individual memory and aggregate individual memory




*Notes:* This figure illustrates the evolution of current individual memory $IM^1$ from eq. (8) and aggregate individual memory $AIM^1$ from (9). Class 1 refers to Higher Professionals; Class 2 to Lower Professionals; Class 3 includes Higher Routine Non-Manual workers, High-Grade Technicians, and Supervisors; Class 4 comprises Farmers, Higher Skilled Manual workers, and Lower-Grade Technicians; and Class 5 includes Lower Routine Non-Manual and Lower Skilled Manual workers. We use standard bootstrap bias-corrected estimator. Shaded areas represent 95% reverse percentile CIs, derived from 2,000 bootstrap samples.

According to Figure 7, the average distance between the current "lottery"—defined as the distribution of probabilities of reaching each destination class conditional on origin class—and the steady-state lottery (captured by the aggregate individual memory, $AIM^1$) has remained largely stable across birth cohorts. This indicates that the extent of class-origin persistence in the U.S. has not changed markedly over time. This pattern is consistent with the stability of our preferred measure of movement-based mobility—steady state mobility—discussed earlier.

As shown by the $IM_i^1$ estimates, Class 1 (higher professionals) consistently exhibits the highest level of class-origin memory (i.e., the lowest mobility) across all cohorts, relative to other origin classes. In contrast, Class 2 (lower professionals) displays a fluctu-

ating increase in memory until the 1960 birth cohort, after which it oscillates and begins to weave around Class 5 (lower routine non-manual and lower-skilled manual workers). While Class 5 demonstrates a similar level of memory to Class 2 in later cohorts, it initially exhibited substantially higher memory prior to the 1952 cohort. However, a steady decline in memory for Class 5 between the 1945 and 1957 cohorts leads to convergence with Class 2 by the late 1950s.

Class 4 (farmers, higher-skilled manual workers, and lower-grade technicians) exhibits a steady decline in class-origin memory up to the 1963 birth cohort, followed by a pronounced upward trend in later cohorts – suggesting a resurgence in intergenerational persistence. In contrast, Class 3 (higher routine non-manual workers, high-grade technicians, and supervisors) consistently displays the lowest level of memory across all cohorts, distinguishing it from the other origin classes.

More broadly, the highest-status origin classes – Classes 1 and 2 – consistently exhibit stronger class-origin memory over time, reflecting higher levels of intergenerational persistence. This pattern supports the notion of hierarchical reproduction and aligns with the dynamics observed in the mean time to exit $MTE$ from each class. Notably, Class 5, which represents the lowest occupational stratum, also displays relatively high memory, particularly among earlier birth cohorts – suggesting the presence of a potential mobility trap at the bottom of the class structure. The rising memory observed in Class 4 may be attributable to selection effects: as occupational structures shift, individuals who remain in the same class as their fathers may increasingly constitute a self-selected group characterized by specific constraints or preferences.

# 5 Robustness checks

To ensure the robustness of our results, we report a series of supplementary checks in Appendix D. Our first robustness check involves altering the age restriction for each cohort. To address concerns that early-career trajectories may yield misleading results, we expand the sample to include older respondents by shifting the age window from 25–55 to *25–64* and *30–64*, thereby better capturing mid-career outcomes. These changes do not alter the flat trend in mobility patterns across cohorts, nor the heterogeneity across classes. However, we do observe higher upward mobility when older respondents are included. This result is consistent with expectations based on life-cycle dynamics: individuals often begin their careers in lower-status positions and gradually transition into higher-status roles as they gain experience. This pattern is particularly evident in the 30–64 age sample, where upward mobility consistently exceeds downward mobility

across all cohorts. Even so, the decreasing (increasing) trend in upward (downward) mobility until around 1960 remains, after which both trends flatten.

To analyze gender heterogeneity, we separately examine *father–son* and *father–daughter* mobility patterns. Due to sample limitations in the GSS 2022 (notably the loss of information for Class 4 among daughters in later cohorts), we restrict our comparison to cohorts born between 1945 and 1979. Compared to sons, daughters exhibit significantly greater upward than downward mobility across all cohorts. By contrast, for sons, upward and downward mobility become statistically indistinguishable after 1959. The composition of upward mobility also differs by gender. For daughters, Mean First Passage Time (MFPT) results show that most upward mobility arises from transitions between Class 3 and Class 2, Class 4 to Classes 2 and 3, and Class 5 to Class 3. Relative to sons, daughters face greater difficulty transitioning into Class 1, suggesting a possible "ceiling effect" for women. Furthermore, daughters display greater heterogeneity and more nuanced trends across classes. Turning to Mean Time to Exit (MTE)—largely reflecting the diagonal elements of the transition matrix—we observe relatively flat patterns across cohorts for sons, consistent with a stable transition structure. Among daughters, however, clear dynamics emerge: Class 3 shows a persistent downward trend, while Class 5 exhibits an increasing–decreasing trajectory, mirroring the whole-sample pattern. For sons, by contrast, Class 5 stands out as having consistently higher MTE across all cohorts, reflecting strong persistence within this class relative to others.

Since we employed a penalized smoothing spline model to address the sparsity problem in the transition matrices and thereby construct the sample used in our main analysis, we also conducted robustness checks using three alternative specifications: (1) transition matrices for cohorts 1945–1985 constructed directly from the GSS data *without any smoothing*; and (2) transition matrices constructed by *binning cohorts* with bin widths of *5* and *10 years*, respectively. Returning to the raw transition matrices introduces substantial sampling error, which makes the trends in all measures less interpretable, particularly those measures sensitive to exact cell counts. Nevertheless, the main patterns remain diagnosable. Both overall and steady state mobility remain flat across cohorts, although with more noticeable fluctuations. Exchange mobility in the initial state, however, loses its steady upward trajectory: we observe only a modest upward trend until 1963, followed by large fluctuations thereafter. Upward and downward mobility still exhibit divergent trends prior to 1957, but become statistically indistinguishable thereafter. Measures that summarize the overall association between fathers and children also fluctuate more dramatically in the raw sample, though still without discernible trends. Binning cohorts, in turn, alters the underlying transition matrix structure and can some-

times reverse trends. For example, binning 10 consecutive cohorts produces a pattern in which downward mobility precedes upward mobility in later cohorts, whereas a bin width of 5 restores the pattern in which upward mobility is statistically higher than downward mobility. Comparing the bin width of 5 with our baseline smoothing results reveals broadly similar trends. This exercise underscores the rationale for smoothing: because our measures are highly sensitive to the exact magnitudes in the transition matrices, smoothing allows us to preserve the baseline information at a granular level while trimming out noise without imposing strong assumptions, thereby yielding interpretable trends without materially altering the underlying transition structure.

We also considered an alternative specification focusing on individuals aged 25 to 55 in *each GSS survey year*. To maintain comparability with our baseline results, we smoothed the transition matrices across survey waves under the assumption that a consistent underlying transition dynamic between fathers and children exists across all calendar years within this age range. The overall results remain broadly consistent with the benchmark, though measures of overall dependence exhibit more pronounced trends. Specifically, prior to 1992, all dependence summary measures decline, followed by an increase until 2000, a slight decrease through 2008, and then a continued rise through 2022. Importantly, even though we restrict to the same age range, the set of respondents differs from the benchmark sample: in earlier survey years (e.g., 1972) the sample includes more early cohorts, while in later surveys (e.g., 2022) it incorporates more recent cohorts. For movement measures, overall upward mobility consistently remains statistically higher than overall downward mobility across all years. Regarding class heterogeneity, while the relative rankings are comparable with the benchmark, the trends differ across calendar years. With respect to persistence, the MTE curve for Class 2 declines steadily until around 1990, then rises continuously thereafter, indicating stronger persistence in more recent years. Class 1 shows a persistent upward trend, with steeper increases before 1991 and more moderate growth thereafter. Class 3, by contrast, displays a notable decline in recent years; combined with MFPT results, this suggests faster transitions from Class 3 into Classes 1, 2, and 5 among more recent cohorts. The memory measures also exhibit the same hierarchy as the benchmark results, although the magnitudes in the early survey waves indicate higher dependence, possibly reflecting the influence of earlier cohorts.

Our final robustness check concerns changes in *class typology*. Specifically, we examine three alternative classifications: (1) the six-class typology used in prior literature, which follows the original EGP seven-class scheme but combines Classes V and VI; (2) our benchmark typology with all identified self-employed individuals (in Classes

III, V, VI, VII, and farmers) removed; and (3) our benchmark typology with all farmers removed, without distinguishing self-employed from employed individuals in other classes.

Switching to the six-class typology naturally changes the magnitude of the movement measures, which is intuitive given that individuals transition across different categories more frequently. Under the six-class typology, we observe an inverted U-shaped pattern of exchange mobility in the initial state and a corresponding U-shaped pattern of structural mobility. These results are consistent with the overall trendless pattern of mobility observed across all samples. The mild decline in overall initial exchange mobility beginning in the mid-1960s appears to stem from an imbalance of transition inflows and outflows involving Class IV: self-employed individuals frequently transition out of this class, while few individuals transition in. Furthermore, overall upward mobility rises noticeably when separating Class IIIb from Class VIIab, reflecting substantial transitions from VIIab into IIIb.

With respect to class heterogeneity, the dynamics remain consistent with the benchmark results. For example, combining the Mean Time to Exit (MTE) curves for Classes 3 and 6 under the six-class typology produces results similar to those for Class 5 under the benchmark five-class typology. Likewise, the memory curves for Classes 3 and 6 under the six-class typology closely resemble those for Class 5 under the five-class typology, again aligning with expectations. These findings confirm that our measures capture class-specific dynamics accurately.

Finally, when removing both self-employed individuals and farmers, or farmers only, the results remain broadly comparable to the benchmark. This suggests that the dynamics we identify are driven less by the employment relationship per se, and more by features of the occupational regime—potentially reflecting differences in skill requirements, stereotypes, or other structural factors.

# 6 Discussion

In this paper, we examine long-term trends in occupational class mobility in the United States for cohorts born between 1945 and 1985. We introduce a new nonparametric approach to measuring class mobility based on ”synthetic dynasties” represented within a Markov chain framework. Conceptualizing mobility as movement, we estimate the expected fraction of family dynasties that experience a change in class—both in the observed data (captured by our measure of overall mobility) and in the steady state of the Markov process (captured by the steady state mobility). We find that both mea-

sures remain stable across the studied cohorts. Similarly, the influence of class origin—quantified through our memory measures—also remains stable over time. Despite this overall stability, we uncover substantial class-based heterogeneity in mobility patterns, both in terms of movement and memory dynamics.

These findings suggest important implications for understanding the persistence of occupational mobility in the U.S. over the postwar period. The natural next step in this research program is the exploration of mechanisms that can explain class-specific heterogeneity in mobility trends that cancel out when aggregated.

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# Appendix

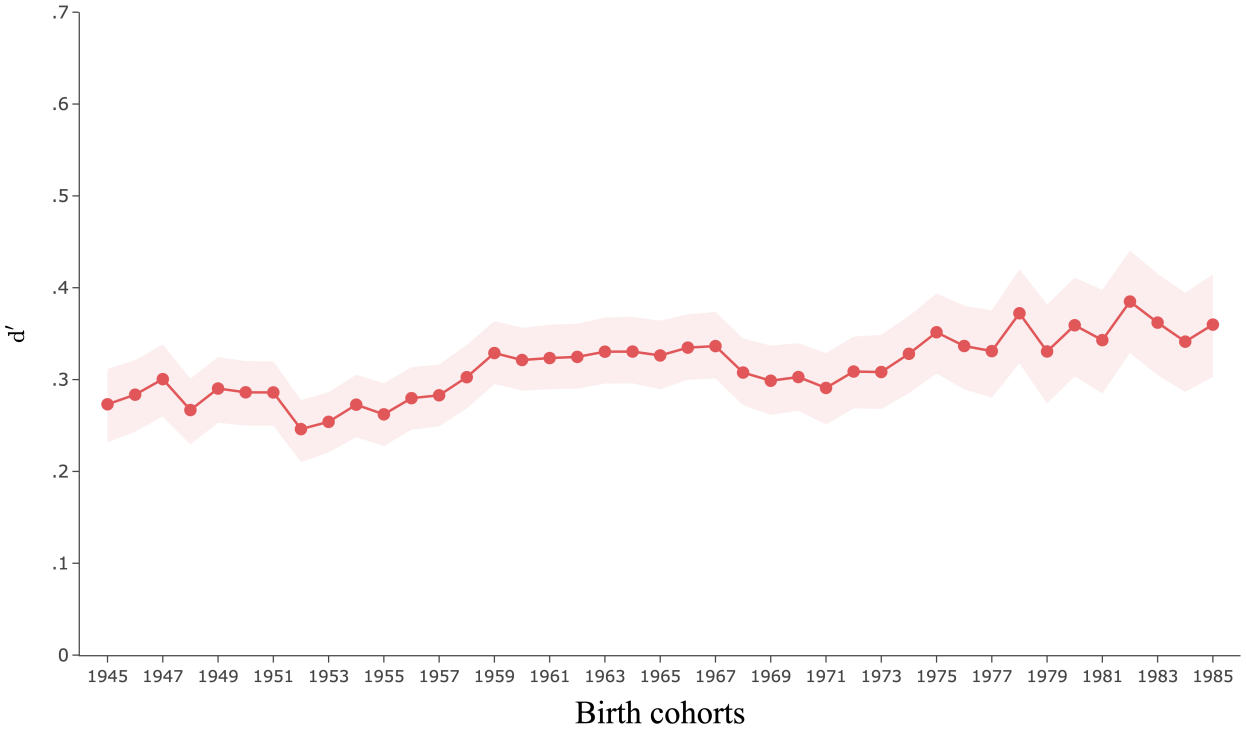
## A Dobrushin contraction coefficient $d'$

$$d'(1) = \max_{i,j} \left\| e_i \cdot P - e_j \cdot P \right\| = \delta(P) \tag{A1}$$

$d'(1)$ is defined as the largest total variation distance between any two rows of the transition matrix.

$$\left\| \mu_0 \cdot P^t - \pi \right\|_{TV} \leq (d'(1))^t \cdot \left\| \mu_0 - \pi \right\|_{TV}.$$

Figure A1: Dobrushin contraction coefficient




*Notes:* This figure illustrates the evolution of Dobrushin contraction coefficient $d'$ from eq. (A1). We use standard bootstrap bias-corrected estimator. Shaded areas represent 95% reverse percentile CIs, derived from 2,000 bootstrap samples.

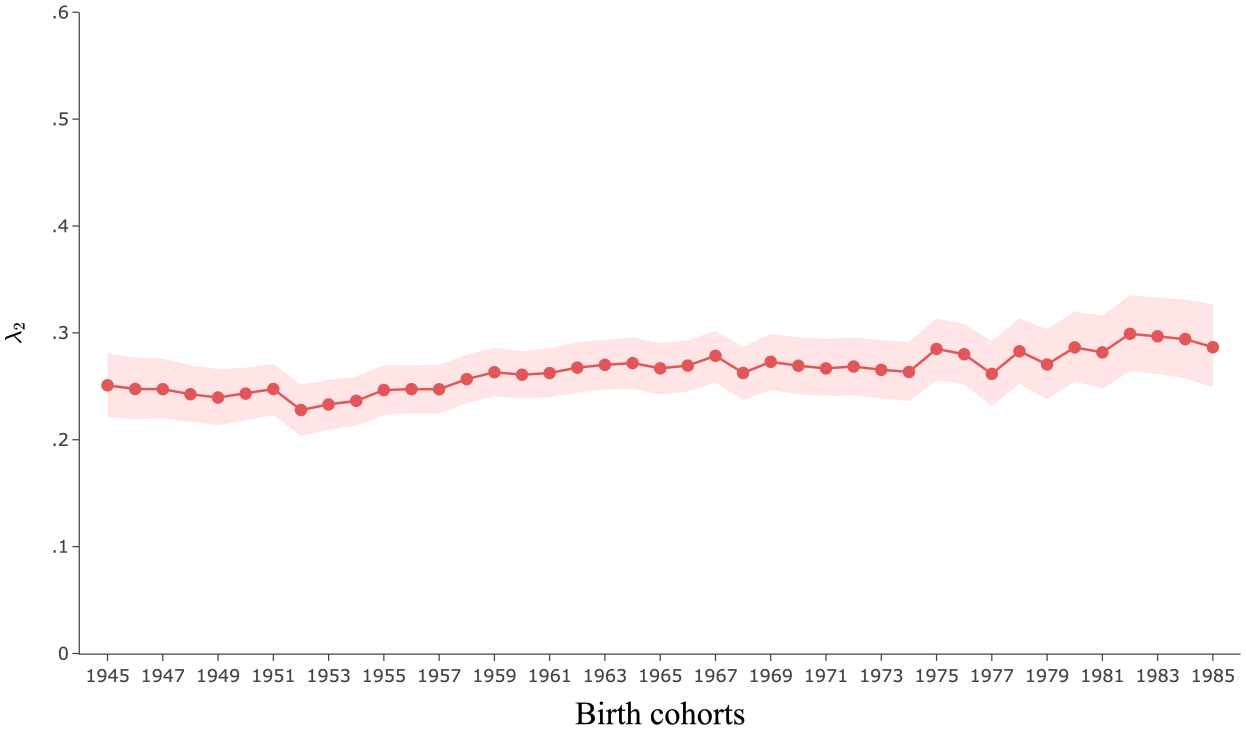
Since $d'(1)$ always falls between 0 and 1, it is natural to interpret it as a contraction parameter, where the magnitude of $d'(1)$ governs the speed of the contraction process—that is, how quickly the marginal distribution at time $t$ (i.e., $\mu_0 \cdot P^t$) approaches the marginal distribution in the steady state (i.e., $\pi$). The smaller this value is, the faster the contraction will happen; the sooner each class will reach the stationary distribution.

Our results reveal two notable periods of increasing trends within the time range of interest. The first occurs between 1955 and 1965, followed by a noticeable decline from 1966 to 1968. This is then followed by another upward trend, indicating a slower decay of memory.

# B Second largest eigenvalue $\lambda_2$

$\lambda_2$, the second largest eigenvalue of the transition matrix, will determine the spectural gap of the transition process, thereby the mixing time. The smaller the $\lambda_2$ is, the faster the mixing process will happen. Consistent with other memory measures, we find that the mixing time will be slightly slower among the 1978-1983 cohorts, while the other cohorts remain comparable with each other.

Figure B1: Second largest eigenvalue $\lambda_2$

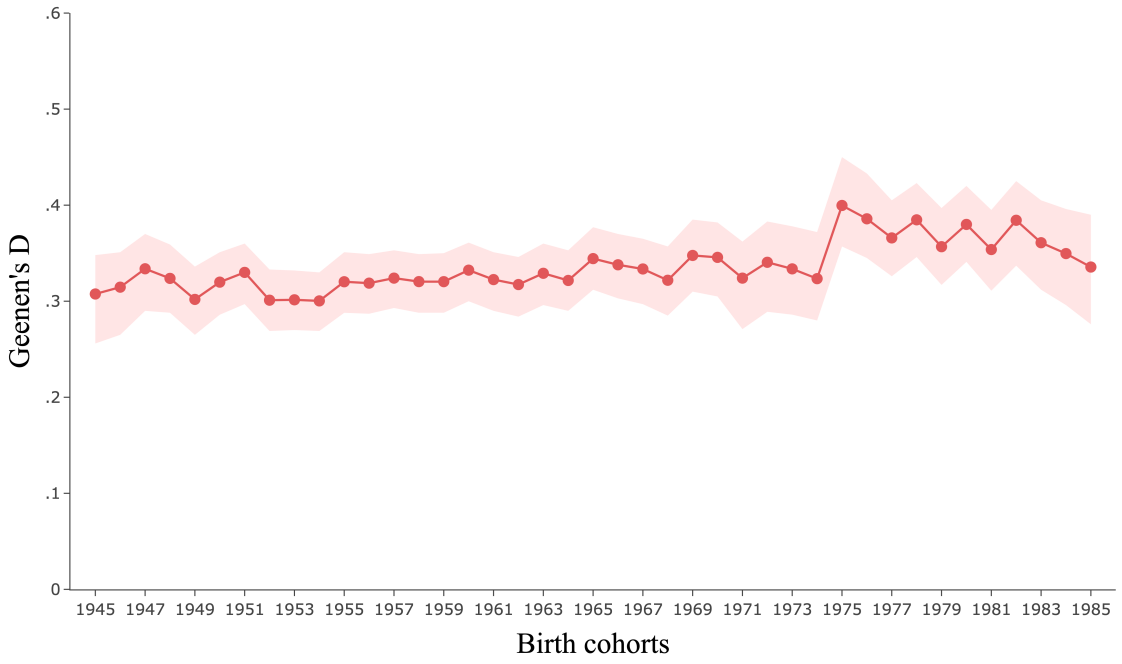



*Notes:* This figure illustrates the evolution of second largest eigenvalue $\lambda_2$. We use standard bootstrap bias-corrected estimator. Shaded areas represent 95% reverse percentile CIs, derived from 2,000 bootstrap samples.

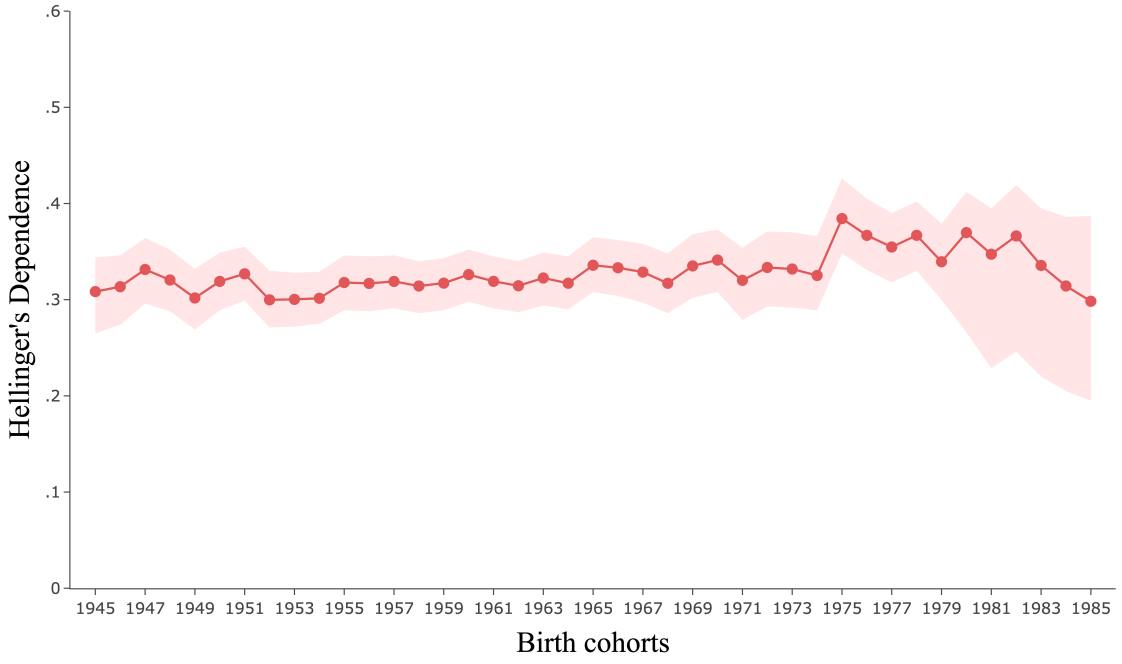
# C Geenen's $D$ and Hellinger dependence

Figure C1: Measures of dependence

(a) Geenen's $D$

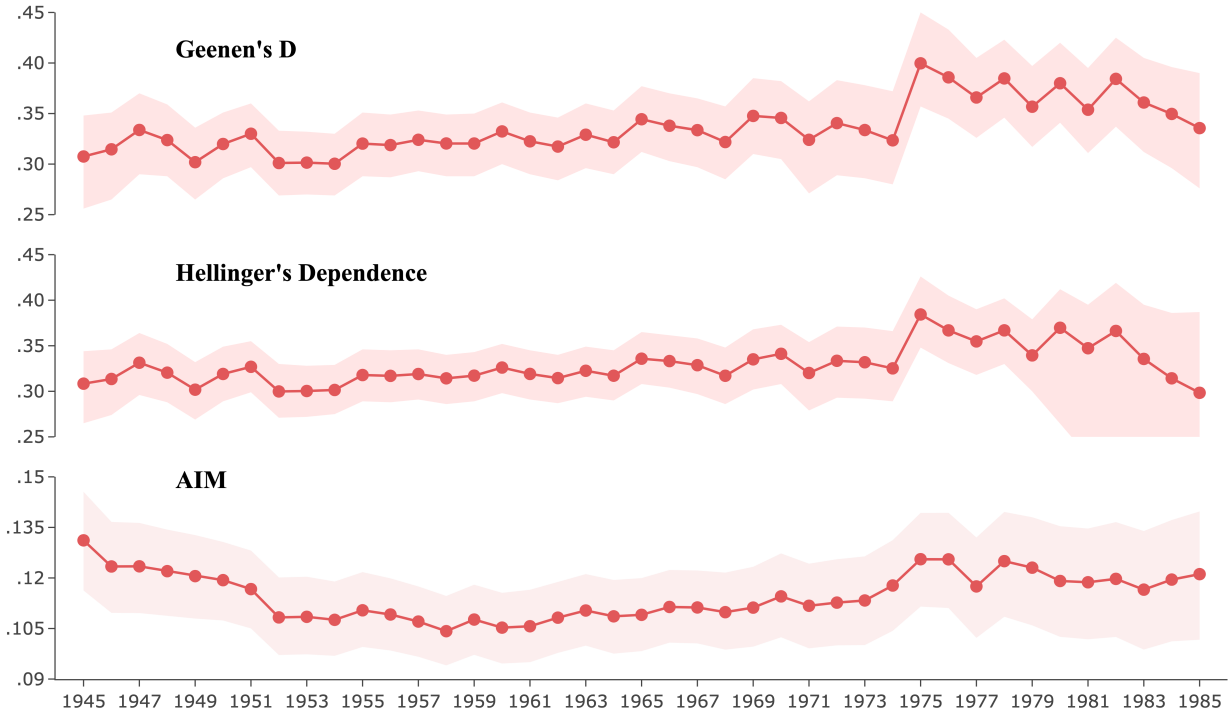



(b) Hellinger's Dependence



Geenen's $D$ and Hellinger's Dependence are two measures used to describe the underlying dependence structure in the observed joint probability distribution. Both measures employ Iterative Proportional Fitting (IPF) to normalize the marginal distributions of the probability matrix while preserving the dependence structure, aiming to characterize deviations from the independent structure (where all cells have equal probability in this setting). As such, they serve as useful counterparts to the Markov Chain measures that characterize the distance to the steady state, such as AIM (or $\log(\text{AIM})$).

Figure C2: Comparison between $AIM$ and dependence measures




Same as the memory decay measures, Geenen's $D$ and Hellinger's Dependence index also indicate that the 1975–1983 cohorts tend to exhibit stronger dependence in the current probability structure, further from the independent state, and thereby experience a slower memory decay process.

# D Robustness Checks

This appendix will be available online.