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

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 **??**.

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.

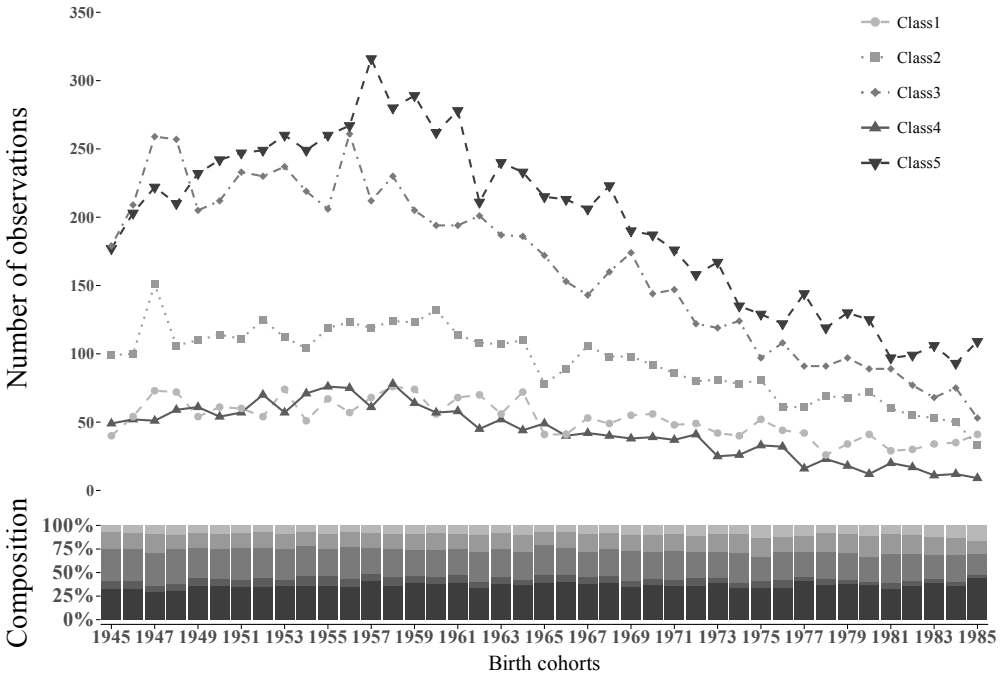
Although the EGP typology is widely used, the details of its implementation vary across studies. We implement our classification using the crosswalk developed by Morgan (2017), which maps 2010 COC codes to EGP classes. To assess the robustness of our key findings, we also conducted a series of parallel 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) 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 **??**, our trend estimates are highly consistent across different approaches to measuring occupational class.

3.3 Analyses

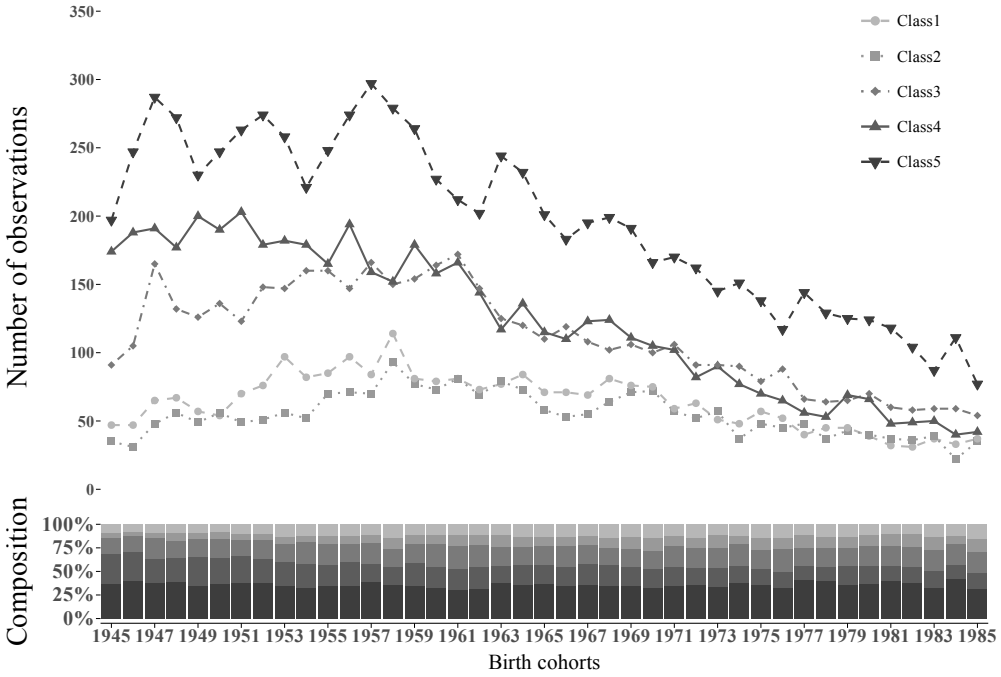
We analyze intergenerational mobility using a new class of measures based on the "synthetic dynasties" represented in Markov chains. This approach begins with the observed transition probabilities between fathers' and children's occupational classes in a particular birth cohort, and then asks what would happen if these probabilities were to remain constant across subsequent generations. In this way, it allows us to characterize mobility not only through the single-generation transitions observed in the GSS but also through the long-run influence of class origins on hypothetical family dynasties constructed as if patterns of occupational inheritance were indefinitely stable.

Formally, let P denote a 5×5 transition matrix, where each element P_{ij} represents the probability of transitioning from origin class $i \in \{1, ..., 5\}$ to destination class $j \in \{1, ..., 5\}$. If μ_p denotes a 1×5 row vector of probabilities capturing the marginal distribution of parental origins, then the corresponding distribution of children's class destinations is given by $\mu_c = \mu_p \cdot P$. Now suppose that the intergenerational transmission of class observed in a given cohort—summarized by P—were to remain unchanged across subsequent generations descended from this cohort. In this situation, the mobility process would take the form of a stationary Markov chain, in which the probability of entering a particular destination class at any generation t is constant and depends only on the origin class of the preceding generation $t-1$. Under this process, the marginal distribution of classes at generation t evolves recursively as $\mu_t = \mu_{t-1} \cdot P$ or, similarly, from an initial distribution μ_0 in the founding generation as $\mu_t = \mu_0 \cdot P^t$.

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



(A) Class destinations of children



(B) Class origins of fathers

Notes: Class 1 refers to higher-grade professionals, administrators, and managers; class 2 refers to lower-grade professionals, administrators, and managers; class 3 includes higher-grade routine non-manual workers, technicians, and supervisors; class 4 comprises higher-grade manual workers, lower-grade technicians, and farmers; and class 5 includes lower-grade routine non-manual and manual workers.

As $t \to \infty$, the marginal distribution of occupational classes converges to an invariant, or steady-state, distribution denoted by μ_∞. At the same time, the transition matrix converges to a limiting matrix, $P^t \to P^\infty$, in which every row is equal to μ_∞.[1] Substantively, this means that once the steady state is reached, the marginal distribution of classes remains constant across generations, and the influence of class origins in the founding generation $t = 0$ has dissipated entirely—that is, descendants share identical chances of occupying different class destinations, regardless of their dynasty's starting point. These limiting properties of Markov chains provide the foundation for our key measures of mobility.

For any given cohort, we only observe a single transition—from fathers to children—in the GSS. We do not observe subsequent generations of descendants, and their true mobility process may not resemble a stationary Markov chain. In reality, transition probabilities could shift across generations or depend on the class origins of more distal ancestors. Thus, we refer to these dynasties as *synthetic*: they are hypothetical lineages formed as if observed patterns of class transmission for a single cohort were to remain constant. By extension, Markov chains, and the synthetic dynasties they generate, serve merely as an analytic device for summarizing the influence of class origins on destinations. Their role in our study is analogous to period life tables in demography, which summarize levels of mortality by imagining a synthetic cohort that is exposed throughout its life course to the age-specific death rates observed in a single cross-section of the population. Analogously, our measures based on Markov chains characterize levels of mobility by imagining synthetic dynasties that are exposed indefinitely to the transition probabilities observed among a single cohort.

Building on the limiting properties of Markov chains, we distinguish between two complementary notions of mobility: mobility as movement and mobility as memory. Measures of *movement* capture the extent to which children's class positions differ from those of their parents both in the observed data and within the synthetic dynasties implied by the Markov chain. Measures of *memory*, by contrast, assess how strongly class origins shape the destinations of later generations within these synthetic dynasties and the rate at which their influence fades.

3.3.1 Mobility as Movement

With measures of movement, mobility is higher when children's occupational classes differ from those of their parents'. At one extreme—perfect mobility—every child enters

[1] Formally, these limiting properties require that P is primitive, meaning that there exists a positive integer v such that P^v is strictly positive.

a different class than their parent, producing a transition matrix with zeros along the main diagonal. At the other extreme—perfect immobility—every child remains in the same class as their parent, such that the transition matrix is equal to the identity matrix. In general, measures of movement quantify how much probability mass lies off the main diagonal of the transition matrix: the greater this off-diagonal mass, the higher the level of intergenerational mobility.

Movement measures have a long history in empirical research on mobility. A classic example is the decomposition of overall mobility into "structural" and "exchange" components (Erikson and Goldthorpe, 1992; Featherman and Hauser, 1978). In this decomposition, overall mobility is defined as the proportion of children who occupy a different class than their parents; structural mobility refers to the portion of these movements driven by shifts in the marginal distribution of classes; and exchange mobility represents the residual movements that occur net of structural change.

Whereas prior studies evaluate these measures only for the observed transitions from fathers to children, we trace how they evolve across generations of synthetic dynasties governed by a stationary Markov chain. Specifically, we define *overall mobility* as the proportion of descendants in generation t that experience a change in occupational class compared to the previous generation $t-1$:

$$OM_t = 1 - \sum_i \mu_{i,t-1} \cdot P_{ii}. \tag{1}$$

where $\mu_{i,t-1}$ denotes the marginal proportion of descendants in class i at generation $t-1$, and P_{ii} represents the ith diagonal element of the transition matrix. This measure captures the total amount of movement between classes from one generation to the next within a set of synthetic dynasties.

At any generation of these dynasties, overall mobility can then be decomposed into structural and exchange components. *Structural mobility* is formally defined as follows:

$$SM_t = \frac{1}{2} \cdot \sum_i |\mu_{i,t-1} - \mu_{i,t}|. \tag{2}$$

It captures the movements necessitated by shifts in the marginal distribution of classes from generation $t-1$ to t. *Exchange mobility* is defined residually as the difference between overall and structural mobility:

$$EM_t = OM_t - SM_t. \tag{3}$$

This formulation merely extends the familiar decomposition of overall mobility to each generation t of a stationary Markov chain.

As the Markov chain converges to its steady state, the recursive relation $\mu_t = \mu_{t-1} \cdot P$ stabilizes at $\mu_\infty = \mu_\infty \cdot P$. In this state, structural mobility vanishes because the marginal distribution of classes no longer changes across generations, and thus overall mobility becomes equal to exchange mobility. We refer to this limiting quantity as *steady-state mobility*, which can be formally defined as follows:

$$SSM = 1 - \sum_i \mu_{i,\infty} \cdot P_{ii}. \tag{4}$$

Steady-state mobility measures the amount of intergenerational movement that persists among synthetic dynasties in a Markov chain, once the occupational structure has stabilized. In other words, SSM isolates an intrinsic level of movement that is not driven by changes in the marginal distribution of classes and instead arises solely from the association of parental origins with child destinations.

To examine class-specific heterogeneity in intergenerational movement, we additionally compute the mean time to exit (MTE; Kemeny et al. 1969) from each origin class in the founding generation of the synthetic dynasties. This measure can be formally defined as follows:

$$MTE_i = (1 - P_{ii}) \cdot \sum_{t=1}^{\infty} t \cdot P_{ii}^{t-1}. \tag{5}$$

In substantive terms, MTE_i represents the expected number of generations it takes for descendants to leave origin class i. Higher values reflect lower chances of movement away from the class, while lower values signal a greater likelihood of departure.

3.3.2 Mobility as Memory

In contrast to movement, measures of memory capture the persistent influence of class origins within synthetic dynasties. Mobility is higher when descendants from different origins quickly come to face similar chances of entering each destination. Conversely, mobility is lower when class origins continue to shape occupational outcomes many generations into the future. In general, measures of memory quantify the distance between a focal transition matrix and the limiting matrix of a stationary Markov chain, in which descendants share identical chances of entering each destination regardless of their dynasty's starting point.

Formally, "equality of opportunity" corresponds to a transition matrix in which all rows are the same. In a stationary Markov chain, this state arises in the limit as $\mu_t =$

$\mu_0 \cdot P^t$ converges to the steady-state distribution μ_∞ and the transition matrix converges to P^∞, where each row equals μ_∞. Because P^∞ has identical rows, it represents a state in which class destinations are independent of origins in the founding generation of the dynasties.

Using this limiting matrix as a benchmark, we define aggregate *intergenerational memory* at generation t as follows:

$$AIM_t = \frac{1}{2} \cdot \sum_{i,j} |P_{ij}^t - \mu_{j,\infty}| \cdot \mu_{i,0}. \tag{6}$$

This measure captures the deviation of P^t from the limiting matrix characterized by equality of opportunity. At generation $t = 1$, it provides a concise summary of how strongly class origins shape outcomes across future generations, with larger values signaling slower dissipation of their influence over time.

To examine class-specific heterogeneity, we decompose AIM_t into components that measure the distance between the transition probabilities of a given origin class and their limit at the steady state. This yields a measure of intergenerational memory for each origin class i at generation t, which can be defined as follows:

$$IM_{i,t} = \frac{1}{2} \cdot \sum_{j} |P_{ij}^t - \mu_{j,\infty}|. \tag{7}$$

By construction, the weighted average of $IM_{i,t}$ across origin classes, using their relative size as weights, is equal to AIM_t. Plotting these class-specific measures highlights variation in the influence of different origins across subsequent generations. Higher values indicate that descendants of class i are slower to achieve equality of opportunity, while lower values signal faster dissipation of ancestral influence.

3.3.3 Estimation and Inference

We estimate all the measures outlined previously, separately for each birth cohort, using our analytic sample from the GSS. To improve the precision of our estimates and reduce sampling variability—especially for recent cohorts with fewer observations—we smooth our mobility tables using thin-plate splines before computing measures of movement and memory (Wood, 2003). Specifically, we smooth cell counts in the three-way contingency table of origin class (row), destination class (column), and birth cohort (layer)

using the following model:

$$\log\left(n_{ijk}\right) = \alpha_{ij} + f_{ij}(k) + \epsilon_{ijk}, \tag{8}$$

where n_{ijk} denotes the number of respondents from origin class $i \in \{1, ..., 5\}$ observed in destination class $j \in \{1, ..., 5\}$ for cohort $k \in \{1945, ..., 1985\}$. The parameters α_{ij} represent a set of origin-by-destination fixed effects, while $f_{ij}(k)$ is a smooth function of cohort that is allowed to vary across each origin-destination pair. We specify these functions using thin-plate splines, which flexibly smooth over random variation in cell counts across cohorts.

The model is estimated via penalized maximum likelihood, where the penalty is designed to limit excessive curvature, or "wiggliness," in the spline functions. This is achieved by augmenting the likelihood with an additional term that takes the form an integrated second derivative multiplied by a smoothing parameter: $\sum_{i,j} \lambda_{ij} \int f''_{ij}(k)^2 \, dt$. Larger values of the smoothing parameters λ_{ij} produce smoother fits and greater resistance to deviations from linearity. These parameters can be selected by generalized cross-validation (GCV) or restricted maximum likelihood (REML); we use REML, as it performs better in most settings (Wood, 2011).

After fitting Equation 8, we generate predicted counts, denoted by $\hat{n}_{ijk}$, which are then used to compute all the probabilities on which our measures of movement and memory are based. For example, we estimate the transition matrix for a particular cohort k as $\hat{P}_{ij} = \hat{n}_{ijk} / \sum_j \hat{n}_{ijk}$. This approach smooths both the cell counts and the marginal totals while avoiding restrictive assumptions about how mobility may vary across cohorts. It results in cohort-specific estimates for our focal measures that are less variable and more precise. It also obviates the need to pool adjacent cohorts into larger groups, a common but arbitrary strategy for dealing with sparsity that can distort trends. To assess the robustness of this approach, we experimented with a variety of alternative specifications, including models that did not smooth the marginal totals, that used different spline bases, and that optimized the smoothing parameters via GCV, all of which produced similar results.

To quantify the uncertainty in our estimates, we use the nonparametric bootstrap. Specifically, we resample the observed data with replacement $b = 2000$ times and replicate our entire analysis on each bootstrap sample, including estimation of the smoothed counts. This procedure yields an approximate sampling distribution for every measure of interest. We then construct confidence intervals from these distributions using a percentile estimator that adjusts for any bias or skew (Davison and Hinkley, 1997). A full

set of replication files for this analysis is available at [INSERT URL TO GITHUB REPO].

4 Results

4.1 Overall, Structural, and Exchange Mobility

Panel A of Figure 2 displays trends in overall mobility at generation $t = 1$, which reflects the total amount of movement in the observed transitions between fathers and their children in the GSS. Across cohorts who grew up or entered the labor market during the era of rising inequality, overall mobility remained remarkably stable. In the 1945 birth cohort, about 70% of children entered a different occupational class than their fathers. In the 1985 cohort, this share declined only slightly to about 68%. More broadly, across all cohorts born between 1945 and 1985, overall mobility hovered around 70%. These results indicate that the likelihood of children entering a different class than their fathers was consistently high and largely invariant over time.

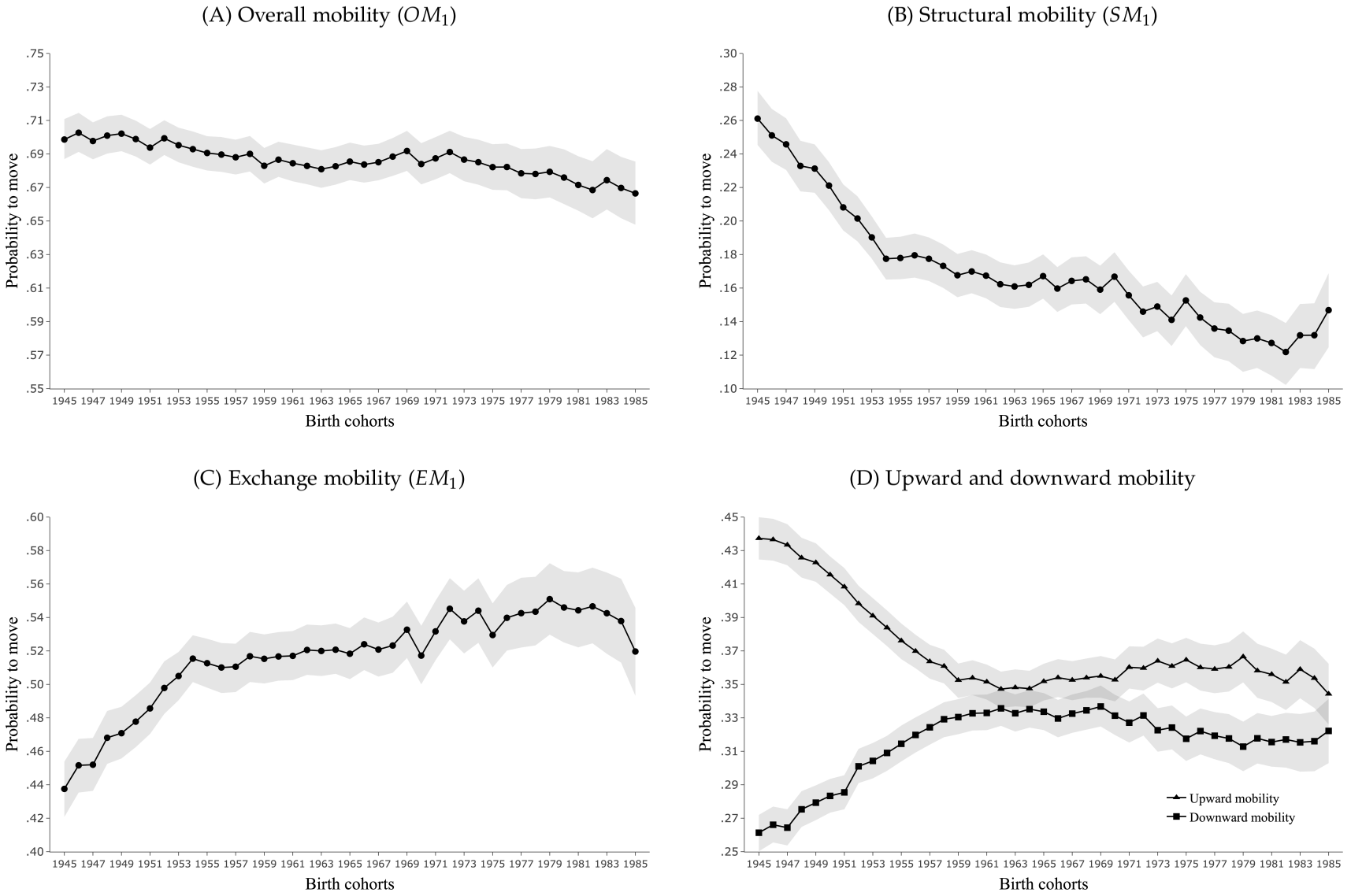
Overall mobility reflects differences in the marginal distribution of classes between fathers and children as well as the transition probabilities linking them. It can be decomposed into structural mobility, capturing the portion of movements driven by shifts in the marginal distribution of classes, and exchange mobility, which captures the residual movements net of these structural changes. Panels B and C of Figure 2 display trends in structural and exchange mobility, respectively, at generation $t = 1$, showing that the stability of overall mobility conceals offsetting trends in these components.

Specifically, structural mobility declined from about 25% in the 1945 birth cohort to less than 15% among those born after the mid-1970s. This decline was driven largely by two factors: the slowing contraction of class 4 (higher-grade manual workers, lower-grade technicians, and farmers), whose share of the workforce stabilized at a relatively low level, and the deceleration of growth in classes 2 (lower-grade professionals, administrators, and managers) and 3 (higher-grade routine non-manual workers, technicians, and supervisors).

By contrast, exchange mobility increased from about 45% to nearly 55% over the same period. The countervailing trends in structural and exchange mobility offset one another, producing a flat trajectory in overall mobility across cohorts. Together, they indicate that, over time, a growing share of intergenerational movements came to reflect transitions between fathers and their children that left the marginal distribution of occupational classes unchanged.

Overall mobility can also be decomposed into upward and downward movements,

Figure 2: Measures of movement at generation $t = 1$.



Notes: Shaded areas represent 95% confidence intervals.

provided that an ordering is imposed on the occupational classes. Although the EGP typology does not encode a hierarchy, we assume our five classes are ordered by their numeric labels, such that a destination class j is considered higher in rank than an origin class i if $j < i$.[1] Under this ordering, overall mobility at generation $t = 1$ can be partitioned into upward mobility, or the proportion of children who attain a higher-ranked class than their fathers, and downward mobility, which captures the proportion of children who fall to a lower-ranked class.

Panel D of Figure 2 displays trends in upward and downward mobility across cohorts, showing that the stability of overall mobility also reflects offsetting changes in these components. Upward mobility declined sharply from about 45% in the 1945 cohort to approximately 35% in cohorts born in the late 1950s, while downward mobility increased over the same period. Both rates then stabilized, remaining mostly flat and roughly equivalent for cohorts born since the 1960s. In other words, upward mobility far exceeded downward among cohorts born before mid-century, but the two metrics converged and are now at roughly similar levels among more recent birth cohorts.

To summarize, overall mobility between classes in the observed transitions from fathers to children remained fairly stable during the era of rising inequality. Beneath this stability, however, lies a more complex set of underlying dynamics: structural mobility declined steadily, reflecting a slowdown in occupational upgrading and a corresponding drop in upward movements, while exchange mobility increased. As a result, recent cohorts experienced levels of overall mobility comparable to earlier ones, but with less upward movement driven by professional-sector expansion and agricultural-sector contraction, and more circulation both up and down the class hierarchy.

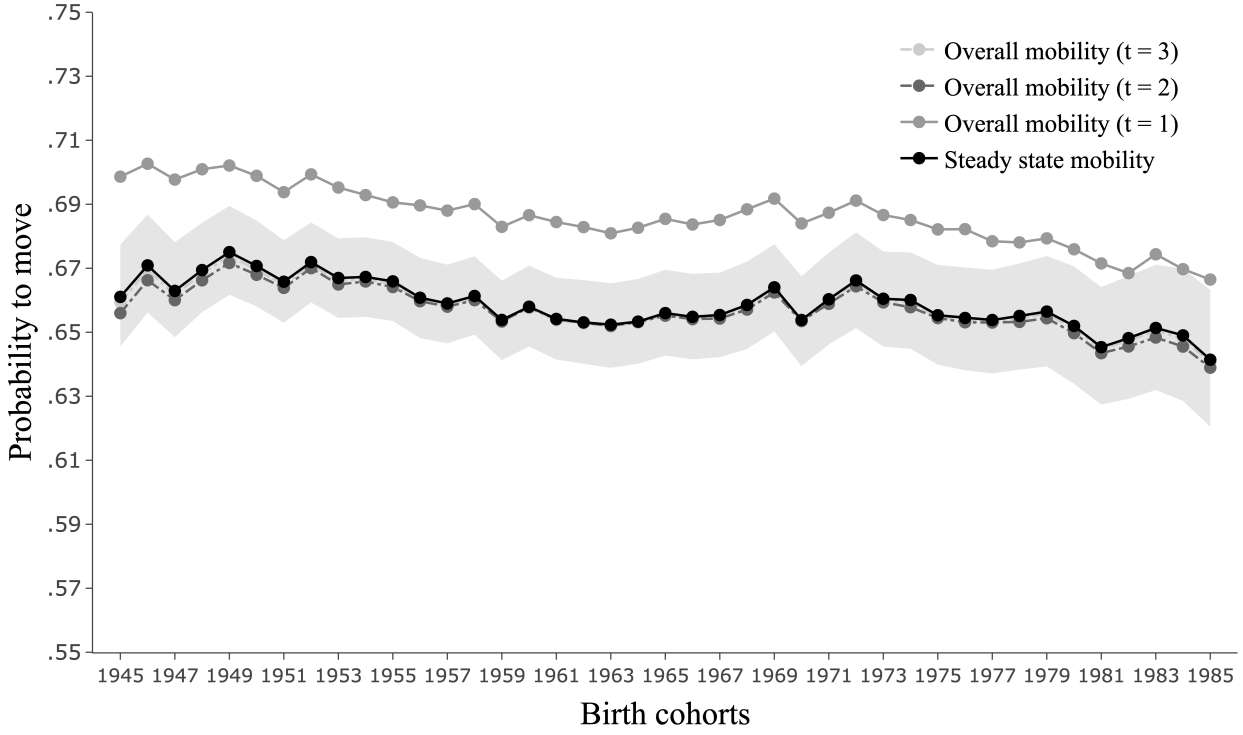
4.2 Movement in Synthetic Dynasties

Figure 3 plots trends in overall mobility across generations in a stationary Markov chain. At generation $t = 1$, the figure reproduces the empirical trend shown in Panel A of Figure 2. For subsequent generations ($t \geq 1$), it traces how mobility evolves as these synthetic dynasties unfold. The solid black line depicts steady-state mobility, which captures the total amount of intergenerational movement between classes once the Markov chain has reached its equilibrium. In this state, structural mobility is absent entirely, and

[1] That is, we assume the class hierarchy begins with (1) higher-grade professionals, administrators, and managers at the top, followed by (2) lower-grade professionals, administrators, and managers, (3) higher-grade routine non-manual workers, technicians, and supervisors, (4) higher-grade manual workers, lower-grade technicians, and farmers, and lastly, (5) lower-grade routine non-manual and manual workers, who compose the lowest-ranked class.

movements between classes reflect only the association between parental origins and child destinations.

Figure 3: Overall mobility (OM_t) across synthetic generations



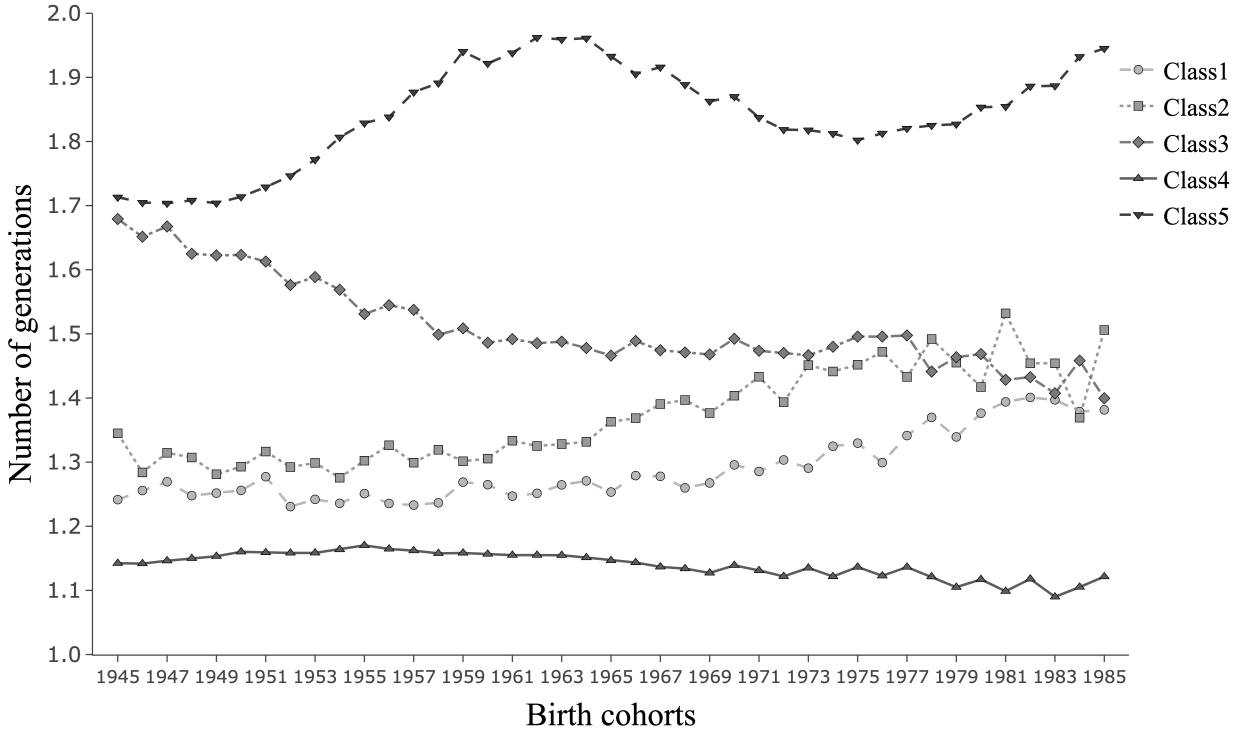
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for all cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence intervals, which are shown only for the trend in steady-state mobility.

Two key patterns are evident in this figure. First, the steady state is reached rather quickly: across all cohorts, the Markov chain converges to an invariant marginal distribution of classes within four generations. By generation $t = 2$, overall mobility has largely stabilized, with little change across subsequent generations of the synthetic dynasties. Second, the level of steady-state mobility is remarkably flat, remaining close to 65% across all cohorts. In other words, once the occupational structure has stabilized in the Markov chain, the probability that a descendant exits their parental class is consistently around 65%. This suggests that the "intrinsic" level of intergenerational movement has remained stable across cohorts who grew up or entered the labor market during the period of rising inequality.

Nearly flat trends in overall and steady-state mobility suggest a stable concentration of probability mass along the diagonal of the cohort-specific transition matrices. Such

stability, however, does not preclude heterogeneity in movement across origin classes and could reflect offsetting dynamics. To investigate this possibility, Figure 4 plots trends in the mean time to exit, which captures the average number of generations it takes for descendants of a given origin class to transition into a different destination class. A higher mean time to exit indicates that descendants in synthetic dynasties tend to remain longer in their origin class, signaling a lower likelihood of movement and greater persistence.

Figure 4: Mean time to exit from each origin class (MTE_i)



Notes: This figure plots the mean time to exit from each origin class (MTE_i), separately by cohort. Class 1 refers to higher-grade professionals, administrators, and managers; class 2 refers to lower-grade professionals, administrators, and managers; class 3 includes higher-grade routine non-manual workers, technicians, and supervisors; class 4 comprises higher-grade manual workers, lower-grade technicians, and farmers; and class 5 includes lower-grade routine non-manual and manual workers.

The figure reveals considerable variation in trends across classes. Specifically, for classes 1 and 2 (higher- and lower-grade professionals, administrators, and managers), mean time to exit has steadily increased, indicating greater persistence and reduced movement across cohorts. A similar trend appears for class 5 (lower-grade routine non-manual and manual workers), where the mean time to exit increased from about 1.7 generations among the 1945 cohort to nearly two full generations among more recent

cohorts. Together, these trends point to declining mobility at both the top and bottom of the occupational hierarchy during the era of rising inequality. By contrast, for classes in the middle of the hierarchy—particularly class 3 (higher-grade routine non-manual workers, technicians, and supervisors)—the mean time to exit has declined, indicating reduced persistence and greater movement.

In sum, movement has declined at the upper and lower ends of the class structure while rising in the middle. These patterns are also evident in Appendix **??**, which shows similar trends in class outflow probabilities at generation $t = 1$ and in the Markov steady state. Thus, what appears as stability in overall levels of intergenerational movement actually reflects countervailing dynamics: growing persistence at the top and bottom versus increasing movement in the middle of the class structure.

4.3 Intergenerational Memory

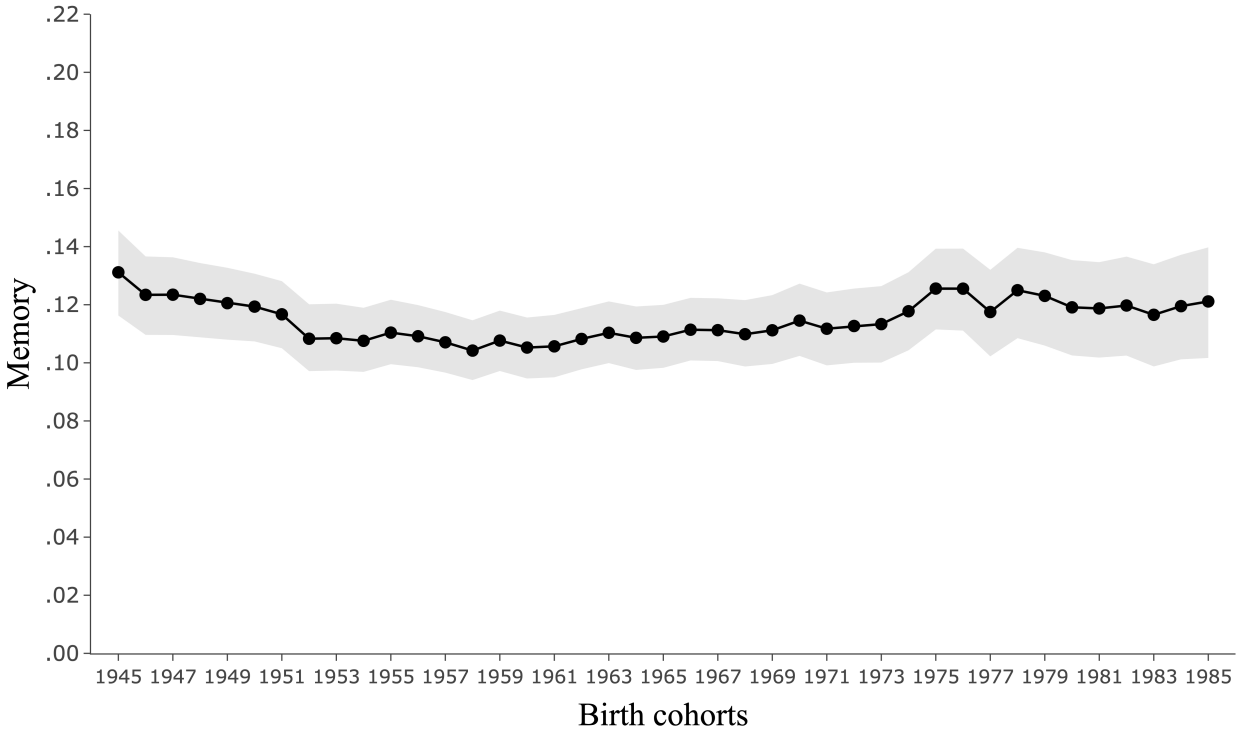
Figure 5 shows trends in aggregate intergenerational memory at generation $t = 1$. This measure captures the degree to which the observed transition matrix between fathers and children deviates from the limiting matrix of a stationary Markov chain. In the limit, each row of this matrix converges to the steady-state distribution of occupational classes, meaning that the destinations of descendants are completely independent of the founding generation's origins. Larger values therefore indicate greater distance from this benchmark of "equality of opportunity" and, by extension, slower dissipation of the influence of class origins across generations in the synthetic dynasties.

As Figure 6 illustrates, aggregate intergenerational memory at generation $t = 1$ changed vary little across birth cohorts. For the 1945 cohort, the estimated AIM_1 is about .13, compared with .12 for the 1985 cohort. Across all cohorts, our estimates of aggregate memory cluster narrowly between .10 and .14, indicating minimal change over time. These results suggest that the influence of class origins on destinations has persisted with little variation throughout the era of rising inequality. This stability mirrors the patterns we observed previously in our measures of overall and steady-state mobility.

Figure 6 plots trends in intergenerational memory separately for each origin class. These measures highlight variation in how strongly different class origins shape the destinations of descendants across generations in the synthetic dynasties. Higher values indicate that descendants from a given origin class are farther from the Markov steady-state and therefore take longer to converge toward equal opportunities.

The figure reveals modest but nontrivial variation in memory across class origins. Class 1 (higher-grade professionals, administrators, and managers) consistently exhibits

Figure 5: Aggregate intergenerational memory at generation $t = 1$ (AIM_1)



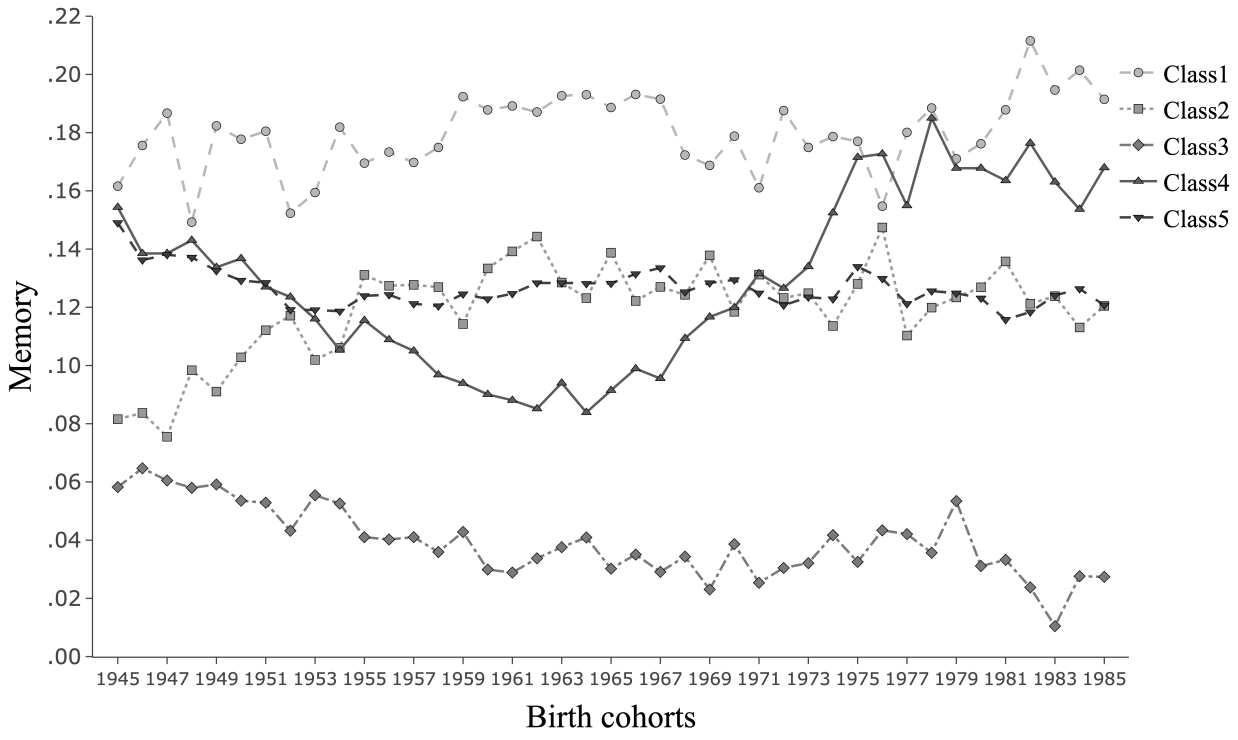
Notes: Shaded areas represent 95% confidence intervals.

the highest level of memory, rising slightly from about .17 among earlier cohorts to around .20 among more recent cohorts. Intergenerational memory has also increased for class 2 (lower-grade professionals, administrators, and managers), climbing from below .10 for cohorts born in the 1940s to about .13 for those born since the 1960s.

At the lower end of the class structure, memory has remained relatively stable for class 5 (lower-grade routine non-manual and manual workers). For class 4 (higher-grade manual workers, lower-grade technicians, and farmers), memory exhibits a steady decline among cohorts born through the 1960s, followed by a sharp upward trend in later cohorts. This reversal suggests a renewed influence of these origins on descendants' occupational destinations. Among the most recent cohorts, memory for class 4 approaches the high levels observed at the top of the hierarchy among those from class 1.

By contrast, in the middle of the occupational hierarchy, class 3 (higher-grade routine non-manual workers, technicians, and supervisors) stands out for its consistently low level of memory across all cohorts. Moreover, the limited influence of these origins has declined even further over time.

Figure 6: Intergenerational memory at generation $t = 1$ by origin class ($IM_{i,1}$)

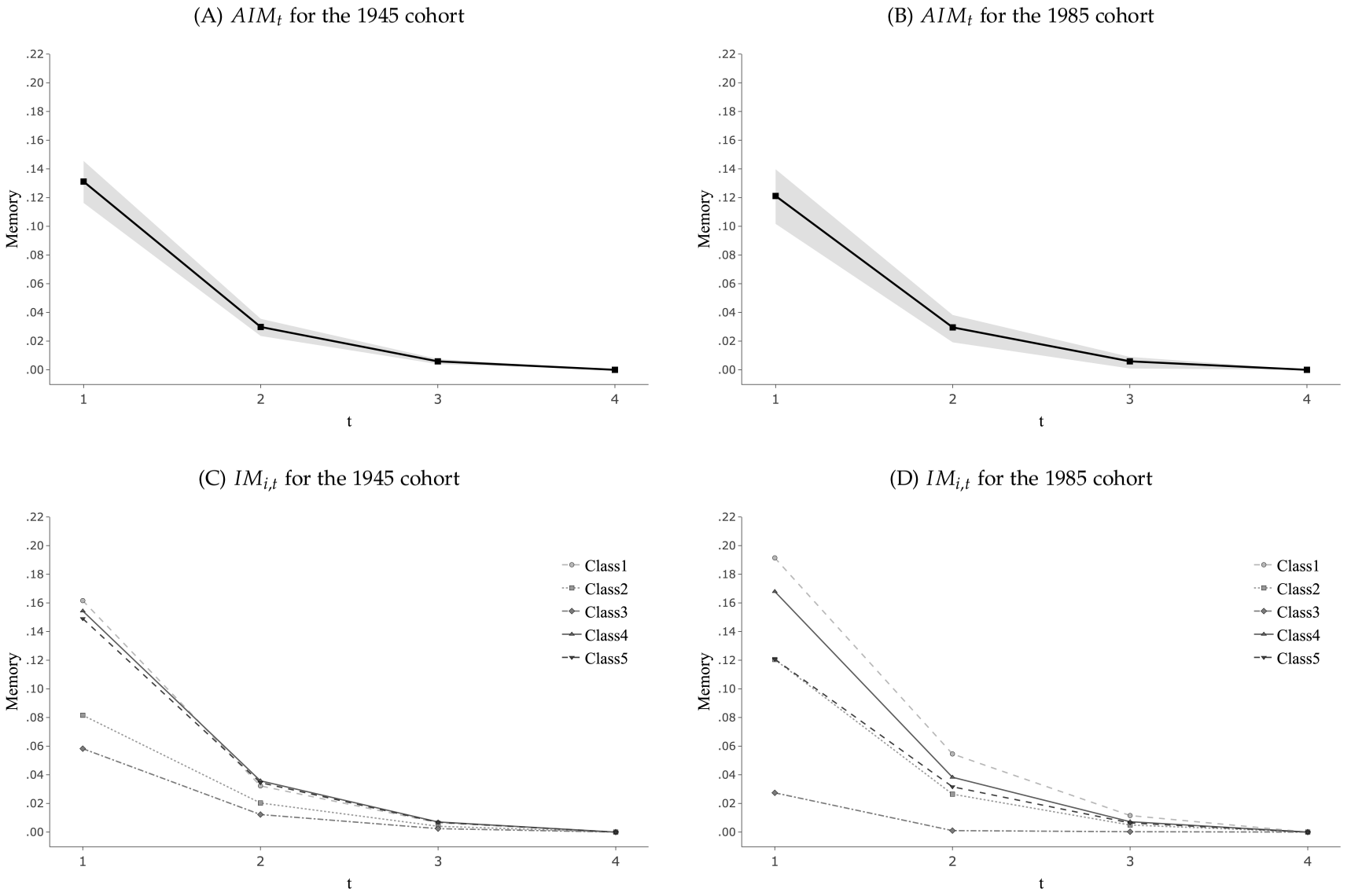


Notes: This figure plots intergenerational memory at generation $t = 1$, separately for each origin class ($IM_{i,1}$) and by cohort. Class 1 refers to higher-grade professionals, administrators, and managers; class 2 refers to lower-grade professionals, administrators, and managers; class 3 includes higher-grade routine non-manual workers, technicians, and supervisors; class 4 comprises higher-grade manual workers, lower-grade technicians, and farmers; and class 5 includes lower-grade routine non-manual and manual workers.

Figure 7 plots measures of memory across generations in a stationary Markov chain, separately for the 1945 and 1985 birth cohorts, to illuminate change over time. At generation $t = 1$, the figure reproduces our estimates for these two cohorts shown earlier in Figures 5 and 6. For later generations ($t \geq 1$), it traces how memory decays as the synthetic dynasties unfold, converging to zero by generation $t = 4$, when the Markov chains reach their steady state. At this point, class origins in the founding generation of the dynasties no longer shape the class destinations of descendants. The rate at which memory declines to zero therefore captures how quickly the influence of class origins dissipates. Comparing this decay process across cohorts helps to describe how class mobility has changed over time.

Panels A and B of Figure 7 show that aggregate intergenerational memory decays in nearly the same way for both the 1945 and 1985 birth cohorts. In each case, it begins .12 and .14 at generation $t = 1$, drops to about .04 by generation $t = 2$, and approaches zero

Figure 7: Memory across synthetic generations in the 1945 and 1985 birth cohorts



Notes: This figure illustrates the evolution of AIM_t and $IM_{i,t}$ across generations in a stationary Markov chain, separately for the 1945 and 1985 cohorts. By $t = 4$, both transition matrices have converged to the steady state, implying zero memory of class origins. Shaded areas represent 95% confidence intervals.

thereafter. However, despite these aggregate similarities, Panels C and D suggest shifts in the dissipation of memory for specific class origins. For the 1985 cohort, memory associated with the professional, administrative, and managerial classes (classes 1 and 2) is higher and fades more slowly than for the 1945 cohort, while memory of class 3 (higher-grade routine non-manual workers, technicians, and supervisors) is lower and declines more rapidly.

To summarize, aggregate intergenerational memory has remained highly stable across cohorts who grew up or entered the labor market during the era of rising inequality. Beneath this stability, however, we find some evidence that the influence of particular class origins may have shifted. Over time, memory appears to increase at the top of the class structure, decrease in the middle, and either remain stable or rebound following a decline at the bottom. These patterns are largely consistent with the trends we documented previously in our measures of movement.

4.4 Comparison with Traditional Measures

In this section, we compare results from our synthetic dynasty analysis to more conventional measures of "mobility as association." These measures—based on odds ratios—capture the association of origins and destinations in the observed mobility tables while remaining invariant to shifts in the marginal distribution of classes. To this end, we estimate a standard log-multiplicative layer effect model, in which the natural logarithms of odds ratios are given by linear combinations of regression coefficients. Specifically, this model can be expressed as follows:

$$\log\left(n_{ijk}\right) = \tau + \tau_i + \tau_j + \tau_k + \tau_{ik} + \tau_{jk} + \theta_{ij}\phi_k + \epsilon_{ijk}, \tag{9}$$

where the parameters are normalized using baseline constraints but are otherwise unrestricted (Xie, 1992). With this specification, the θ_{ij} parameters capture the pattern of association between origins and destinations in a reference cohort, while the "layer effects" ϕ_k scale the magnitude of these associations up or down for each comparison cohort. To improve the precision of our estimates, we fit this model to data that variously groups cohorts into 5-year or 10-year bins.

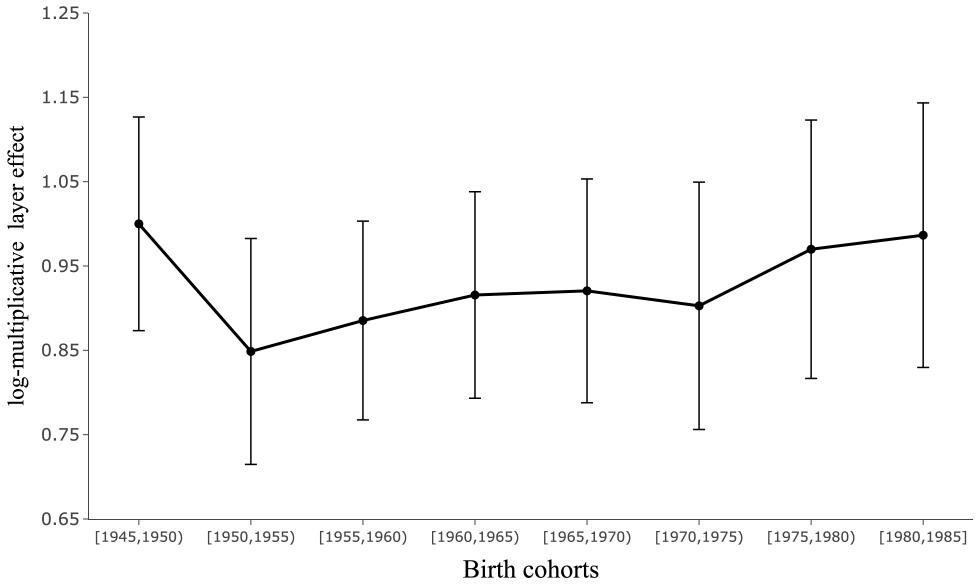
A distinctive feature of this model is that it cleanly distinguishes changes in class composition from changes in intergenerational associations. Variation in the marginal distribution of origins and destinations is absorbed by the τ parameters, which account for shifts in class size across cohorts. This leaves the θ_{ij} parameters to capture the dependence structure between origins and destinations, while the ϕ_k parameters capture

whether the strength of these associations is rising or falling. Functions of these two parameters give the log-odds-ratios summarizing the dependence of destinations on origins for each cohort k.

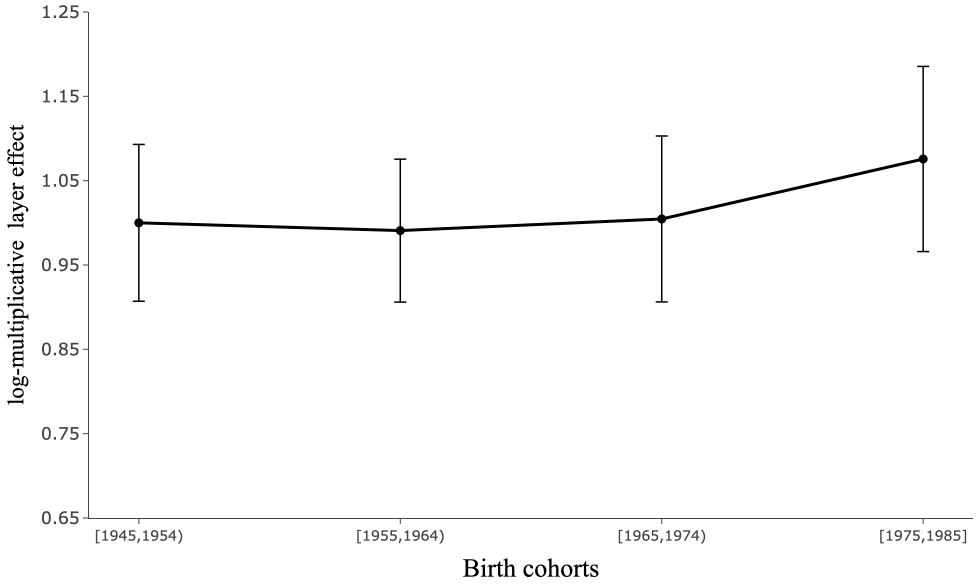
Figure 8 plots the estimated layer effects across cohorts, using both 5-year and 10-year bins. Based on these results, the strength of the origin-destination associations appears fairly stable, with estimates of the layer effects fluctuating but confined to a relatively narrow range. For example, we estimate that the origin-destination associations for cohorts born after 1975 are about 5% stronger than for cohorts born earlier. Although there is faint evidence of an upward trend, particularly when comparing cohorts born after 1975 to those born in the 1950s and 1960s, the differences are small and they fall within the margin of sampling error.

Figure 8: Log-multiplicative layer effects

(A) Cohorts in 5-year bins



(B) Cohorts in 10-year bins



Notes: This figure plots the log-multiplicative layer effect across birth cohorts using 5-year and 10-year bins, respectively. The vertical bars represent 95% confidence intervals.

4.5 Robustness Analyses

To ensure the robustness of our results, we report a series of supplementary analyses in the Appendix.

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 sometimes 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.

5 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 measures 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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