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

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Abstract

Widely regarded as a barometer for equality of opportunity, intergenerational mobility has attracted renewed attention amid concerns that it has 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 entered the labor market before this period, evidence for more recent cohorts is limited and inconsistent. In this study, we analyze contemporary trends in class mobility using a new approach based on the "synthetic dynasties" represented in Markov chains. This approach yields several novel measures of *movement* and *memory*, which respectively capture how class positions differ from one generation to the next and how the influence of class origins dissipates across generations. Applying these methods to data from the U.S., we find that overall levels of movement and memory have remained largely stable across cohorts born between 1945 and 1990. This stability, however, masks offsetting class-specific trends. Among those from the upper and lower classes, movement has declined and memory has increased. 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 concerns the extent to which socioeconomic attainments are linked across generations within families. This linkage has been conceptualized in several different ways. First, it can be understood as *association*, or the strength of the relationship between the social origins of parents and the destinations of children. Second, it can also be conceived in terms of *memory*, or how the association of a family's social origins with the destinations of descendants dissipates across generations. Lastly, mobility can be viewed as *movement*, or whether a descendant's social position differs from that of an ancestor.

Mobility—whether conceptualized as association, memory, or movement—is widely regarded as a key indicator of societal openness and equality of opportunity (Blau and Duncan, 1967; Featherman and Hauser, 1978; Roemer, 1998). 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. The belief in American exceptionalism has not been confined to domestic observers. For example, Friedrich Engels famously described the U.S. as "a country rich, vast, expanding...unleavened by feudal remnants or monarchical traditions and without a permanent and hereditary proletariat [where] everyone could become, if not a capitalist, at all events an independent man" (Marx and Engels 1942:449). The implications of these beliefs for policy preferences have been explored by Alesina et al. (2018).

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 public interest in mobility and revived controversies over whether American society is straying from its professed commitment to equality of opportunity. They have also spurred a renaissance of empirical research on mobility and its contemporary dynamics (Chetty et al., 2017; Davis and Mazumder, 2024; 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. Modernization theory, for example, anticipates a steady increase in mobility as societies develop economically (Featherman and Hauser, 1978; Lipset and Bendix, 1959; Treiman, 1970). In particular, as modernization expands access to education and

increases the importance of skills 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). An alternative perspective, articulated in the Featherman-Jones-Hauser (FJH) hypothesis, contends that the link between class origins and destinations remains largely stable in market-based societies with nuclear family systems, and that any fluctuations in mobility mainly reflect structural shifts in the distribution of occupations (Erikson and Goldthorpe, 1992; Featherman et al., 1975).

These long-run perspectives contrast with more recent arguments that rising inequality reduces mobility. Many of these arguments are motivated by "The Great Gatsby Curve," an empirical proposition that higher cross-sectional inequality is associated with lower intergenerational mobility (Andrews and Leigh, 2009; Corak, 2006, 2013; Hertel and Groh-Samberg, 2019). DiPrete (2020) and Durlauf et al. (2022) describe mechanisms that can generate this association. One mechanism operates through schooling and labor markets, where Hassler et al. (2007) show how shifts in the distribution of education interact with skill premia to produce an inverse relationship between inequality and mobility. A second set of mechanisms emphasizes social processes, where rising inequality reduces mobility by increasing segregation and deepening disparities in resources between upper- and lower-class families, which then polarize investments in children. These disparities reinforce class differences in the acquisition of human, social, and cultural capital, strengthening the capacity of more advantaged families to transmit their social position across generations (Andrews and Leigh, 2009; Durlauf, 1996; Fogli et al., 2025; Mitnik et al., 2016). Together, these arguments depart from earlier sociological theories that emphasized steady growth or stability in intergenerational mobility over long time horizons.

Prior research on mobility trends in the U.S. provides mixed support for these competing perspectives, particularly during the recent period of rising inequality. For cohorts born well before this period, a large body of evidence indicates that the link between class origins and destinations either remained stable or weakened over much of the twentieth century (e.g., Featherman et al. 1975; Featherman and Hauser 1978; 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 rising 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 (Bloome, 2015; 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 trends in intergenerational mobility—whether measured using occupations 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 in earnings 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, suffer their own drawbacks. They have largely relied on small samples of recent cohorts (e.g., Pfeffer and Hertel 2015; Mitnik et al. 2016), reducing 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 trends in occupational mobility employ log-linear or log-multiplicative models, whose coefficients represent odds ratios capturing the strength of the association between parental origins and child destinations. Although widely used and analytically powerful, these models capture only one dimension of mobility—namely, association—and do not directly reflect movement or memory. They also typically impose 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). In addition, estimates derived from these models are often imprecise due to the instability of odds ratios, particularly in sparse contingency tables (Zhou, 2015). Taken together, these limitations complicate efforts to assess whether, and how, mobility has shifted in recent decades.

In this study, we analyze cohort trends in occupational class mobility during the era of rising inequality. To this end, we draw on the most recent data available from the U.S., 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 the observed 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 conceptualized as movement. 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 association of parental origins with 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; McClendon, 1977; Sobel et al., 1985).[1]

Steady-state mobility, by contrast, measures the amount of movement between classes after a Markov chain has reached its stationary distribution, where the marginal proportions of different occupational classes become invariant across generations and thus structural mobility ceases to exist (Butaeva et al., 2025). 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 parental origins and child destinations.

Second, we also introduce several measures of mobility conceptualized as memory. In particular, we analyze a measure of *aggregate 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. This measure captures how the influence of class origins fades out over successive generations of a synthetic dynasty. Mobility is higher 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 intergenerational transmission of social status (Bartholomew, 1967; Boudon, 1973; Dardanoni, 1993; Prais, 1955; Singer and Spilerman, 1976), and offer several advantages over conventional approaches to analyzing mobility. They provide simple, interpretable summary

indices of movement and memory that can also be disaggregated to reveal more granular, class-specific patterns. They are fully nonparametric, imposing no assumptions about the distribution of parental origins and child destinations or how it changes over time. And lastly, they can be readily combined with smoothing techniques to produce more precise estimates of trends, particularly for cohorts that are sparsely represented in the data.

Applying these methods to the General Social Survey (GSS), we find that overall mobility in the U.S. has remained remarkably stable across cohorts born between 1945 and 1990. In addition, the link between class origins and destinations—as captured by our measures of steady-state mobility and aggregate intergenerational memory—also appears largely unchanged over this period. In general, the stable patterns we observe appear to be robust 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, reflecting a slowdown in occupational upgrading, while exchange mobility has increased. Similarly, the flat trends in steady-state mobility and intergenerational memory conceal 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 that capture multiple dimensions of class mobility, 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 cohorts, 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 invariant. "Great Gatsby" perspectives advance historically contingent arguments about how certain types of socioeconomic economic change may shape intergenerational mobility, suggesting that recent increases in income and wealth inequality are 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 was expected to intensify in the post-industrial era, as service-based economies place an even greater premium on education and human capital, and rapid technological change accelerates the obsolescence of occupational skills, limiting parents' ability to directly transmit competencies that remain relevant in an evolving labor market (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. Mobility is thought to increase not only because of a decline in the direct influence of class origins on destinations, but also through changes brought about by expanded access to education (Beller and Hout, 2006; Hout, 1988). In principle, educational expansion could reduce the importance of family background for attaining higher levels of education, thereby attenuating the indirect link between class origins and destinations that operates through differences in schooling. Empirically, however, class disparities in educational attainment have largely persisted—and in some cases even widened—during recent episodes of expansion (Bailey and Dynarski, 2011; Lucas, 2001; Raftery and Hout, 1993).

But even when disparities in educational attainment persist, expansion nonetheless increases the share of the population attaining higher levels of schooling, particularly college degrees. Because the association of class origins with destinations tends to be weaker among those more education, expansion may promote greater mobility through

a compositional mechanism—that is, by shifting more people into subpopulations where social origins seem to exert less influence. In this way, post-secondary expansion may generate increases in mobility at the population level even when class disparities in educational attainment remain pronounced. While there is considerable evidence that educational expansion promotes mobility through this type of compositional change (Breen, 2010; Hout, 1988; Pfeffer and Hertel, 2015; van de Werfhorst, 2024), several recent studies also raise doubts about the equalizing role of post-secondary education (Fiel, 2020; Zhou, 2019).

In contrast to modernization theory, the FJH hypothesis rejects the possibility that class mobility follows an upward, developmentally driven trajectory. Rather than anticipating that mobility will increase steadily with economic development, this perspective posits that the association between class origins and destinations—typically measured using odds ratios—remains relatively stable over time in societies with market economies and a nuclear family system (Featherman et al., 1975). While overall rates of mobility—conceptualized as movement—may rise or fall, these fluctuations are thought to reflect changes in the occupational structure, driven by technological development, 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 levels of movement between classes, which vary in response to shifts in the distribution of occupations over time (Featherman et al. 1975:339-340).

Empirical research on the U.S. largely supports the modernization or FJH perspectives for cohorts born earlier in the 20th century. Studies of occupational mobility covering these groups generally find that the association between class origins and destinations—the "genotypic pattern of mobility"—either remained stable or declined modestly (Featherman et al., 1975; Featherman and Hauser, 1978; 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; Breen and Müller, 2020). However, most evaluations of the modernization and FJH perspectives are based on data that largely predate the contemporary period of rising inequality.

Since the 1970s, income and wealth inequality in the U.S. have increased (Killewald et al., 2017; Morris and Western, 1999; Piketty and Saez, 2003; Saez and Zucman, 2016). Much of this increase has been driven by disproportionate gains at the top of the dis-

tribution. For example, the share of national income held by the top 1% of families has roughly doubled, climbing from under 10% in the 1970s to around 20% today (Saez and Zucman, 2020). The recent shifts in economic inequality map closely onto occupational classes (Mouw and Kalleberg, 2010; Weeden et al., 2007; Zhou and Wodtke, 2019), with the earnings of professionals and managers 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 number of scholars have argued that rising inequality may reduce intergenerational mobility by exacerbating disparities in the resources that families invest in 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, and access to selective colleges and universities (Bailey and Dynarski, 2011; Kornrich and Furstenberg, 2013; Schneider et al., 2018). Moreover, parental investments may extend beyond adolescence and the transition to adulthood, as affluent parents are also better positioned to support their children later in life—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. This evidence is complemented by research showing that policies which expand investments in disadvantaged children can generate medium- and long-term improvements in educational outcomes (Heckman et al., 2010; Johnson and Jackson, 2019; Gray-Lobe et al., 2022).

Beyond polarizing the resources that families invest in their children's development, rising inequality may also promote intergenerational persistence by reshaping the social contexts in which children grow up. Greater income inequality is associated with higher levels of residential and school segregation, particularly among families with children (Logan et al., 2020; Owens et al., 2016), and the spatial concentration of poverty and affluence is linked, in turn, to disparities in educational attainment and labor market outcomes (Chetty et al., 2016; Wodtke et al., 2011, 2016). Through these mechanisms, higher inequality may further suppress intergenerational mobility by deepening the contextual differences that enhance the development of advantaged children while constraining the

life chances of their more disadvantaged counterparts. Consistent with this account, formal theoretical models and a growing body of empirical studies highlight how segregation and peer effects can generate persistent intergenerational inequalities (Bénabou, 1996; Durlauf, 1996; Durlauf and Seshadri, 2017; Fogli et al., 2025).

According to this perspective, then, mobility should decline following the rise in economic inequality, with a lag determined by the timing and nature of parental investments and any contextual effects on their children. If these influences 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 and neighborhood contexts later in life also play an important role, changes could emerge more quickly. In either case, the effects are likely to appear as a stronger link 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 also be more pronounced among their children. In this scenario, rising inequality would not necessarily produce uniform changes in mobility across class origins but would instead engender a growing capacity for upper class families in particular to secure desirable positions for the next generation (Mitnik et al., 2016).

Research on the relationship between inequality and mobility has produced mixed and sometimes 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 relationship is weaker, or altogether absent, when occupational class rather than income is used to measure mobility between parental origins and child destinations (Bukodi and Goldthorpe, 2018; DiPrete, 2020; Torche, 2015). At the same time, Hertel and Groh-Samberg (2019) find that cross-national associations between economic inequality and class mobility are more evident when inequality is measured across occupational classes rather than individuals or households, suggesting that the link may depend on how these concepts are operationalized. Research examining the association between income inequality and income mobility across American states also has not uncovered a strong 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 (Bloome, 2015; 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 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 relatively small 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 limited and potentially distorted.

In addition, nearly all modern studies of trends have relied on log-linear or log-multiplicative models, such as the "unidiff" or log-multiplicative layer effect model (Erikson and Goldthorpe, 1992; Xie, 1992), to analyze mobility conceptualized as association. Despite their many advantages, these models directly capture only this single dimension of mobility, their parameter estimates can be quite noisy when based on sparse contingency tables, and they impose strong assumptions about the nature of change over time. For example, layer effect models assume 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 set of parameters. These constraints can make it difficult to detect changes in mobility over time and may introduce bias into estimates of trends.

The present study aims to address these limitations and provide new evidence on trends in class mobility during the era of rising inequality. To assemble larger samples of the cohorts most likely to be affected by higher inequality, 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 and enhance precision. Finally, we use these smoothed data to estimate a new set of measures that capture mobility conceptualized as movement and memory, while avoiding any restrictive assumptions about how mobility has changed over time. We conclude by comparing our measures with more conventional indicators of mobility as association and by investigating the sensitivity of our conclusions to alternative analytic choices.

3 Methods

3.1 Data

To study the dynamics of class mobility in the U.S., 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 and employment 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 on both respondents' occupations and those of their parents, enabling comparisons across cohorts spanning multiple decades.

Our analytic sample consists of all GSS respondents who were born between 1945 and 1990, 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 $n = 24,265$ respondents in birth cohorts that grew up or entered the labor market during the era of rising inequality. Sample sizes vary by cohort, ranging from 184 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 64 or 30 to 64) produced similar results, which are reported in Appendix A.

3.2 Occupational Classes

At 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 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 pairs constitute the empirical basis for our analysis.

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, con-

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

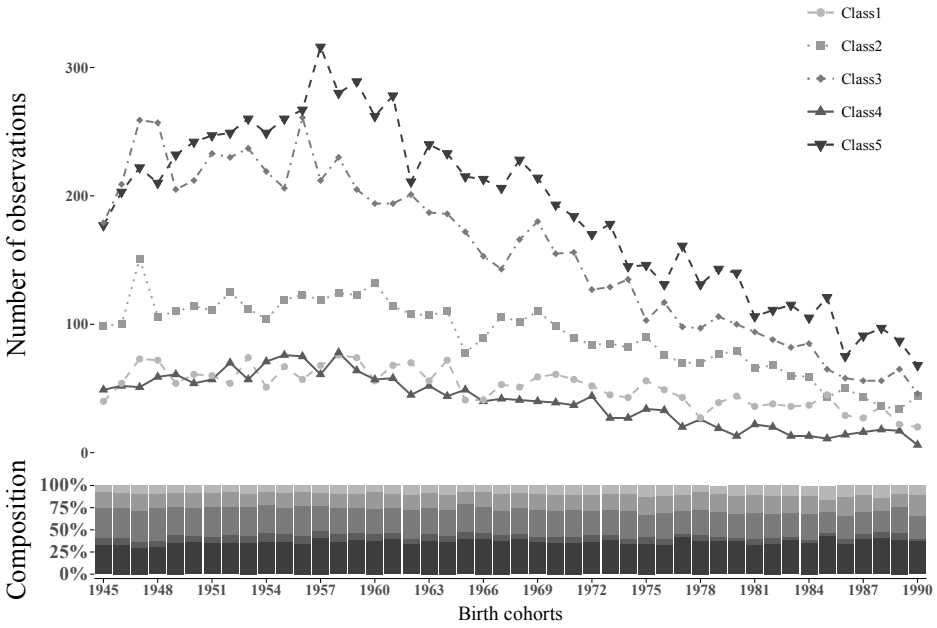
Class	Description	Illustrative Occupations	EGP Labels
1	Higher-grade professionals, administrators, and managers	Accountants, postsecondary teachers, lawyers	I
2	Lower-grade professionals, administrators, and managers	Primary school teachers, registered nurses, managers (all other)	II
3	Higher-grade 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.

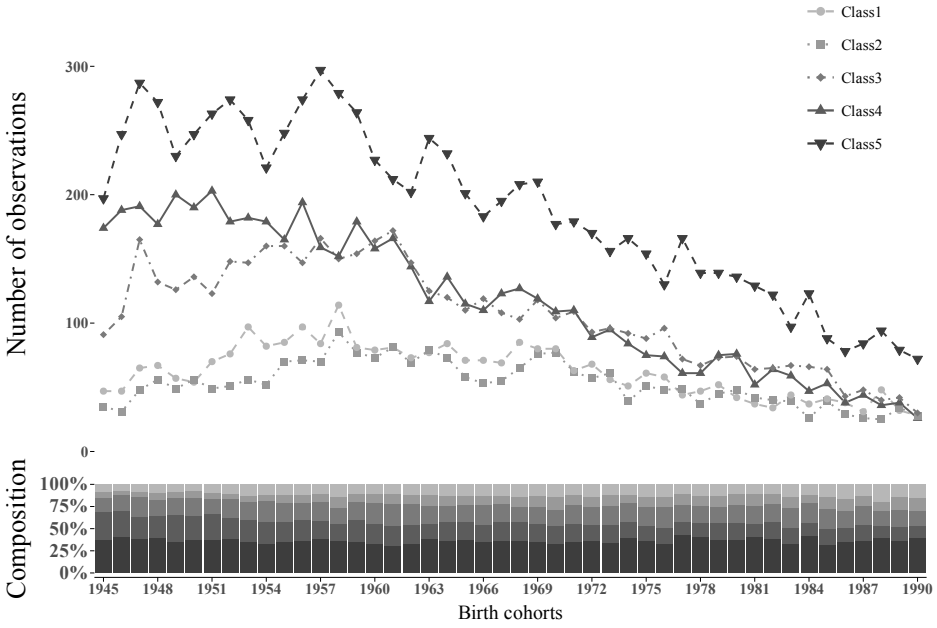
ditions, and employment relations while avoiding overly fine categories that would lead to excessive sparsity. The resulting classes—summarized in Table 1—include: (1) higher-grade professionals, administrators, and managers; (2) lower-grade professionals, administrators, and managers; (3) higher-grade routine non-manual workers, technicians, and supervisors; (4) higher-grade manual workers, lower-grade technicians, and farmers; and (5) lower-grade routine 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). 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. As reported in Appendix B, trend estimates

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; class 2 refers to lower-grade professionals; class 3 includes higher-grade routine non-manual workers and technicians; class 4 comprises higher-grade manual workers, lower-grade technicians, and farmers; and class 5 includes lower-grade routine non-manual and manual workers.

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 father-child transitions observed in the GSS but also through the long-run influence of class origins on hypothetical family dynasties constructed as if patterns of class transmission were indefinitely stable from one generation to the next.

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 and 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, where 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 $\mu_t = \mu_0 \cdot P^t$.

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_∞.[2] 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 their 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, tran-

sition 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 between fathers and children in a single cohort were to persist indefinitely. By extension, Markov chains, and the synthetic dynasties they generate, serve mainly as an analytic device for summarizing the link between class origins and destinations. Their role in our study is akin 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 a Markov chain. Measures of *memory*, by contrast, assess how 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'. More specifically, these measures quantify how much probability mass lies off the main diagonal of the transition matrix. At one extreme, every child could remain in the same class as their parent, such that the transition matrix is equal to the identity matrix. At the other extreme, every child could enter a different class than their parent, producing a transition matrix with zeros along the main diagonal. In general, the greater this off-diagonal mass, the higher the level of mobility when conceptualized as movement.

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; McClendon, 1977; Sobel et al., 1985). 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 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 (Butaeva et al., 2025).

To examine class-specific heterogeneity in intergenerational movement, we additionally compute the mean time to exit (MTE; Kemeny and Snell 1976) 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 enduring influence of class origins across multiple generations 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.

More specifically, measures of memory variously reflect the concepts of distance, time, and decay. Some measures 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. Other measures capture the amount of time required for the mobility process to reach this steady state, at which point class origins no longer predict the destinations of descendants. Still others capture the rate at which the association between class origins and the destinations of descendants is decaying across generations. In colloquial terms, measures of memory indicate how far, and how quickly, a set of synthetic dynasties moves toward a state of multi-generational "equality of opportunity."

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 mem-*

ory 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 distance of P^t from the limiting matrix P^∞, whose rows are all equal to μ_∞. At generation $t = 1$, it provides a concise summary of how strongly class origins shape outcomes across future generations, with larger values signaling greater distance from the state of multi-generational equality of opportunity (Blume et al., 2025).

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 (Blume et al., 2025).

In addition to measures of distance, we also report measures that capture time and decay. Specifically, we examine the number of generations it takes for the influence of class origins to dissipate entirely, denoted by t^*, as well as $\Delta_{AIM} = (AIM_1 - AIM_2)/AIM_1$, which measures the rate at which the influence of class origins declines across generations (Durlauf et al., 2024). Taken together, AIM_t, t^*, and Δ_{AIM} jointly characterize the magnitude, persistence, and rate of decay of the association between a family's origins and the destinations of its descendants.

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 $k \in \{1945, ..., 1990\}$. 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: $\sum_{i,j} \lambda_{ij} \int f''_{ij}(k)^2 \, dk$. Larger values of the smoothing parameters λ_{ij} produce smoother fits and greater resistance to deviations from linearity. We optimized these parameters using restricted maximum likelihood (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 generalized cross-validation, 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). We report unweighted estimates throughout, as a parallel analysis incorporating survey

weights that adjust for different features of the GSS design produced nearly identical results (see Appendix C for details). A full set of replication files for this analysis is available at https://github.com/vigiwang/synthetic_dynasty_analysis_replicate.

4 Results

4.1 Overall, Structural, and Exchange Mobility

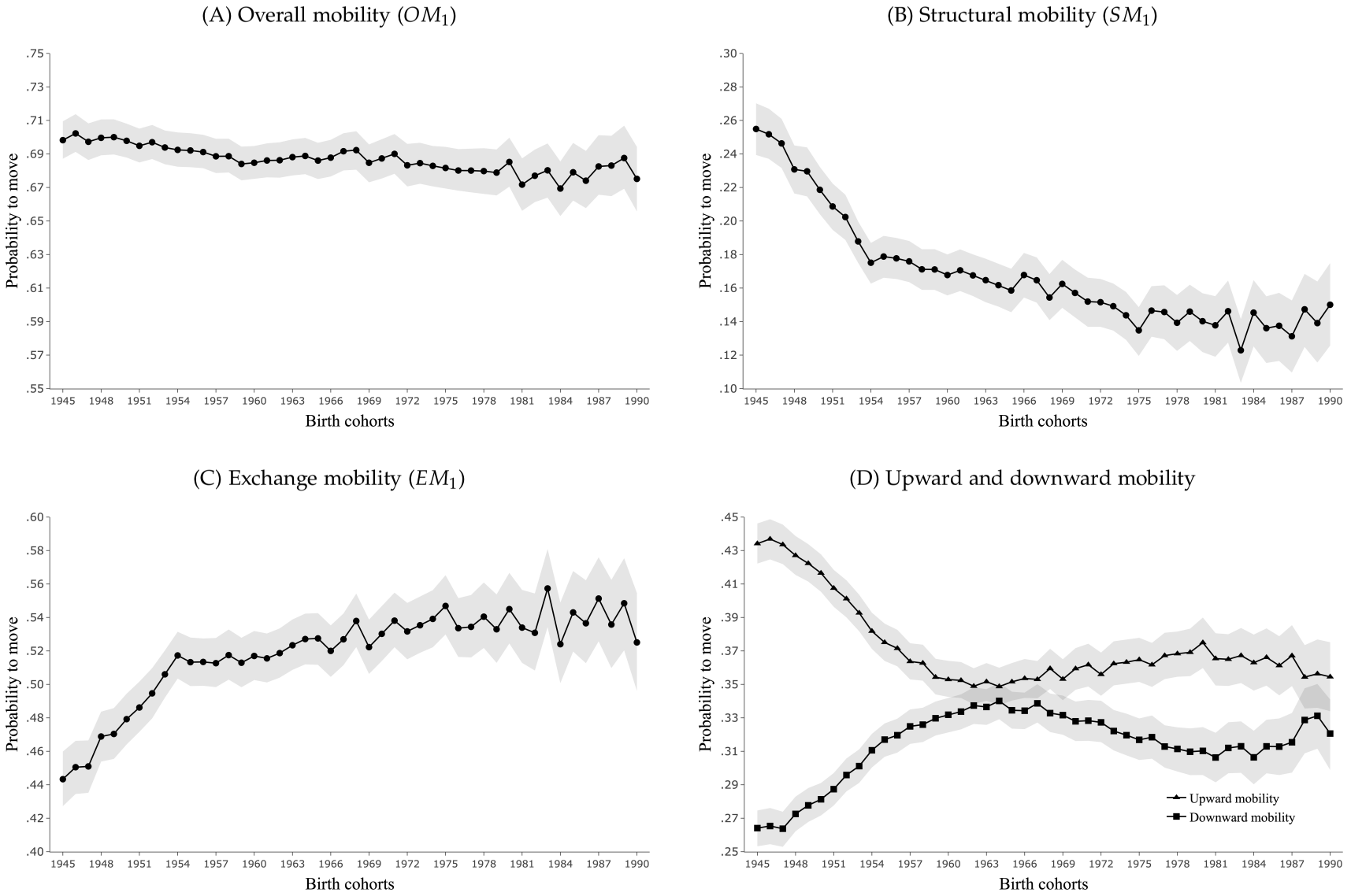
Panel A of Figure 2 displays trends in overall mobility at generation $t = 1$, which reflects the total amount of movement in the observed transitions between fathers and their children. Across cohorts who grew up or entered the labor market during the era of rising inequality, overall mobility remained remarkably stable. In the 1945 birth cohort, about 70% of children entered a different occupational class than their fathers. In the 1990 cohort, this share declined only slightly to about 68%. More broadly, across all cohorts born between 1945 and 1990, overall mobility hovered around 70%. These results indicate that the likelihood of children entering a different class than their fathers was 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 a growing share of intergenerational movements came to reflect transitions between fathers and their children that left the marginal distribution of occupational

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



Notes: Shaded areas represent 95% confidence intervals.

classes unchanged.

Overall mobility can also be decomposed into upward and downward movements, provided that an ordering is imposed on the occupational classes. Although the EGP typology does not natively 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 $j < i$.[3] 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.

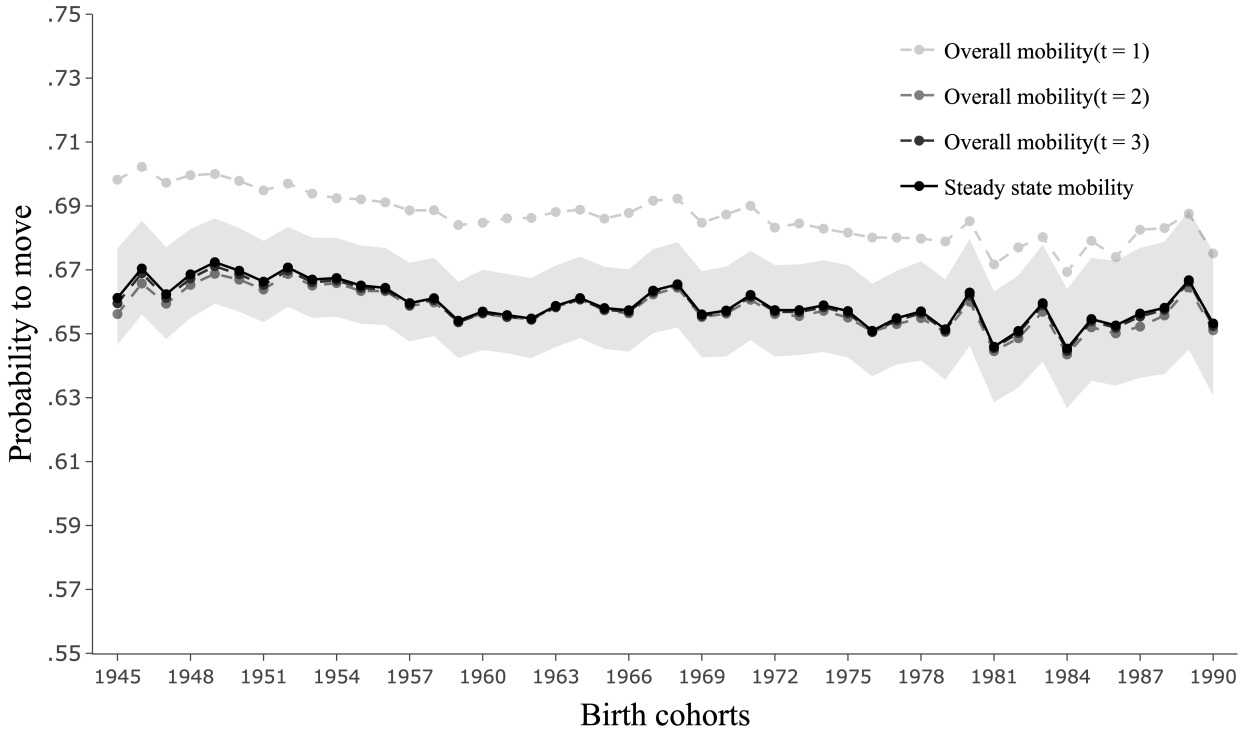
Panel D of Figure 2 displays trends in upward and downward mobility across cohorts, showing that the stability of overall mobility also reflects offsetting changes in these components. Upward mobility declined sharply from about 45% in the 1945 cohort to approximately 35% in cohorts born in the late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

To summarize, overall mobility between classes in the observed transitions from fathers to children remained stable during the era of rising inequality. Beneath this stability, however, lies a more complex set of underlying dynamics: structural mobility declined, 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 stationary Markov chains. 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 movements between classes reflect only the association between parental origins and child destinations.

Figure 3: Overall mobility (OM_t) across synthetic generations

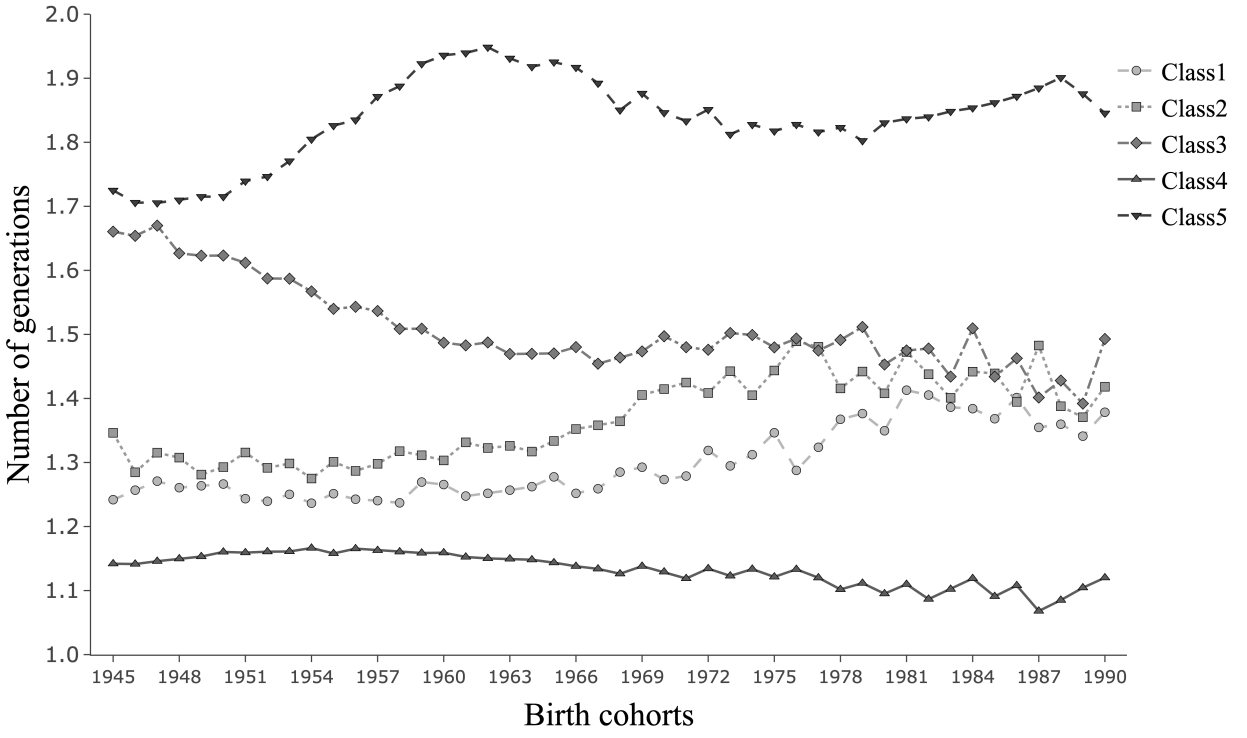


Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for all cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence 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 chains converge to an invariant marginal distribution of classes within four generations. Even by generation $t = 2$, overall mobility has largely stabilized, with little change thereafter. Second, the level of steady-state mobility is also remarkably flat. Once the occupational structure has stabilized in each Markov chain, the probability that a descendant of a synthetic dynasty exits their parental class is close to 66% across all cohorts. This suggests that the "intrinsic" level of intergenerational movement has remained largely stable among those 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

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.

descendants of a given origin class to transition into a different destination. A higher mean time to exit indicates that descendants of synthetic dynasties tend to remain in their origin class for longer, signaling a lower likelihood of movement.

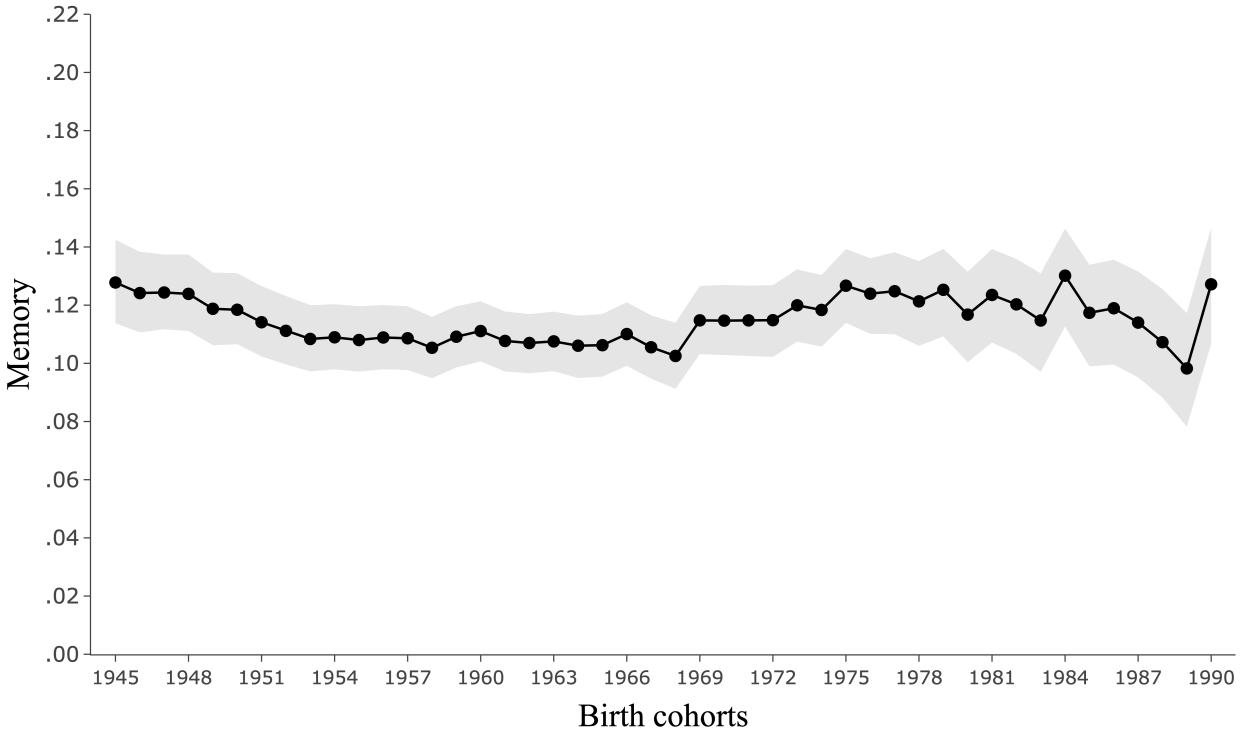
The figure reveals considerable variation in trends across classes. Specifically, for classes 1 and 2 (higher- and lower-grade professionals, administrators, and managers), mean time to exit has increased, indicating greater persistence and reduced movement across cohorts. A similar trend appears for 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. 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.

Thus, what appears as stability in overall levels of intergenerational movement may actually reflect 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 multi-generational "equality of opportunity."

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

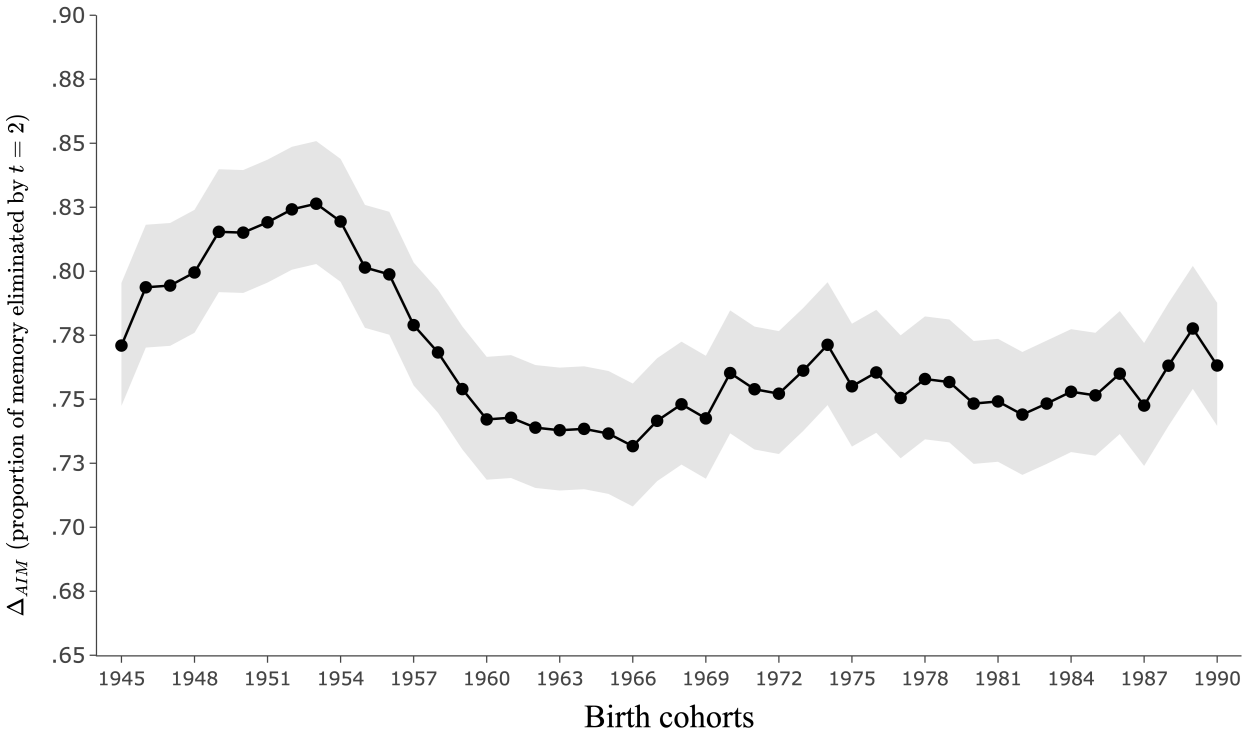


Notes: Shaded areas represent 95% confidence intervals.

As Figure 5 illustrates, aggregate intergenerational memory at generation $t = 1$ changed little across birth cohorts. For the 1945 cohort, the estimated AIM_1 is about .13.

This metric then declines to .11 among cohorts born in the 1950s before rising slightly to just above .12 for more recent cohorts. These results suggest that the influence of class origins across generations has persisted largely unchanged 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: Rate of decay in aggregate intergenerational memory between generation $t = 1$ and $t = 2$



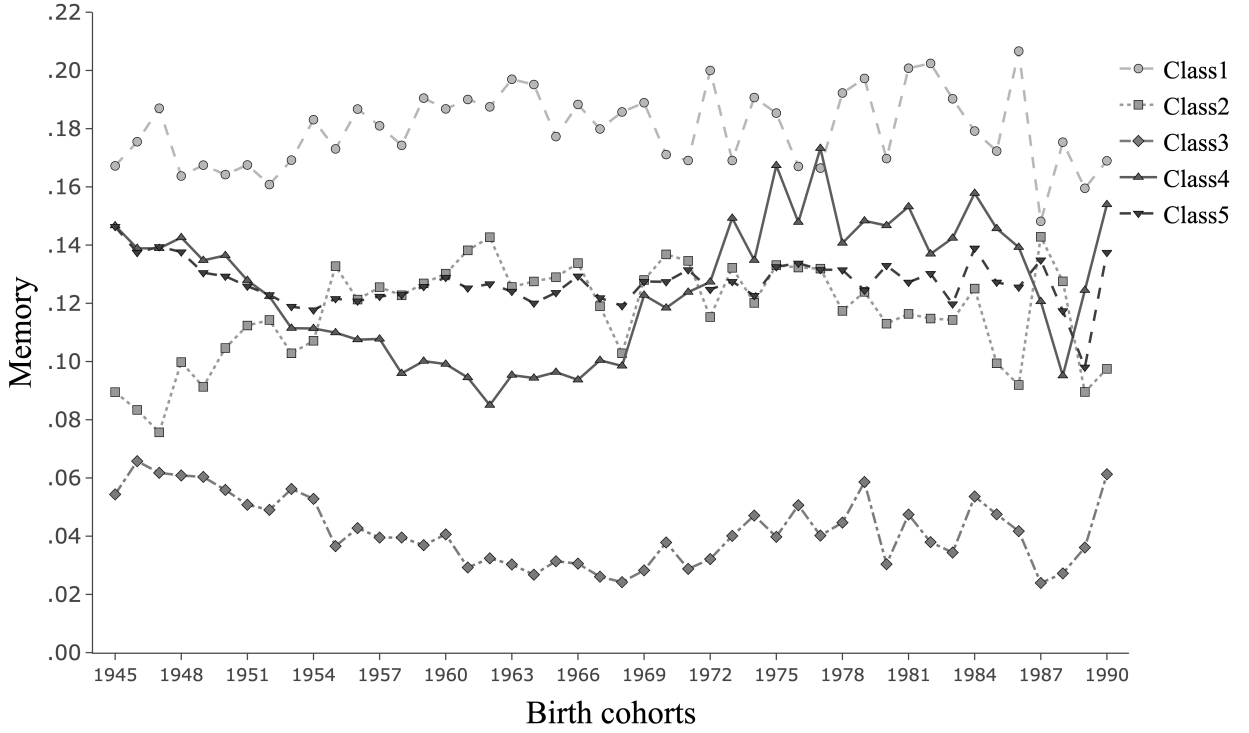
Notes: Shaded areas represent 95% confidence intervals.

In addition to measuring memory as distance, we also examine how quickly the influence of class origins dissipates across generations. As mentioned previously, the Markov chains converge to their steady state, at which point the influence of class origins has vanished entirely, within four generations for all cohorts—that is, $t^* \leq 4$. To characterize the pace of this convergence, Figure 6 reports Δ_{AIM}, which captures the proportion of memory eliminated by the second generation of the synthetic dynasties. In other words, the figure illustrates the rate at which memory decays over the first two generations of the dynasties. For all cohorts, more than 70% of memory is eliminated by generation $t = 2$, indicating a relatively rapid rate of decay throughout the period. This rate varies modestly across cohorts: memory loss hovers around 80% for cohorts born before 1955

and then declines to around 75% thereafter. Taken together, these results suggest that intergenerational memory—including its magnitude, persistence, and rate of decay—have remained largely stable during the era of rising inequality.

Figure 7 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 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.

Figure 7: 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.

The figure reveals nontrivial variation in memory across class origins. Class 1 (higher-grade professionals, administrators, and managers) consistently exhibits the highest level of memory, rising slightly from about .17 among earlier cohorts to nearly .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 decline among cohorts born through the 1960s, followed by a sharp upward trend for subsequent cohorts. This reversal suggests a renewed influence of these origins on descendants' occupational destinations. Among several cohorts born since 1970, memory for class 4 approaches the high levels observed at the top of the hierarchy for class 1.

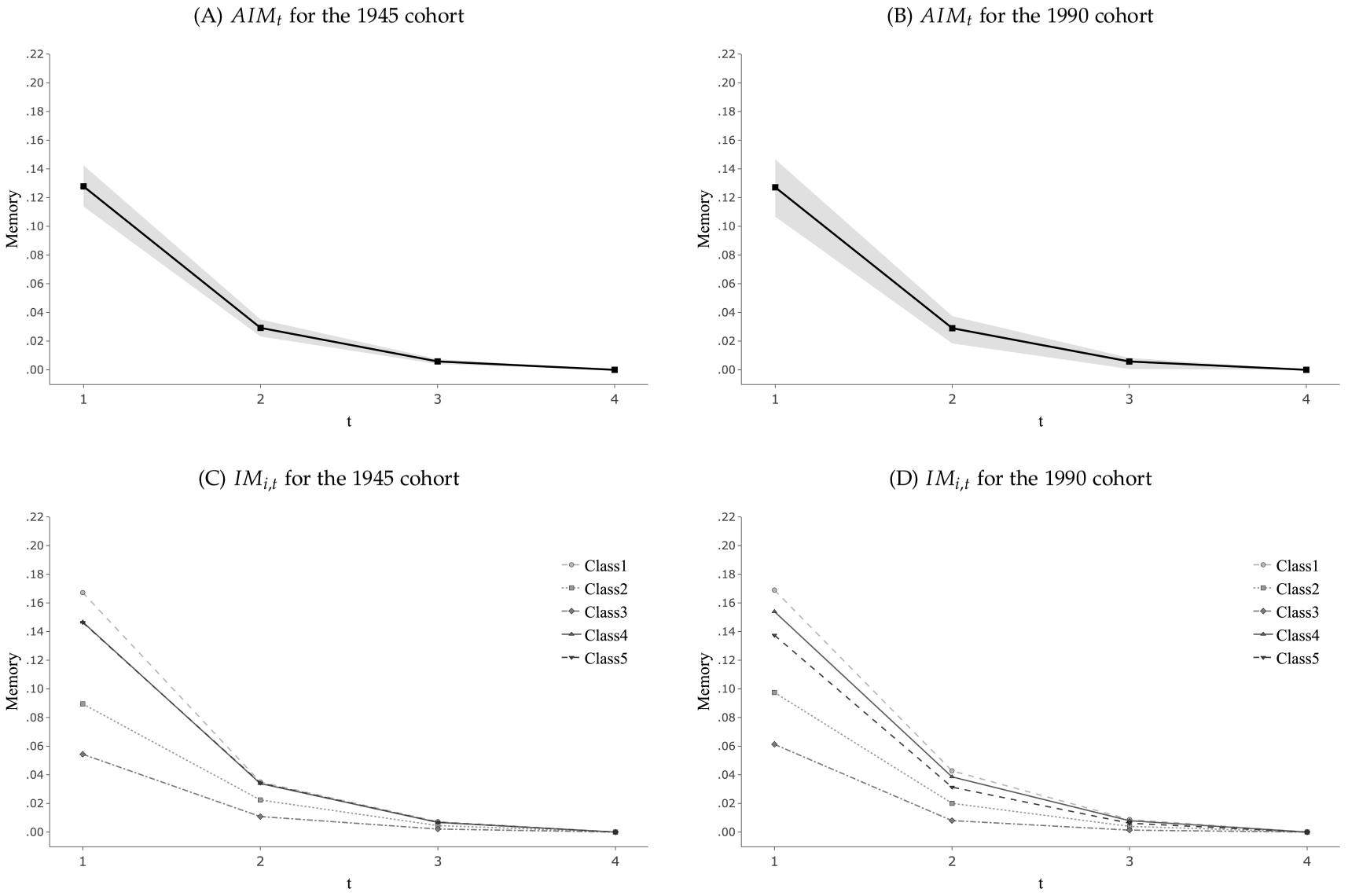
By contrast, in the middle of the occupational hierarchy, class 3 (higher-grade routine non-manual workers, technicians, and supervisors) stands out for its consistently low level of memory across all cohorts. Moreover, the limited influence of these origins has declined slightly over time.

Figure 8 plots measures of memory across generations, separately for the 1945 and 1990 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 7. 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 8 show that aggregate intergenerational memory decays in much the same way for both the 1945 and 1990 birth cohorts. In each case, it begins between .12 and .14 at generation $t = 1$, drops to about .04 by generation $t = 2$, and approaches zero thereafter. However, despite these aggregate similarities, Panels C and D suggest small shifts in the dissipation of memory for specific class origins. In particular, for the 1990 cohort, there are faint indications that memory associated with the professional, administrative, and managerial classes (classes 1 and 2) fades more slowly than for the 1945 cohort.

To summarize, intergenerational memory has remained mostly stable across cohorts who grew up or entered the labor market during the era of rising inequality. Beneath this aggregate stability, we uncover modest evidence that the influence of particular class origins may have shifted in offsetting ways. 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.

Figure 8: Memory across synthetic generations in the 1945 and 1990 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.

4.4 Comparison with Traditional Measures of Association

In this section, we compare results from our synthetic dynasty analysis, which conceptualized mobility as movement and memory, to more conventional measures that assess mobility as association. Whereas measures of movement capture departures from complete immobility, and measures of memory capture departures from multi-generational equality of opportunity, measures of association assess deviations from statistical independence between parental origins and child destinations. When child destinations are independent of parental origins, equality of opportunity holds not only for distal generations within synthetic dynasties but also in the immediate transition from parents to children. Thus, zero association implies zero memory. However, while higher levels of association typically imply greater memory, nonzero measures of association alone do not precisely indicate how far or how quickly dynasties converge to a state in which ancestral origins no longer predict the the destinations of descendants.

Typically, measures of association aim to capture the strength of dependence between parental origins and child destinations while remaining insensitive to shifts in the marginal distribution of classes. To this end, a standard practice is to estimate a log-multiplicative layer effect model, in which the natural logarithms of odds ratios are given by functions of the model's coefficients. Formally, 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.

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. The θ_{ij} parameters, then, encode 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 θ_{ij} and ϕ_k yield the odds ratios that summarize how destinations depend on origins in each cohort k.

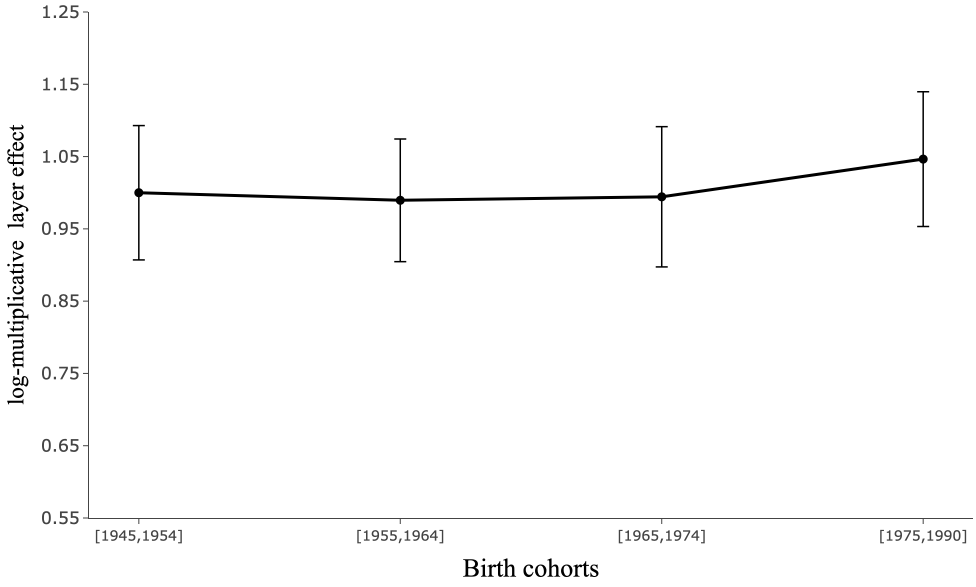
Figure 9 plots a series of estimated layer effects across cohorts. To improve the precision of these estimates, we fit the model in Equation 9 after grouping cohorts into 5-year or approximately 10-year bins. The results suggest that the strength of the origin-

Figure 9: 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.

destination associations has remained fairly stable over time. For example, we estimate that the origin-destination associations for cohorts born after 1975 are only about 5% stronger than for cohorts born earlier. These differences are small, and they all lie within the margin of sampling error. In general, any changes are difficult to detect in this analysis because the estimated layer effects are quite imprecise even after binning cohorts, with confidence intervals consistently spanning a wide range of values.

To summarize, our analysis of mobility as association, using log-multiplicative models, provides little evidence of an upward or downward trend. These findings are consistent with results from our analysis based on Markov chains, which capture mobility in terms of movement and memory. Each approach highlights a different aspect of class mobility and brings distinct advantages. Log-linear and log-multiplicative models isolate the strength of origin-destination associations net of differences in class composition. Markov chains, by contrast, trace intergenerational transitions and the persistent influence of class origins across generations within synthetic dynasties. They also avoid functional form assumptions and generate measures that can be easily disaggregated to reveal class-specific dynamics. Taken together, these complementary approaches indicate that class mobility—whether conceptualized and measured as movement and memory in Markov chains or as association in parametric models—has remained largely unchanged throughout the era of rising inequality.

4.5 Robustness Analyses

To assess the robustness of our findings, we conducted a series of ancillary analyses examining the sensitivity of our conclusions to alternative measures, analytic samples, and smoothing techniques.

Appendix D presents trends in mobility based on several different measures of movement, memory, and association. For movement, we additionally consider class outflows—both in the observed transition matrix and in the steady state of a Markov chain—as well as mean first passage time, a measure that characterizes transitions between specific pairs of classes across generations within synthetic dynasties. For memory, we also compute the maximum distance to the stationary distribution and the second-largest eigenvalue of the transition matrix, which reflects how fast a Markov chain converges to its steady state (Levin et al., 2009; Sommers and Conlisk, 1979). Finally, for association, we examine the Altham index (Altham, 1970), which measures the extent to which the observed odds ratios in a mobility table depart from independence, and the Hellinger index, which is based on a discrete copula (Coleman and Lukina, 2025; Geenens and

Lafaye de Micheaux, 2022). Across all these approaches, the results are broadly consistent: they indicate that each dimension of mobility has mostly remained stable.

To examine potential heterogeneity by gender, we also estimated mobility trends separately for father–son, father–daughter, and mother–child pairs, rather than focusing on all father–child pairs as in the analyses discussed previously. These results are reported in Appendix E. Because the GSS only began collecting information on maternal occupations in 1994, analyses of mother–child pairs are based on smaller samples and a shorter series of cohorts, which reduces precision and precludes separate analyses for sons and daughters. While mobility *levels* differ by gender, the *trends* are broadly similar: across cohorts, most measures of movement and memory appear fairly stable. Thus, we find little evidence of either upward or downward trends in our focal measures when stratifying by gender, although the more limited statistical power of these analyses requires that they be interpreted cautiously.

Our sample is not large enough to estimate trends separately for each racial group in the GSS, but we conducted a parallel analysis that excludes non-White respondents in an effort to explore potential heterogeneity by race. These results, reported in Appendix F, are nearly identical to those based on the full analytic sample discussed previously.

Finally, in addition to smoothing our data with penalized splines, we evaluated several other strategies for addressing sparsity and improving precision. Specifically, we replicated our analysis of movement and memory in synthetic dynasties using transition matrices constructed by binning cohorts into 5-year and 10-year intervals. For reference, we also computed estimates from the raw transition matrices for individual birth cohorts, without any smoothing. These results are presented in Appendix G. As expected, the raw transition matrices introduce considerable sampling variability, but the point estimates exhibit broadly similar patterns—despite fluctuating much more from cohort to cohort, they still show no discernible trend. Binning cohorts substantially reduces sampling variability and produces trend estimates for all our measures that align with those based on smoothing splines, albeit at a coarser temporal resolution.

5 Discussion

This study examined whether patterns of class mobility shifted during an era of rising inequality in the U.S. Focusing on Americans born between 1945 and 1990, we tracked trends among cohorts who grew up or entered the labor market after inequality began to increase in the 1970s. To evaluate competing theoretical perspectives that predict different trends over this period, we adopted a nonparametric approach that constructs

synthetic dynasties with Markov chains. This approach simulates the long-run trajectories of hypothetical family lines based on observed cross-sectional links between parents and their children. From these simulations, we analyzed novel measures of mobility that variously capture the amount of movement between classes and the persistent influence of class origins across generations.

Our analysis provides little evidence that mobility declined across cohorts born between 1945 and 1990. Overall mobility, which captures the amount of movement across classes from one generation to the next, was largely stable. This stability was evident both in the observed transitions between parents and their children and among synthetic generations in the Markov steady state, where movements no longer reflect changes in the marginal distribution of classes. Intergenerational memory, which captures how class origins influence the destinations of descendants within synthetic dynasties, also changed little throughout the era of rising inequality. These trends in movement and memory align with more traditional measures of mobility conceptualized as association, and they appear robust to alternative sample definitions, class typologies, and measurement strategies.

Despite this overall stability, trends in movement and memory varied by class origin. Among the upper and lower classes, we found declining movement and increasing memory across cohorts. In contrast, among the middle classes, we observed increases in movement and declines in memory. While these patterns suggest a potential decline in mobility at the top and bottom of the class structure, and an increase in the middle, the changes we document are small and should be interpreted with caution. Nevertheless, there is at least some evidence that the flat trends in our summary measures may reflect offsetting dynamics among different classes.

These findings challenge several established theories of social mobility in different ways. First, they do not align with modernization theory (Lipset and Bendix, 1959; Featherman and Hauser, 1978), which predicts a steady increase in mobility as societies grow economically, develop technologically, and expand access to education. Second, our results provide only limited support for the contemporary view that rising inequality will reduce mobility (Andrews and Leigh, 2009; Durlauf and Seshadri, 2017; Mitnik et al., 2016). Although we observe some faint indications of declining mobility and increasing persistence at the poles of the class hierarchy, these changes are relatively small and our aggregate measures are flat. Overall, then, our results are most consistent with the FJH hypothesis (Featherman et al., 1975), which predicts that the relationship between class origins and destinations should remain relatively stable over time. Even here, however, our findings are only partly consistent, as we observe stability in aggregate measures

of movement, memory, and association that appears to reflect shifts in the underlying pattern of mobility across different class origins. Thus, all three perspectives warrant at least some reconsideration, as none fully align with the trends we document during the contemporary period of rising inequality in the U.S.

What are the social and political implications of rising inequality alongside relatively stable levels of class mobility? When the pecuniary rewards attached to different classes of occupations become increasingly unequal (Weeden et al., 2007; Zhou and Wodtke, 2019), but the chances of moving across classes remain largely unchanged, public concerns about growing inequality may be tempered and support for redistribution blunted (Alesina et al., 2018; Manza and Brooks, 2020). At the same time, stable mobility in a context of rising inequality may amplify the significance of "mobility effects," which refer to the social and psychological consequences of moving up or down the class hierarchy (Sorokin, 1927; Wei and Xie, 2025). Upward mobility may feel especially rewarding, while downward mobility carries steeper penalties. As a result, when mobility is still prevalent but its stakes are higher, the divergent experiences of upward or downward movement could deepen social and political divisions.

Beyond its empirical and theoretical contributions, our study also introduced novel methods for analyzing class mobility using Markov chains. This approach conceptualizes mobility as patterns of movement and memory across generations of synthetic dynasties, highlighting aspects of the mobility process that may not be apparent from measures of association between parental origins and child destinations alone. In this way, it provides a valuable complement to established methods, such as log-linear models or other measures based on odds ratios. A key feature of our approach is that it requires no parametric assumptions, which may distort analyses of trends when violated. Markov chains and synthetic dynasty analyses therefore hold the potential for wide application in the social sciences, wherever there is interest in examining additional dimensions of the mobility process beyond origin-destination associations without restrictive modeling assumptions.

These contributions must, of course, be weighed against several limitations of our study. First, we are unable to provide precise estimates of trends separately by race, gender, or geographic region owing to small samples for certain subgroups. This is a nontrivial constraint, as patterns of mobility could have evolved quite differently across demographic subpopulations during the era of rising inequality (e.g., Chetty et al. 2024; Durlauf et al. 2024).

Second, our analyses focused exclusively on aggregate occupational classes. Although aggregate typologies provide a useful summary of an individual's location within

a complex, multidimensional system of social stratification (Wodtke, 2017; Zhou and Wodtke, 2019), they inevitably obscure some features of the mobility process that are better captured by more detailed occupational categories or "microclasses" (Weeden and Grusky, 2005). In principle, Markov chains and synthetic dynasty measures can be constructed from transition matrices based on either aggregate or disaggregate class typologies. In practice, however, the GSS sample is too small for trend analyses of microclass mobility, as it produces extremely sparse tables at the level of detailed occupations that preclude reliable estimation.

Another limitation is that small sample sizes and the potential for life-cycle bias make it difficult to confidently analyze a longer series of cohorts. Expanding the analysis to include both younger and older cohorts introduces two problems: greater sparsity and systematic age differences in when members of these cohorts are observed. Older cohorts born before 1945 are disproportionately interviewed by the GSS later in their careers, when occupational attainment is at its peak and non-random selection out of the labor force is common. In contrast, younger cohorts born after 1990 are disproportionately observed when their careers are just beginning and many remain in school. These differences amplify the risk that apparent trends are actually artifacts of selection or life-cycle bias rather than genuine changes in mobility across cohorts.

Nevertheless, extending our series of cohort estimates backward suggests a noteworthy pattern. As shown in Appendix H, cohorts born before 1945 exhibit noisy but suggestive evidence of rising mobility—characterized by pronounced increases in movement and declines in memory and association. These trends level off around the time our focal series of cohorts begins, indicating that the stable pattern we observe from 1945 onward may not represent continuity with the past but rather a break with a previous trajectory of increasing mobility. One possible explanation is that the mechanisms highlighted by modernization theory, such as technological change and educational expansion, continued to promote mobility, while mechanisms emphasized by the inequality perspective, such as polarized investments in children and deepening segregation, began to suppress it, potentially offsetting one another. This interpretation is admittedly speculative, however, both because estimating reliable trends for distal cohorts is challenging in the GSS and because our study does not directly examine the mechanisms thought to underlie these trends.

The limitations of our study point toward promising directions for future research. Directly analyzing the influence of educational expansion versus polarized investments in children on movement and memory will be essential. This could be achieved by integrating our synthetic dynasty approach with inverse probability weighting to con-

struct counterfactual trends in mobility under hypothetical scenarios where, for example, parental spending on children remains constant over time within each origin class. These empirical and methodological extensions would help disentangle the potentially opposing forces shaping trends in mobility over the past several decades.

In conclusion, the era of rising inequality in the U.S. has not been marked by a clear decline in class mobility, but the subtle changes we do observe warrant ongoing attention. The full impact of heightened inequality may still be unfolding, especially for cohorts entering the labor market today. These individuals spent their entire childhood in a highly unequal society and are now beginning careers amid technological and political changes that could transform labor demand and exacerbate inequality even further (Manning, 2024; Rockall et al., 2025). Although class mobility appears to have remained mostly stable thus far, continued scrutiny of signals suggesting a decline in equality of opportunity will remain essential as the economy and social policy continue to evolve.

Notes

1. The concept we refer to as exchange mobility has also been commonly described as "circulation mobility" in earlier work (e.g., Featherman and Hauser 1978; Jones 1985).
2. Formally, these limiting properties require that P is primitive, meaning that there exists a positive integer v such that P^v is strictly positive.
3. 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.

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References

Aaronson, D. and Mazumder, B. (2008). Intergenerational Economic Mobility in the United States, 1940 to 2000. *Journal of Human Resources*, 43(1):139–172.

Alesina, A., Stantcheva, S., and Teso, E. (2018). Intergenerational Mobility and Preferences for Redistribution. *American Economic Review*, 108(2):521–554.

Altham, P. (1970). The Measurement of Association of Rows and Columns for an r×s Contingency Table. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 32(1):63–73.

Andrews, D. and Leigh, A. (2009). More Inequality, Less Social Mobility. *Applied Economics Letters*, 16(15):1489–1492.

Bailey, M. J. and Dynarski, S. M. (2011). Inequality in Postsecondary Education. In Duncan, G. J. and Murnane, R. J., editors, *Whither Opportunity? Rising Inequality, Schools, and Children's Life Chances*. Russell Sage Foundation, New York, NY.

Bartholomew, D. J. (1967). *Stochastic Models for Social Processes*. Wiley Series in Probability and Statistics. Wiley, New York.

Bell, D. (1976). *The Coming of Post-Industrial Society*. Basic Books, New York.

Beller, E. (2009). Bringing Intergenerational Social Mobility Research into the Twenty-first Century: Why Mothers Matter. *American Sociological Review*, 74(4):507–528.

Beller, E. and Hout, M. (2006). Intergenerational Social Mobility: The United States in Comparative Perspective. *The Future of Children*, 16(2):19–36.

Bhatia, R. (1997). *Matrix Analysis*. Graduate texts in mathematics. Springer, New York.

Blanden, J. (2013). Cross-Country Rankings in Intergenerational Mobility. *Journal of Economic Surveys*, 27:38–73.

Blau, P. M. and Duncan, O. D. (1967). *The American Occupational Structure*. Wiley, New York.

Bloome, D. (2015). Income Inequality and Intergenerational Income Mobility in the United States. *Social Forces*, 93(3):1047–1080.

Blume, L., Cholli, N., Durlauf, S., and Lukina, A. (2025). Immobility as Memory: Some New Approaches to Characterizing Intergenerational Persistence via Markov Chains. *Sociological Methods & Research*, 54(4):1396–1434.

Boudon, R. (1973). *Mathematical Structures of Social Mobility*, volume 2. The Josey Bass, San Francisco, California.

Breen, R. (2004). *Social Mobility in Europe*. Oxford University Press, Oxford.

Breen, R. (2010). Educational Expansion and Social Mobility in the 20th Century. *Social Forces*, 89(2):365–388.

Breen, R. and Müller, W. (2020). *Education and Intergenerational Social Mobility in Europe and the United States*. Stanford University Press, Stanford.

Bucca, M. and Urbina, D. R. (2021). Lasso Regularization for Selection of Log-linear Models: An Application to Educational Assortative Mating. *Sociological Methods & Research*, 50(4):1763–1800.

Bukodi, E. and Goldthorpe, J. H. (2018). Social Inequality and Social Mobility: Is There an Inverse Relation? *SocArXiv*, 10:31235.

Butaeva, K., Chen, L., Durlauf, S., and Park, A. (2025). A Tale of Two Transitions: Mobility Dynamics in China and Russia after Central Planning. Working Paper 34124, National Bureau of Economic Research.

Bénabou, R. (1996). Heterogeneity, Stratification, and Growth: Macroeconomic Implications of Community Structure and School Finance. *The American Economic Review*, 86(3):584–609.

Chetty, R., Dobbie, W. S., Goldman, B., Porter, S., and Yang, C. (2024). Changing Opportunity: Sociological Mechanisms Underlying Growing Class Gaps and Shrinking Race Gaps in Economic Mobility. Working Paper 32697, National Bureau of Economic Research.

Chetty, R., Grusky, D., Hell, M., Hendren, N., Manduca, R., and Narang, J. (2017). The Fading American Dream: Trends in Absolute Income Mobility Since 1940. *Science*, 356(6336):398–406.

Chetty, R., Hendren, N., and Katz, L. F. (2016). The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Project. *American Economic Review*, 106(4):855–902.

Chetty, R., Hendren, N., Kline, P., Saez, E., and Turner, N. (2014). Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility. *American Economic Review*, 104(5):141–147.

Coleman, T. and Lukina, A. (2025). Discrete Copulas and Rank Correlation: New Measures for Assortative Matching. *University of Chicago Stone Center Working Paper Series*, 25-11.

Conlisk, J. and Sommers, P. (1979). Eigenvector Status Proxies in Markov Chain Mobility Models. *Sociological Methods & Research*, 8(2):159–178.

Connelly, R., Gayle, V., and Lambert, P. S. (2016). A Review of Occupation-based Social Classifications for Social Survey Research. *Methodological Innovations*, 9:2059799116638003.

Corak, M. (2006). Do Poor Children Become Poor Adults? Lessons for Public Policy from a Cross Country Comparison of Generational Earnings Mobility. In Creedy, J. and Kalb, G., editors, *Dynamics of Inequality and Poverty*, volume 13 of *Research on Economic Inequality*. Elsevier, Amsterdam.

Corak, M. (2013). Income Inequality, Equality of Opportunity, and Intergenerational Mobility. *Journal of Economic Perspectives*, 27(3):79–102.

Dardanoni, V. (1993). Measuring Social Mobility. *Journal of Economic Theory*, 61(2):372–394.

Davern, M., Bautista, R., Freese, J., Herd, P., and Morgan, S. L. (2025). General Social Survey 1972-2024 [Machine-readable data file]. Data accessed at https://gssdataexplorer.norc.org.

Davis, J. M. and Mazumder, B. (2024). The Decline in Intergenerational Mobility after 1980. *Review of Economics and Statistics*, 108(1):1–15.

Davison, A. C. and Hinkley, D. V. (1997). *Bootstrap Methods and Their Application*. University Press, Cambridge.

DeParle, J. (2012). Harder for Americans to Rise from Lower Rungs. *The New York Times*. Available from http://www.nytimes.com/2012/01/05/us/harder-for-americans-to-rise-from-lower-rungs.html.

DiPrete, T. A. (2020). The Impact of Inequality on Intergenerational Mobility. *Annual Review of Sociology*, 46(1):379–398.

Durlauf, S. N. (1996). A Theory of Persistent Income Inequality. *Journal of Economic Growth*, 1(1):75–93.

Durlauf, S. N., Kim, G., Lee, D., and Song, X. (2024). The Evolution of Black-White Differences in Occupational Mobility Across Post-Civil War America. Working Paper 32370, National Bureau of Economic Research.

Durlauf, S. N., Kourtellos, A., and Tan, C. M. (2022). The Great Gatsby Curve. *Annual Review of Economics*, 14(1):571–605.

Durlauf, S. N. and Seshadri, A. (2017). Understanding the Great Gatsby Curve. In *NBER Macroeconomics Annual 2017*, volume 32, pages 333–393. University of Chicago Press.

Erikson, R. and Goldthorpe, J. H. (1992). *The Constant Flux: A Study of Class Mobility in Industrial Societies*. Clarendon Press, Oxford.

Erikson, R. and Goldthorpe, J. H. (2010). Has Social Mobility in Britain Decreased? Reconciling Divergent Findings on Income and Class Mobility. *The British Journal of Sociology*, 61(2):211–230.

Erikson, R., Goldthorpe, J. H., and Portocarero, L. (1979). Intergenerational Class Mobility in Three Western European Societies: England, France and Sweden. *The British Journal of Sociology*, 30(4):415–441.

Featherman, D. L. and Hauser, R. M. (1978). *Opportunity and Change*. Academic Press, New York.

Featherman, D. L., Jones, F. L., and Hauser, R. M. (1975). Assumptions of Social Mobility Research in the US: The Case of Occupational Status. *Social Science Research*, 4(4):329–360.

Fiel, J. E. (2020). Great Equalizer or Great Selector? Reconsidering Education as a Moderator of Intergenerational Transmissions. *Sociology of Education*, 93(4):353–371.

Fogli, A., Guerrieri, V., Ponder, M., and Prato, M. (2025). The End of the American Dream? Inequality and Segregation in US Cities. *Journal of Political Economy*. Forthcoming.

Geenens, G. and Lafaye de Micheaux, P. (2022). The Hellinger Correlation. *Journal of the American Statistical Association*, 117(538):639–653.

Gray-Lobe, G., Pathak, P. A., and Walters, C. R. (2022). The Long-Term Effects of Universal Preschool in Boston. *The Quarterly Journal of Economics*, 138(1):363–411.

Grinstead, C. M. and Snell, J. L. (1997). *Introduction to Probability*. American Mathematical Society, Providence, RI.

Grusky, D. B. and Hauser, R. M. (1984). Comparative Social Mobility Revisited: Models of Convergence and Divergence in 16 Countries. *American Sociological Review*, 49(1):19–38.

Haldane, A. (2025). Governments are Chasing the Wrong Rainbows. *Financial Times*. Available from https://www.ft.com/content/50e79018-83ac-4cf0-8747-237a8696baa6?utm_source=chatgpt.com.

Hassler, J., Rodríguez Mora, J. V., and Zeira, J. (2007). Inequality and Mobility. *Journal of Economic Growth*, 12(3):235–259.

Hauser, R. M., Koffel, J. N., Travis, H. P., and Dickinson, P. J. (1975). Temporal Change in Occupational Mobility: Evidence for Men in the United States. *American Sociological Review*, 40(3):279–297.

Heckman, J. J., Moon, S. H., Pinto, R., Savelyev, P. A., and Yavitz, A. (2010). The Rate of Return to the HighScope Perry Preschool Program. *Journal of Public Economics*, 94(1):114–128.

Hertel, F. R. and Groh-Samberg, O. (2019). The Relation between Inequality and Intergenerational Class Mobility in 39 Countries. *American Sociological Review*, 84(6):1099–1133.

Hout, M. (1988). More Universalism, Less Structural Mobility: The American Occupational Structure in the 1980s. *American Journal of Sociology*, 93(6):1358–1400.

Johnson, R. C. and Jackson, C. K. (2019). Reducing Inequality through Dynamic Complementarity: Evidence from Head Start and Public School Spending. *American Economic Journal: Economic Policy*, 11(4):310–49.

Jones, F. L. (1985). Structural and Circulation Mobility are Alive and Well. *Sociology*, 19(1):139–142.

Kemeny, J. and Snell, J. (1976). *Finite Markov Chains*, volume 26 of *Undergraduate Texts in Mathematics*. Springer-Verlag, New York.

Killewald, A., Pfeffer, F. T., and Schachner, J. N. (2017). Wealth Inequality and Accumulation. *Annual Review of Sociology*, 43:379–404.

Kornrich, S. and Furstenberg, F. (2013). Investing in Children: Changes in Parental Spending on Children, 1972–2007. *Demography*, 50(1):1–23.

Krueger, A. (2012). The Rise and Consequences of Inequality. *Presentation made to the Center for American Progress, January 12th*.

Lee, C.-I. and Solon, G. (2009). Trends in Intergenerational Income Mobility. *The Review of Economics and Statistics*, 91(4):766–772.

Levin, D. A., Peres, Y., and Wilmer, E. L. (2009). *Markov Chains and Mixing Times*. American Mathematical Society, Providence, RI.

Lipset, S. M. and Bendix, R. (1959). *Social Mobility in Industrial Society*. University of California Press, Berkeley.

Logan, J. R., Foster, A., Xu, H., and Zhang, W. (2020). Income Segregation: Up or Down, and for Whom? *Demography*, 57(5):1951–1974.

Lucas, S. R. (2001). Effectively Maintained Inequality: Education Transitions, Track Mobility, and Social Background Effects. *American Journal of Sociology*, 106(6):1642–1690.

Manning, S. (2024). AI's Impact on Income Inequality in the US: Interpreting Recent Evidence and Looking to the Future. *Brookings*. Available from https://www.brookings.edu/articles/ais-impact-on-income-inequality-in-the-us/.

Manza, J. and Brooks, C. (2020). Mobility Optimism in an Age of Rising Inequality. *The Sociological Quarterly*, 62(2):343–368.

Marx, K. and Engels, F. (1942). *Karl Marx and Frederick Engels: Selected Correspondence*. International Publishers, New York.

McClendon, M. J. (1977). Structural and Exchange Components of Vertical Mobility. *American Sociological Review*, 42(1):56–74.

Meyer, C. D. (2000). *Matrix Analysis and Applied Linear Algebra*. Society for Industrial and Applied Mathematics (SIAM), Philadelphia.

Mitnik, P. A., Cumberworth, E., and Grusky, D. B. (2016). Social Mobility in a High-inequality Regime. *The ANNALS of the American Academy of Political and Social Science*, 663(1):140–184.

Morgan, S. L. (2017). A Coding of Social Class for the General Social Survey. GSS Methodological Report 125, NORC at the University of Chicago, Chicago, IL.

Morris, M. and Western, B. (1999). Inequality in Earnings at the Close of the Twentieth Century. *Annual Review of Sociology*, 25:623–657.

Mouw, T. and Kalleberg, A. L. (2010). Occupations and the Structure of Wage Inequality in the United States, 1980s to 2000s. *American Sociological Review*, 75(3):402–431.

Nybom, M. and Stuhler, J. (2016). Heterogeneous Income Profiles and Lifecycle Bias in Intergenerational Mobility Estimation. *Journal of Human Resources*, 51(1):239–268.

Owens, A., Reardon, S. F., and Jencks, C. (2016). Income Segregation Between Schools and School Districts. *American Educational Research Journal*, 53(4):1159–1197.

Pfeffer, F. T. and Hertel, F. R. (2015). How has Educational Expansion Shaped Social Mobility Trends in the United States? *Social Forces*, 94(1):143–180.

Piketty, T. and Saez, E. (2003). Income Inequality in the United States, 1913–1998. *The Quarterly Journal of Economics*, 118(1):1–41.

Prais, S. J. (1955). Measuring Social Mobility. *Journal of the Royal Statistical Society. Series A (General)*, 118(1):56–66.

Putnam, R. D. (2015). *Our Kids: The American Dream in Crisis*. Simon & Schuster, New York, NY.

Raftery, A. E. and Hout, M. (1993). Maximally Maintained Inequality: Expansion, Reform, and Opportunity in Irish Education. *Sociology of Education*, 66(1):41–62.

Rockall, E., Mendes Tavares, M., and Pizzinelli, C. (2025). AI Adoption and Inequality. *IMF Working Papers*, 25(68):1–64.

Roemer, J. E. (1998). *Equality of Opportunity*. Harvard University Press, Cambridge, MA.

Saez, E. and Zucman, G. (2016). Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data. *Quarterly Journal of Economics*, 131(2):519–578.

Saez, E. and Zucman, G. (2020). The Rise of Income and Wealth Inequality in America: Evidence from Distributional Macroeconomic Accounts. *Journal of Economic Perspectives*, 34(4):3–26.

Schneider, D., Hastings, O. P., and LaBriola, J. (2018). Income Inequality and Class Divides in Parental Investments. *American Sociological Review*, 83(3):475–507.

Shorrocks, A. (1978). The Measurement of Mobility. *Econometrica: Journal of the Econometric Society*, 46(5):1013–1024.

Singer, B. and Spilerman, S. (1976). The Representation of Social Processes by Markov Models. *American Journal of Sociology*, 82(1):1–54.

Sobel, M. E., Hout, M., and Duncan, O. D. (1985). Exchange, Structure, and Symmetry in Occupational Mobility. *American Journal of Sociology*, 91(2):359–372.

Sommers, P. M. and Conlisk, J. (1979). Eigenvalue Immobility Measures for Markov Chains. *Journal of Mathematical Sociology*, 6(2):253–276.

Song, X., Massey, C. G., Rolf, K. A., Ferrie, J. P., Rothbaum, J. L., and Xie, Y. (2020). Long-term Decline in Intergenerational Mobility in the United States Since the 1850s. *Proceedings of the National Academy of Sciences*, 117(1):251–258.

Sorokin, P. A. (1927). *Social Mobility*. Harper and Brothers, New York.

Torche, F. (2015). Analyses of Intergenerational Mobility: An Interdisciplinary Review. *The Annals of the American Academy of Political and Social Science*, 657:37–62.

Treiman, D. J. (1970). Industrialization and Social Stratification. *Sociological Inquiry*, 40(2):207–234.

van de Werfhorst, H. G. (2024). Is Meritocracy Not So Bad After All? Educational Expansion and Intergenerational Mobility in 40 Countries. *American Sociological Review*, 89(6):1181–1213.

Wachter, K. W. (2014). *Essential Demographic Methods*. Harvard University Press, Cambridge, MA.

Weeden, K. A. and Grusky, D. B. (2005). The Case for a New Class Map. *American Journal of Sociology*, 111(1):141–212.

Weeden, K. A., Kim, Y.-M., Di Carlo, M., and Grusky, D. B. (2007). Social Class and Earnings Inequality. *American Behavioral Scientist*, 50(5):702–736.

Wei, L. and Xie, Y. (2025). Social Mobility as Causal Intervention. *Sociological Methods & Research*, 54(4):1463–1504.

Wodtke, G. T. (2017). Social Relations, Technical Divisions, and Class Stratification in the United States: An Empirical Test of the Death and Decomposition of Class Hypotheses. *Social Forces*, 95(4):1479–1508.

Wodtke, G. T., Elwert, F., and Harding, D. J. (2016). Neighborhood Effect Heterogeneity by Family Income and Developmental Period. *American Journal of Sociology*, 121(4):1168–1222.

Wodtke, G. T., Harding, D. J., and Elwert, F. (2011). Neighborhood Effects in Temporal Perspective: The Impact of Long-Term Exposure to Concentrated Disadvantage on High School Graduation. *American Sociological Review*, 76(5):713–736.

Wood, S. N. (2003). Thin Plate Regression Splines. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 65(1):95–114.

Wood, S. N. (2011). Fast Stable Restricted Maximum Likelihood and Marginal Likelihood Estimation of Semiparametric Generalized Linear Models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 73(1):3–36.

Xie, Y. (1992). The Log-multiplicative Layer Effect Model for Comparing Mobility Tables. *American Sociological Review*, pages 380–395.

Xie, Y. and Killewald, A. (2013). Intergenerational Occupational Mobility in Great Britain and the United States since 1850: Comment. *American Economic Review*, 103(5):2003–2020.

Zhou, X. (2015). Shrinkage Estimation of Log-odds Ratios for Comparing Mobility Tables. *Sociological Methodology*, 45(1):320–356.

Zhou, X. (2019). Equalization or Selection? Reassessing the Meritocratic Power of a College Degree in Intergenerational Income Mobility. *American Sociological Review*, 84(3):459–485.

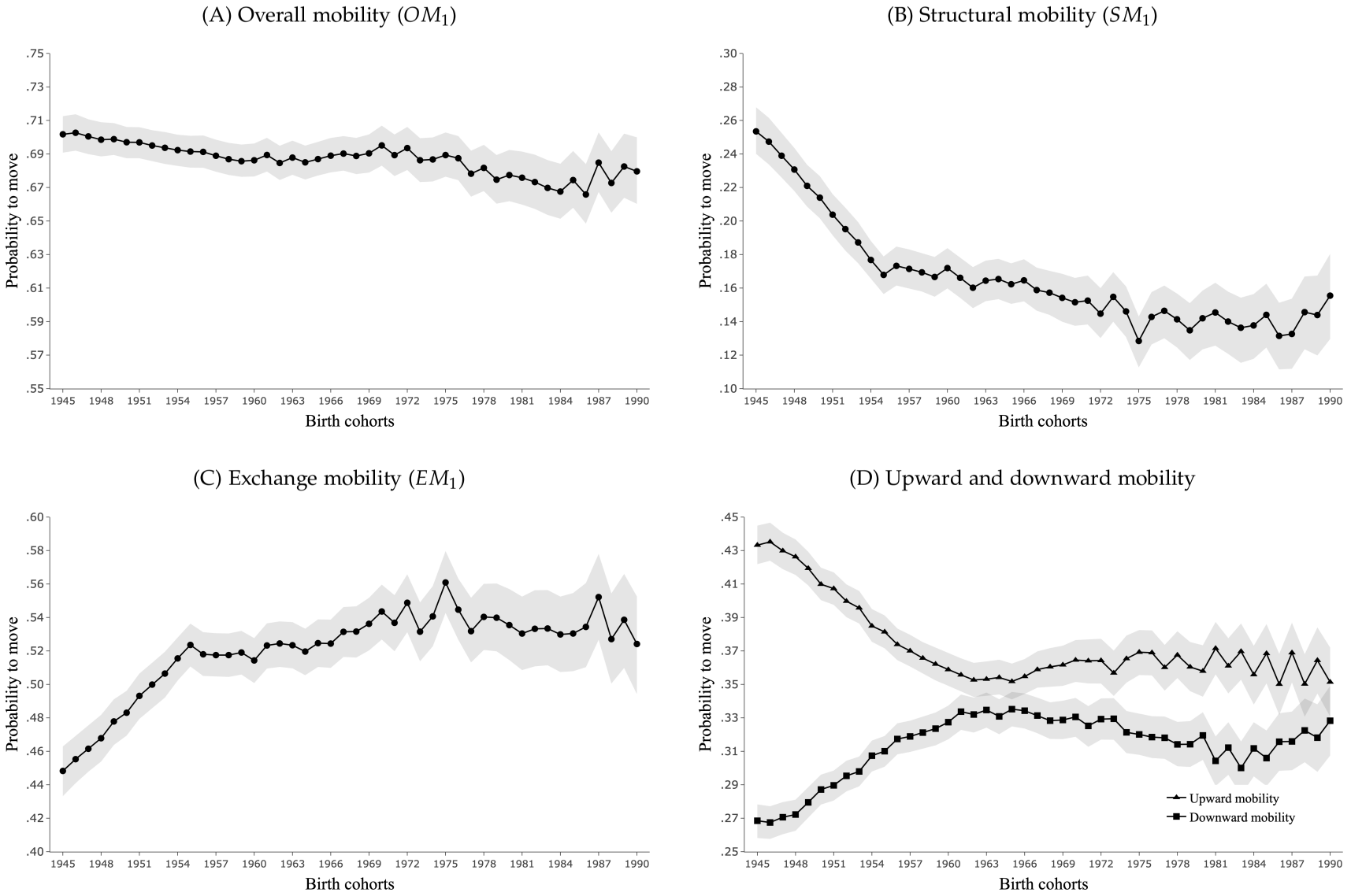
Zhou, X. and Wodtke, G. T. (2019). Income Stratification among Occupational Classes in the United States. *Social Forces*, 97(3):945–972.

Appendix

A Alternative Age Restrictions

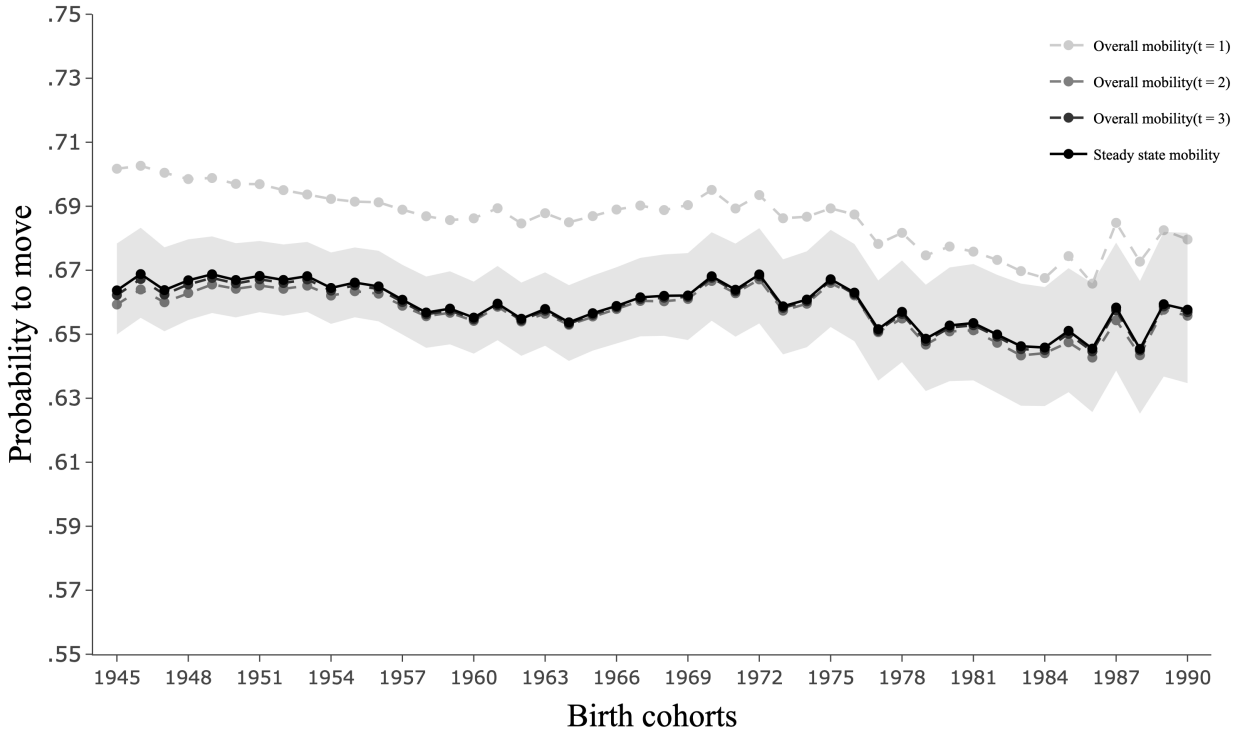
In this section, we replicate our main analyses after varying the age restriction applied to respondents at the time of their GSS interview, when information on their current occupations is collected. Specifically, we expand the sample to include older respondents by shifting the age window from 25–55 to 25–64 and also 30–64. As shown in Figures A.1 to A.8, these changes to the age range do not materially alter the estimated trends in movement, memory, or association. Across these samples, the trends remain largely flat, with at most a faint suggestion of declining mobility in some point estimates.

Figure A.1: Measures of movement at generation $t = 1$ computed from samples of respondents age 25-64



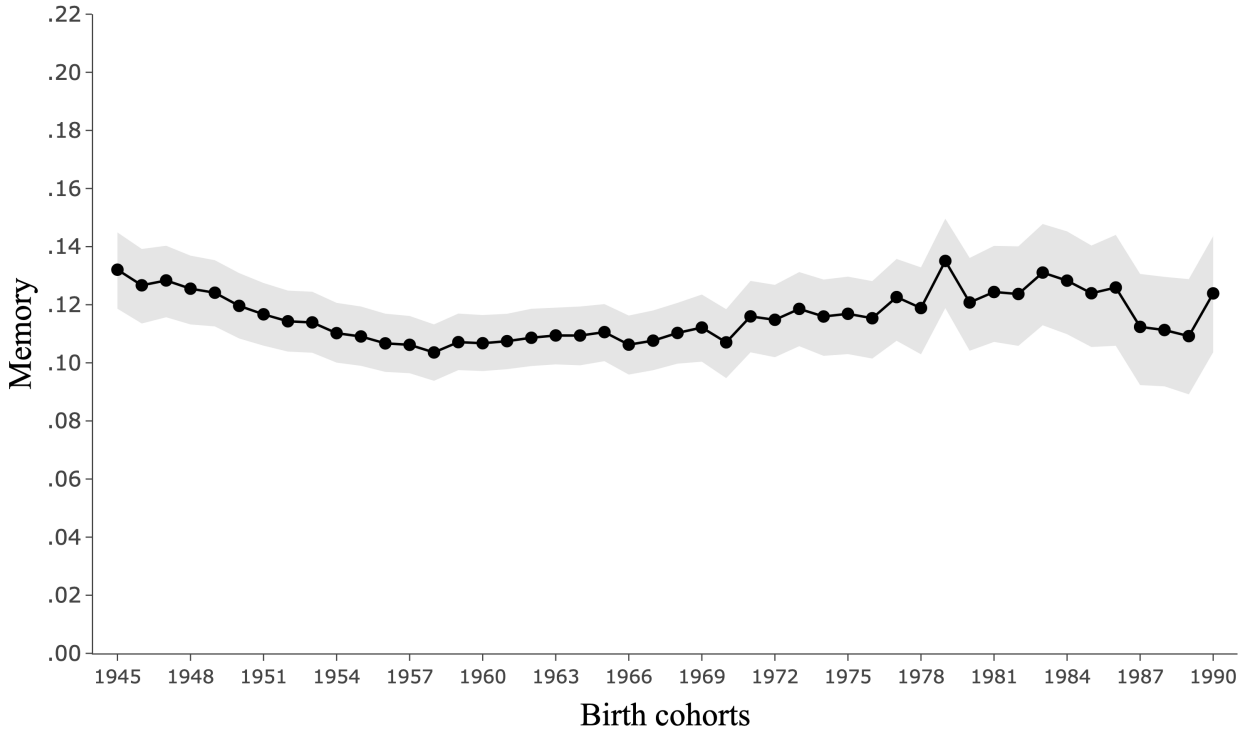
Notes: Shaded areas represent 95% confidence intervals.

Figure A.2: Overall mobility (OM_t) across synthetic generations computed from samples of respondents age 25-64



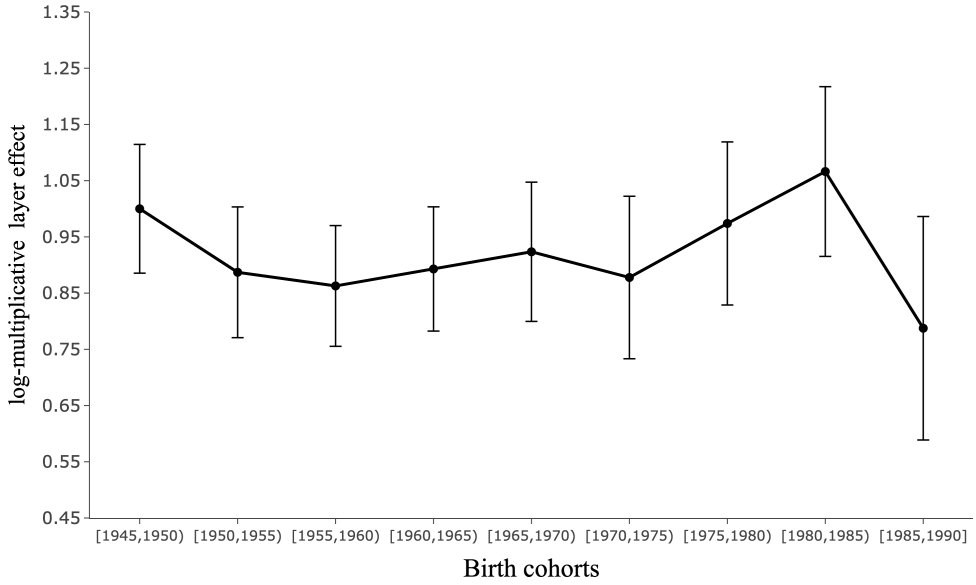
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure A.3: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) computed from samples of respondents age 25-64



Notes: Shaded areas represent 95% confidence intervals.

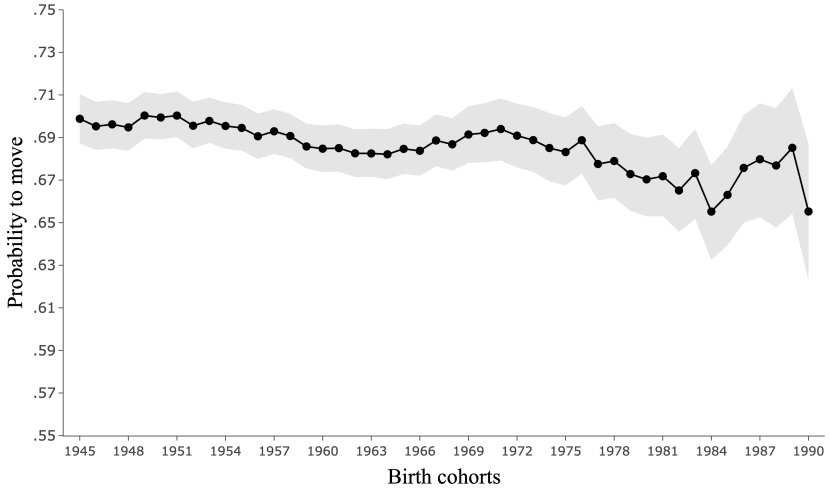
Figure A.4: Log-multiplicative layer effects computed from samples of respondents age 25-64



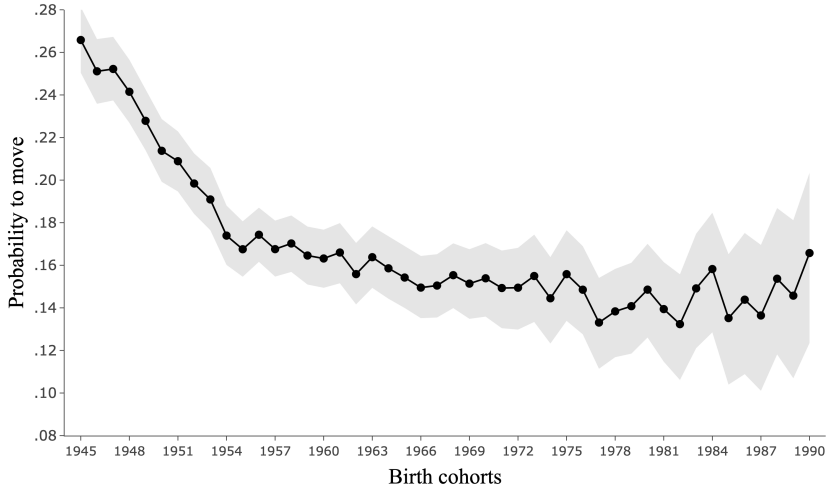
Notes: This figure plots the log-multiplicative layer effect across birth cohorts using 5-year bins. The vertical bars represent 95% confidence intervals.

Figure A.5: Measures of movement at generation $t = 1$ computed from samples of respondents age 30-64

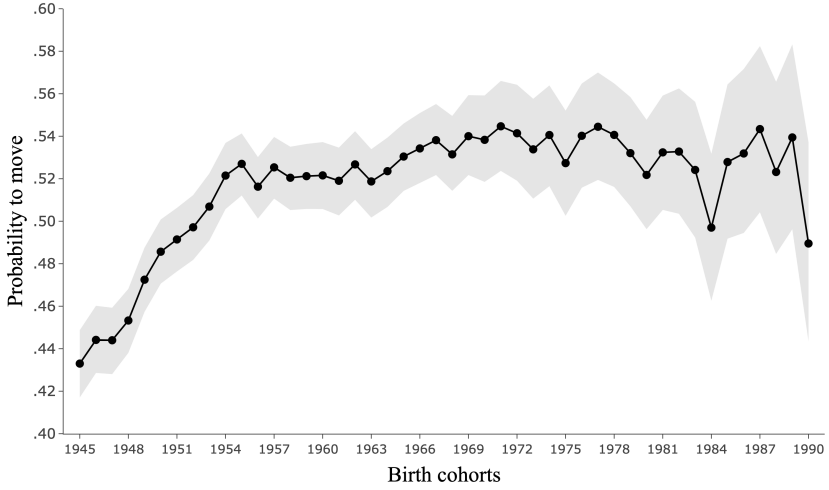
(A) Overall mobility (OM_1)



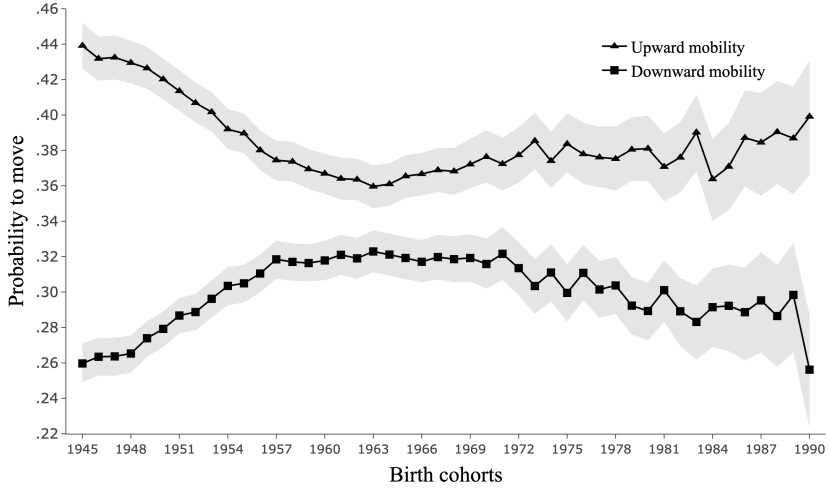
(B) Structural mobility (SM_1)



(C) Exchange mobility (EM_1)

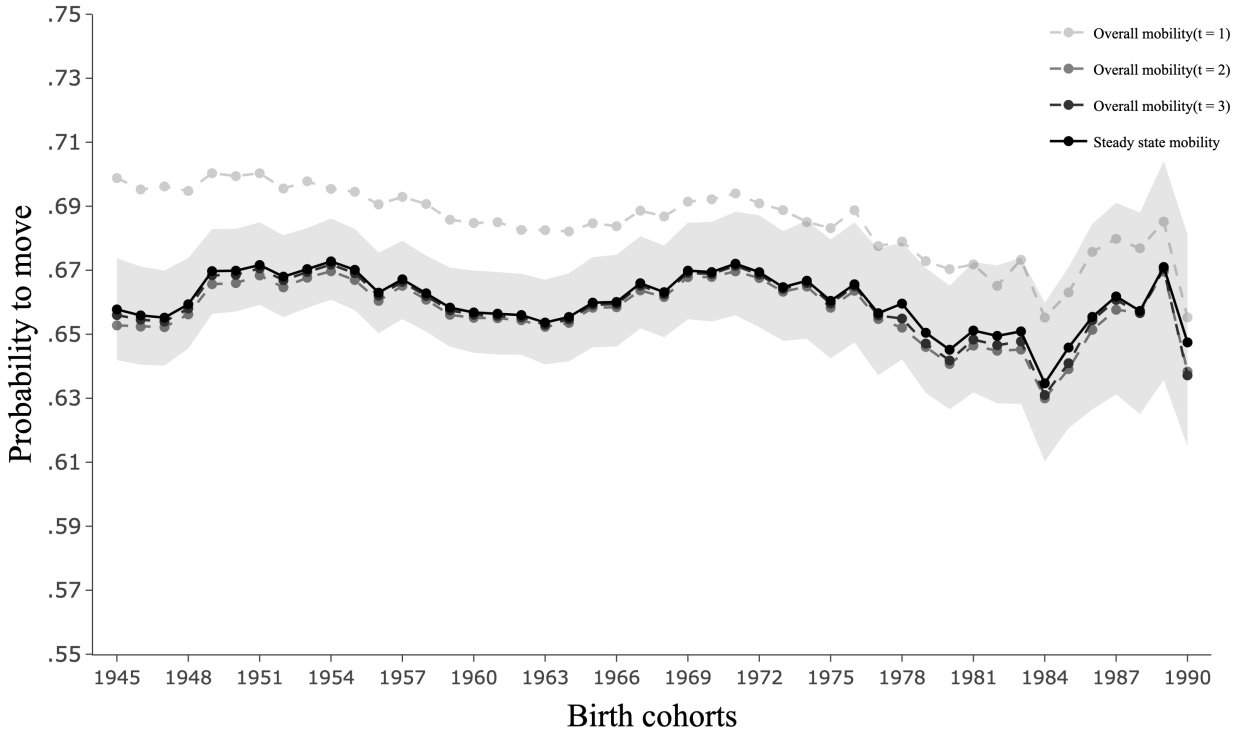


(D) Upward and downward mobility



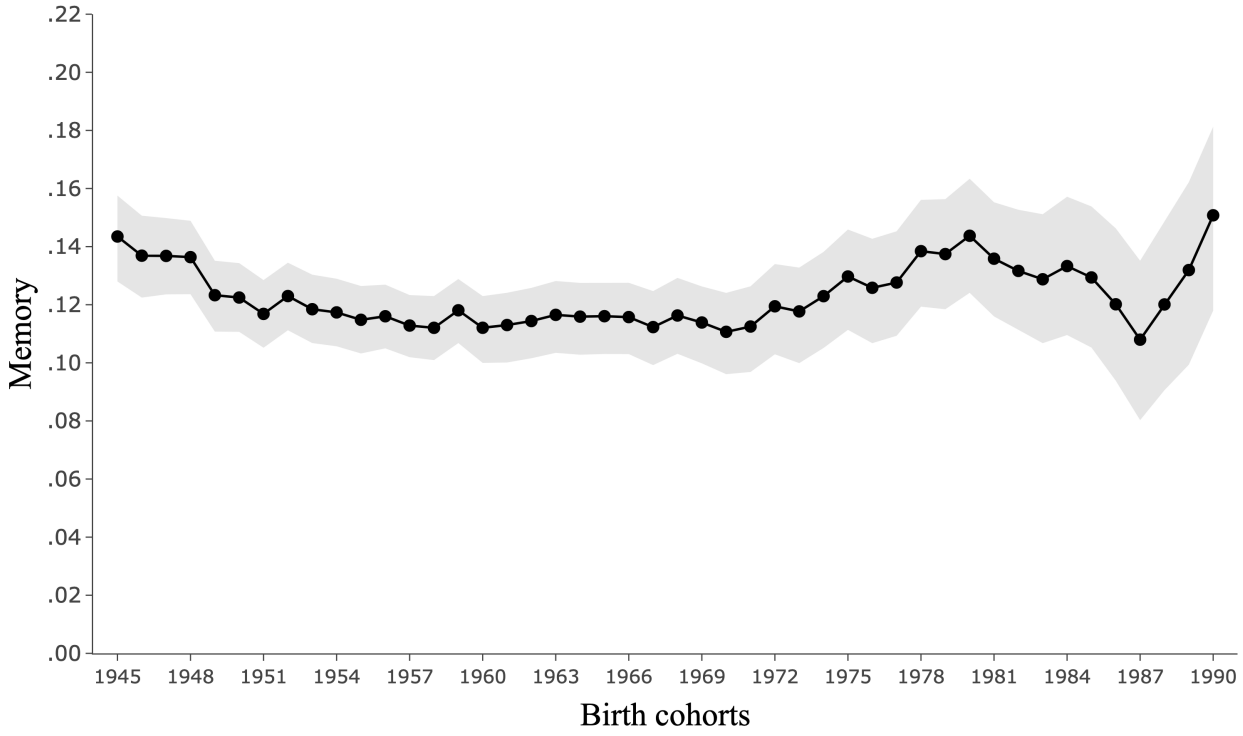
Notes: Shaded areas represent 95% confidence intervals.

Figure A.6: Overall mobility (OM_t) across synthetic generations computed from samples of respondents age 30-64



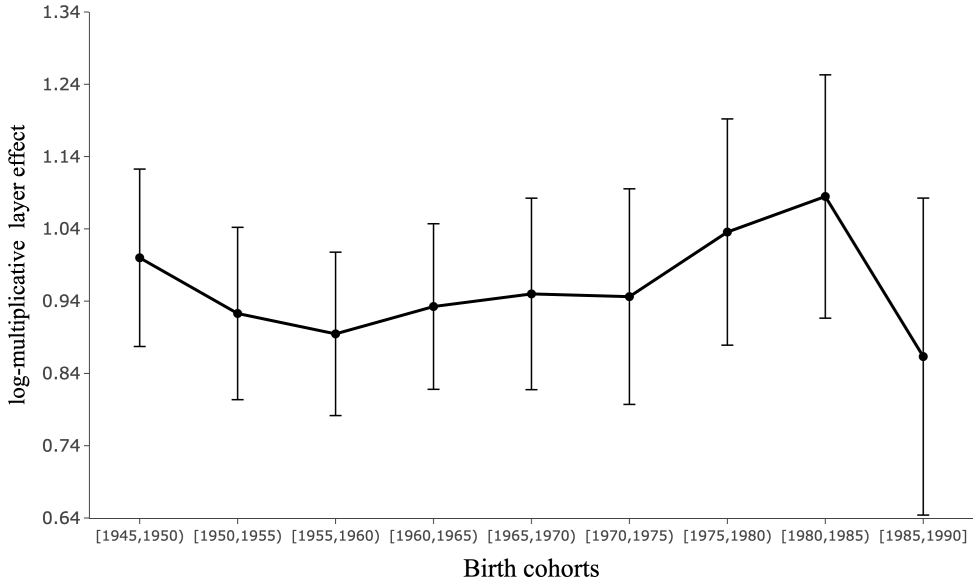
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure A.7: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) computed from samples of respondents age 30-64



Notes: Shaded areas represent 95% confidence intervals.

Figure A.8: Log-multiplicative layer effects computed from samples of respondents age 30-64



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

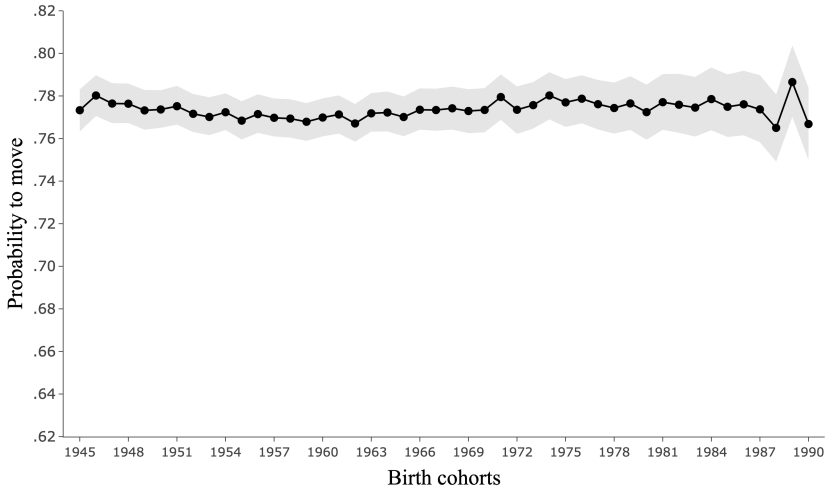
B Alternative Class Typologies

In this section, we replicate our main analyses using several alternative EGP typologies. Specifically, we employ the six-class typology adopted by Pfeffer and Hertel (2015) and the seven-class typology developed by Morgan (2017). The primary difference between our five-class typology and these alternatives is that we combine Class IIIa (higher-grade routine non-manual occupations) with Class V (lower-grade technicians) as a "middle class," while grouping Class IIIb (lower-grade routine non-manual occupations) with Class VII (unskilled manual workers). A second distinction is that both the six- and seven-class typologies classify all self-employed respondents outside the professional classes together with farmers in Class IV. We also replicate our analyses with the five-class typology after excluding all self-employed respondents, following the approach employed by Erikson and Goldthorpe (2010). In addition, we conduct replications excluding farmers, as prior research suggests that long-term trends in mobility can be particularly sensitive to changes involving this group (Xie and Killewald, 2013).

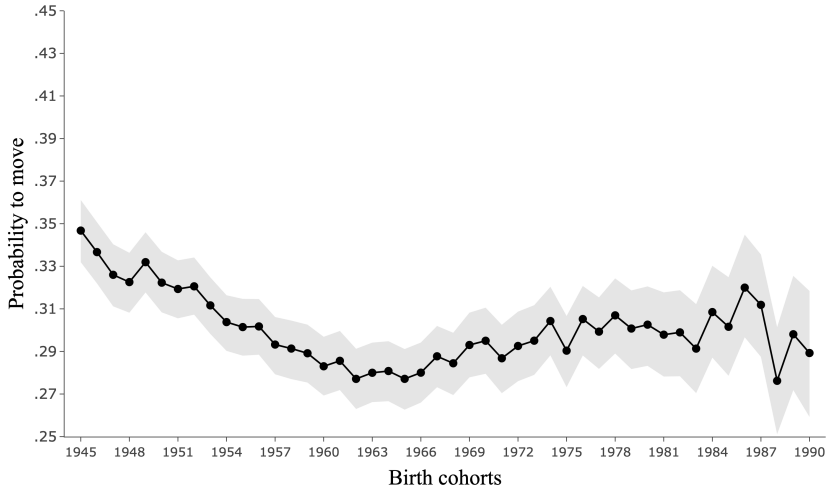
Overall, adopting these alternative typologies affects the levels of estimated mobility but not its trends. Across all approaches to measurement, we find relatively little evidence of an increase or decrease in mobility, whether assessed in terms of movement, memory, or association. With some of these typologies—particularly those employed by Pfeffer and Hertel (2015), Morgan (2017), our five-class typology excluding farmers—we find a slight downward shift in steady-state mobility and a slight upward shift in memory among cohorts born after the late 1960s. However, these changes are small, and we often cannot rule out that they are merely due to sampling variability.

Figure B.1: Measures of movement at generation $t = 1$ based on the Pfeffer and Hertel (2015) typology

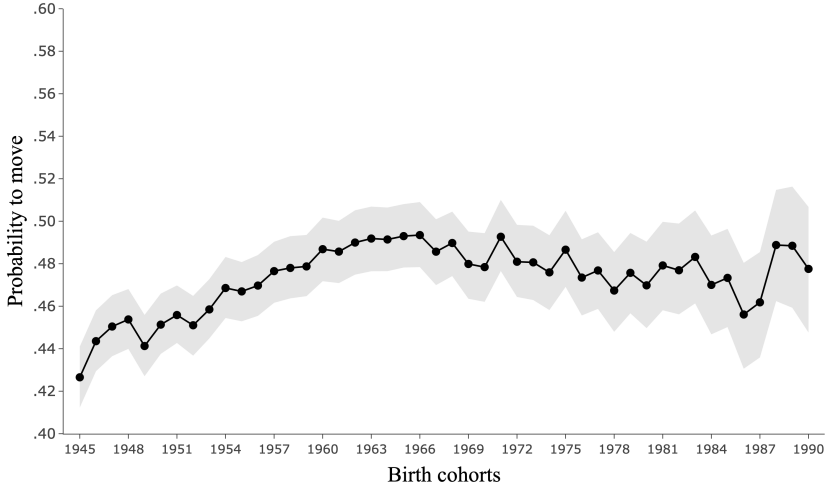
(A) Overall mobility (OM_1)



(B) Structural mobility (SM_1)



(C) Exchange mobility (EM_1)

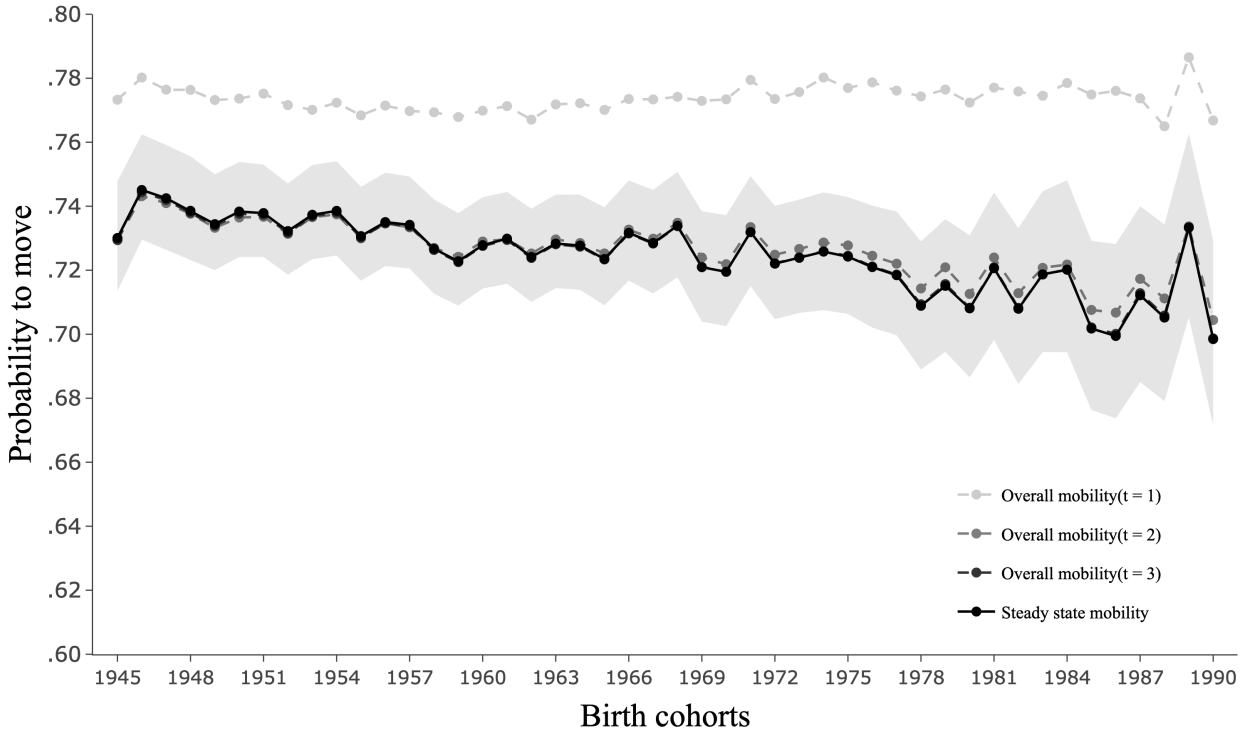


(D) Upward and downward mobility



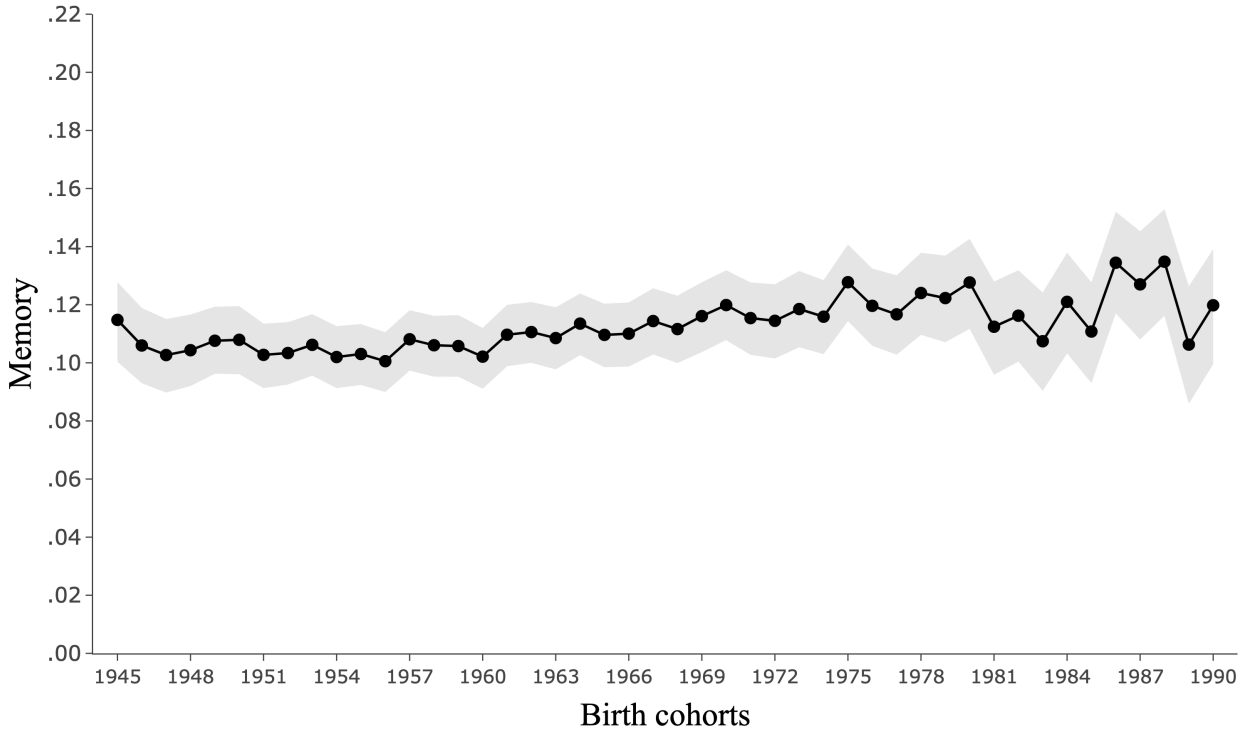
Notes: Shaded areas represent 95% confidence intervals.

Figure B.2: Overall mobility (OM_t) across synthetic generations based on the Pfeffer and Hertel (2015) typology



Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the 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.

Figure B.3: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on the Pfeffer and Hertel (2015) typology



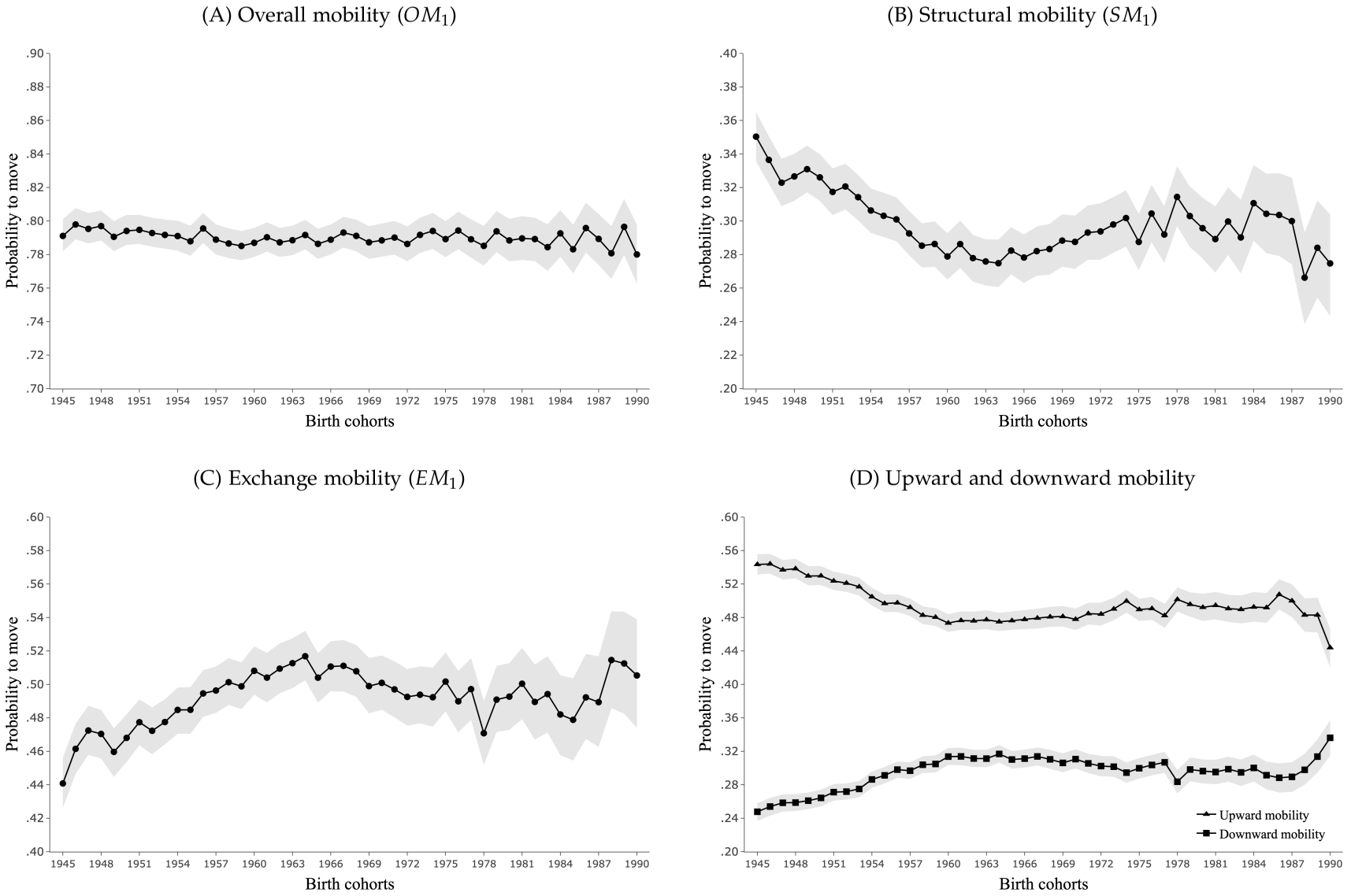
Notes: Shaded areas represent 95% confidence intervals.

Figure B.4: Log-multiplicative layer effects based on the Pfeffer and Hertel (2015) typology



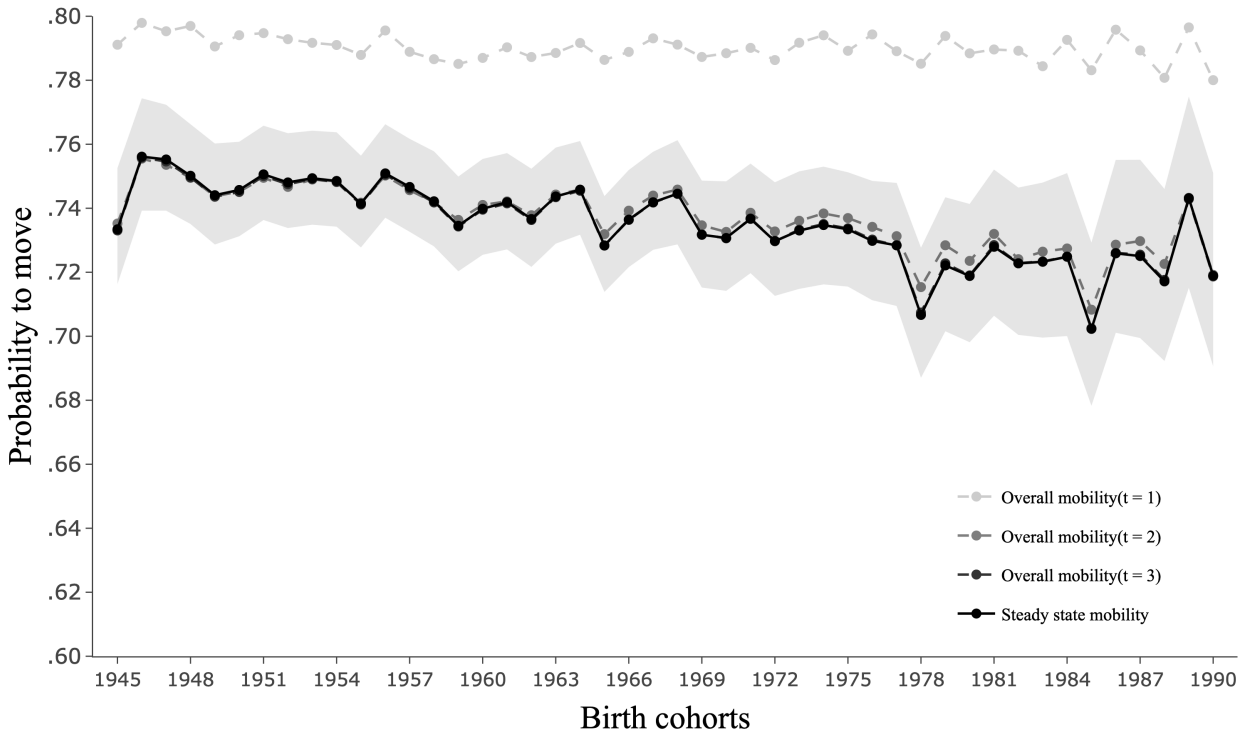
Notes: This figure plots the log-multiplicative layer effect across birth cohorts using 5-year bins. The vertical bars represent 95% confidence intervals.

Figure B.5: Measures of movement at generation $t = 1$ based on the Morgan (2017) typology



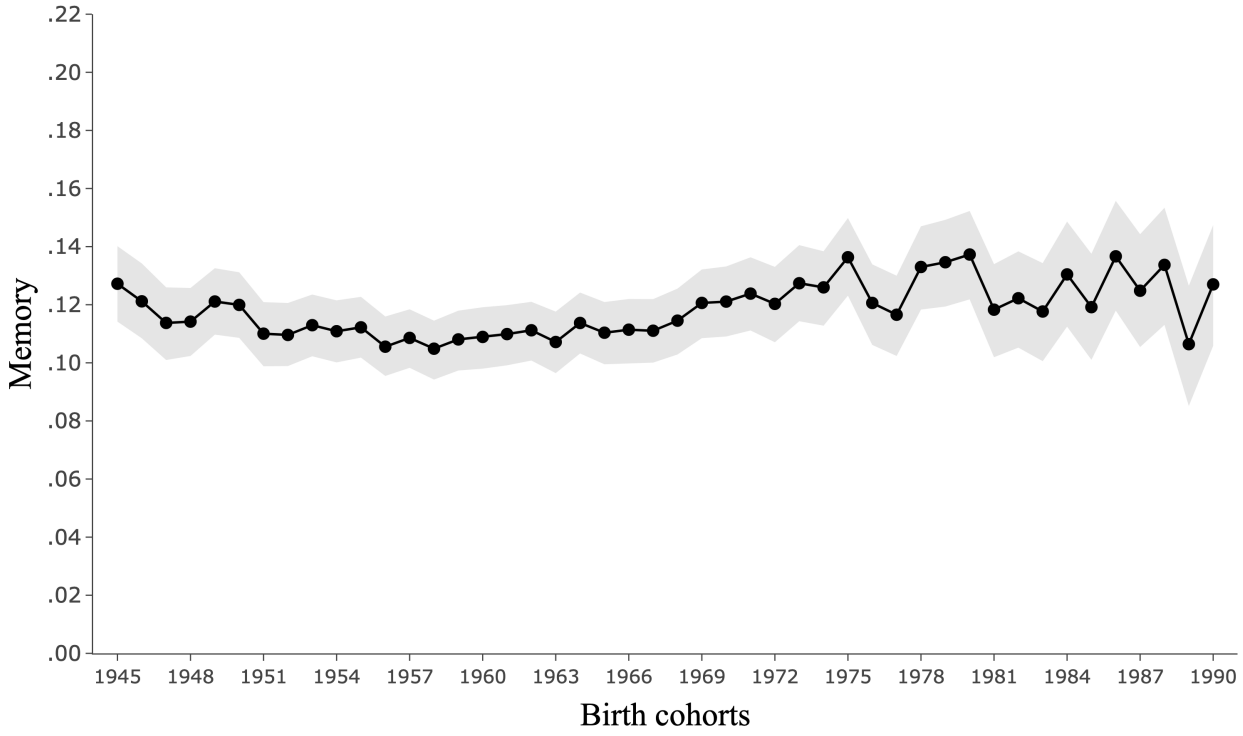
Notes: Shaded areas represent 95% confidence intervals.

Figure B.6: Overall mobility (OM_t) across synthetic generations based on the Morgan (2017) typology



Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the 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.

Figure B.7: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on the Morgan (2017) typology



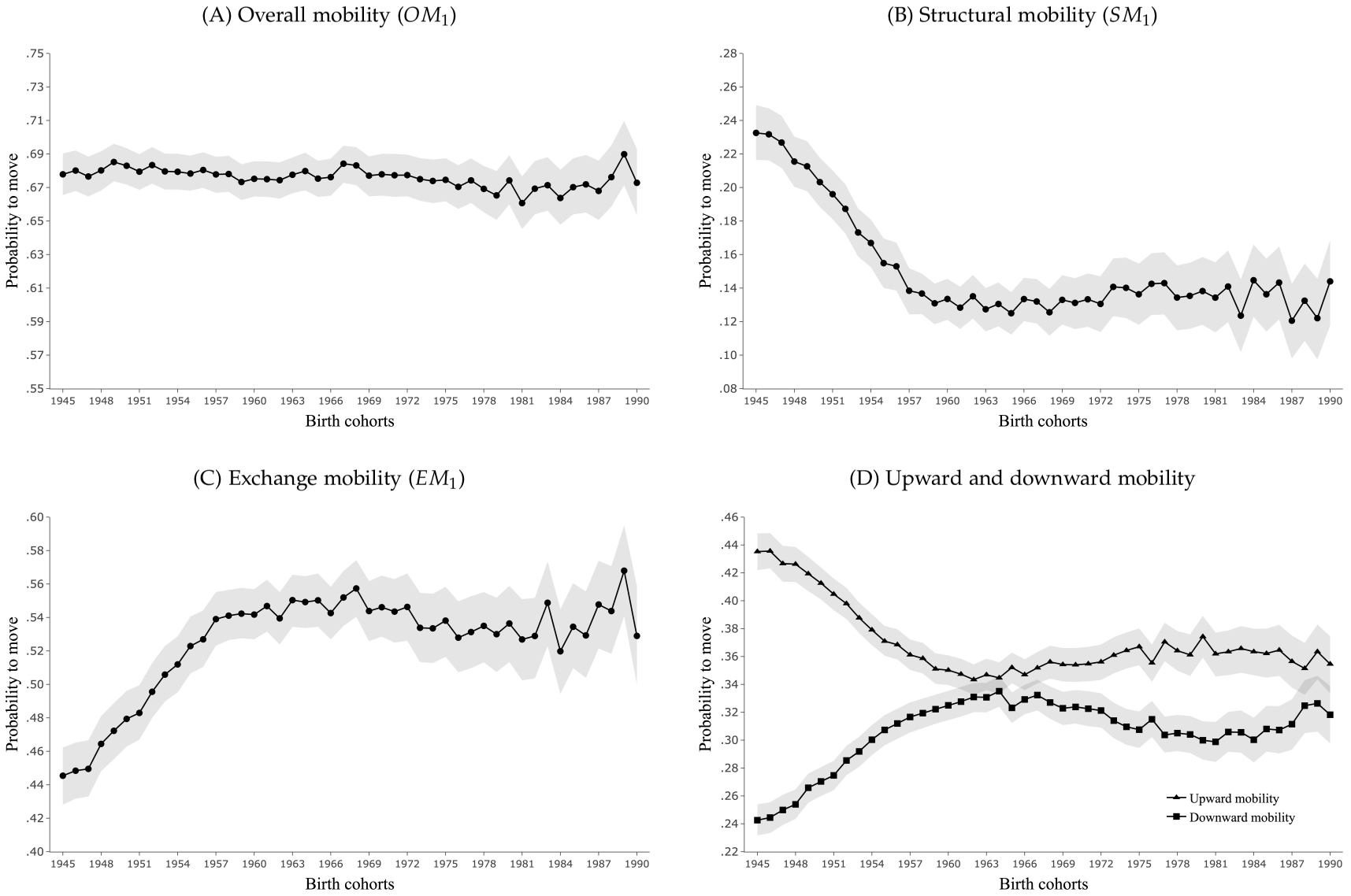
Notes: Shaded areas represent 95% confidence intervals.

Figure B.8: Log-multiplicative layer effects based on the Morgan (2017) typology



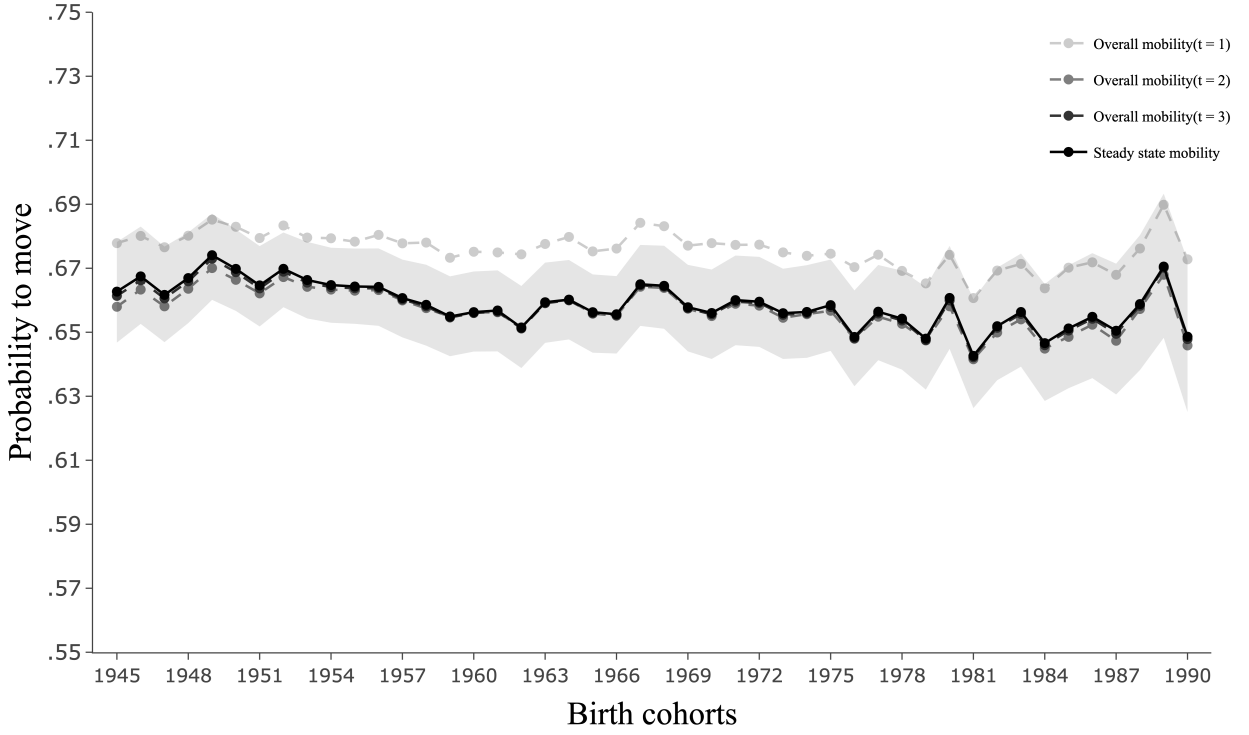
Notes: This figure plots the log-multiplicative layer effect across birth cohorts using 5-year bins. The vertical bars represent 95% confidence intervals.

Figure B.9: Measures of movement at generation $t = 1$ excluding farmers



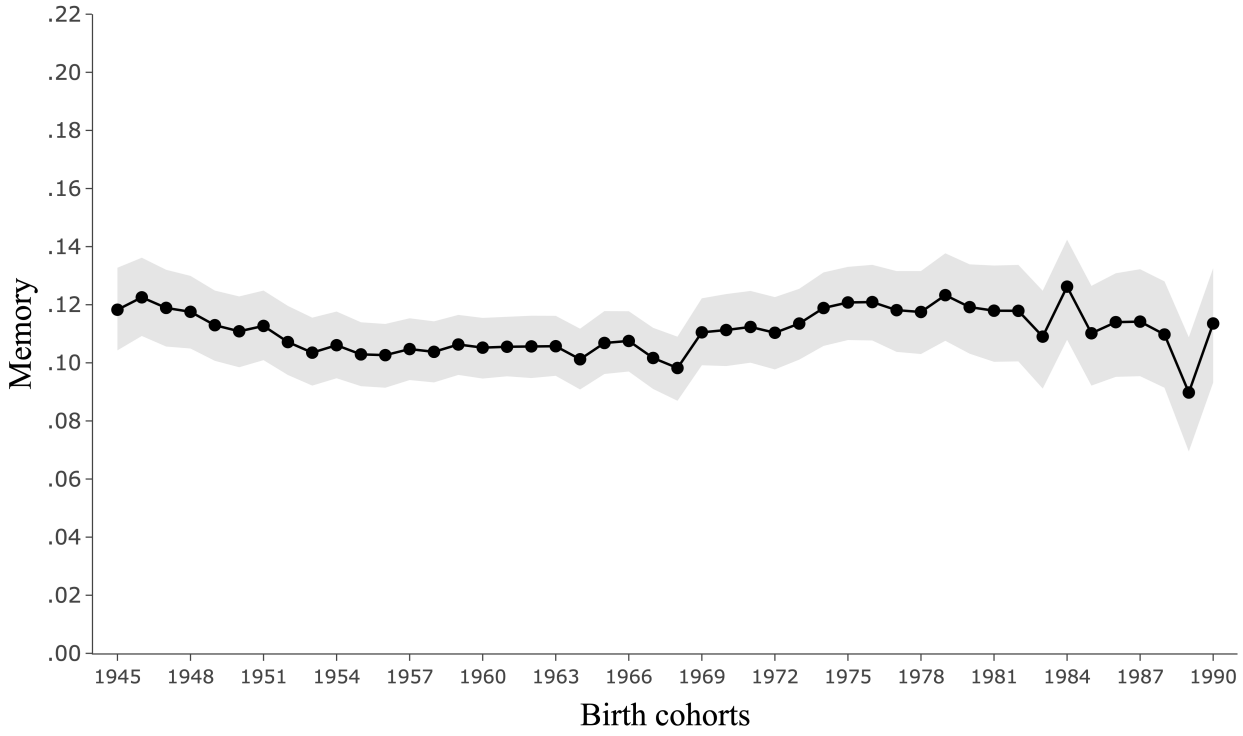
Notes: Shaded areas represent 95% confidence intervals.

Figure B.10: Overall mobility (OM_t) across synthetic generations excluding farmers



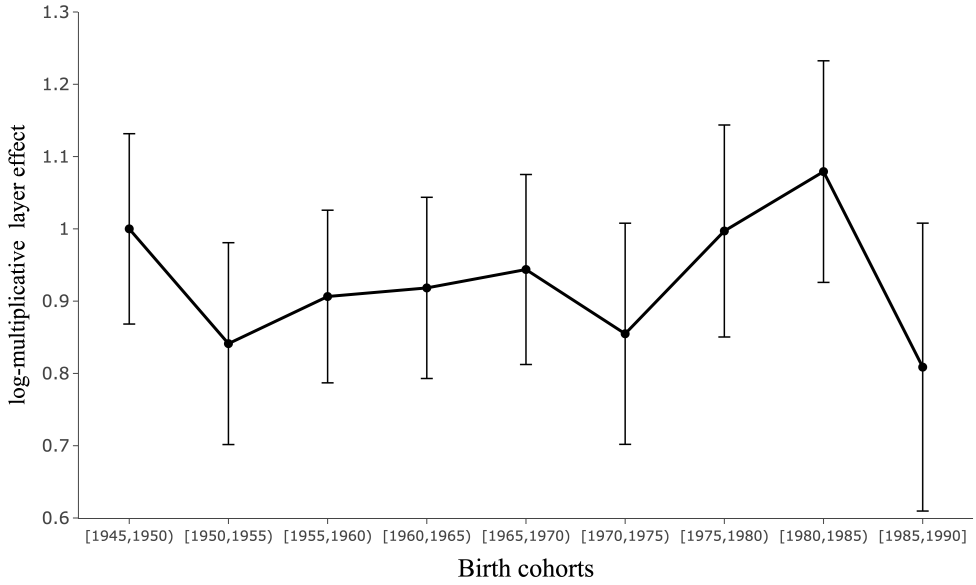
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure B.11: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) excluding farmers



Notes: Shaded areas represent 95% confidence intervals.

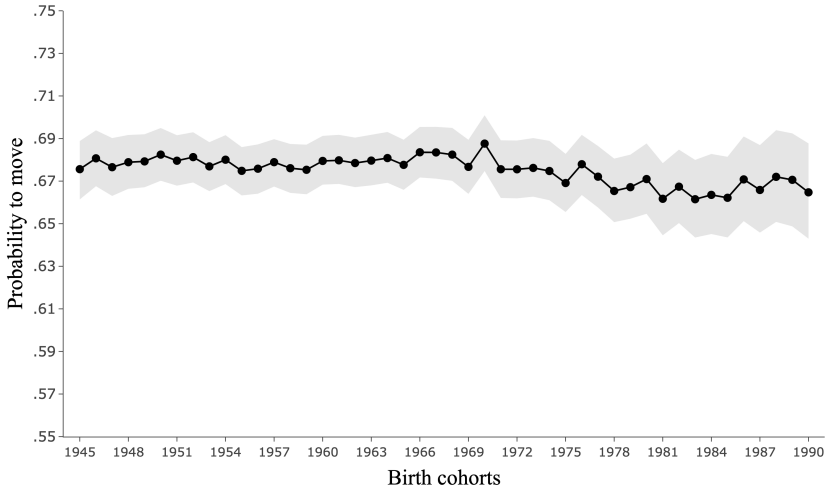
Figure B.12: Log-multiplicative layer effects excluding farmers



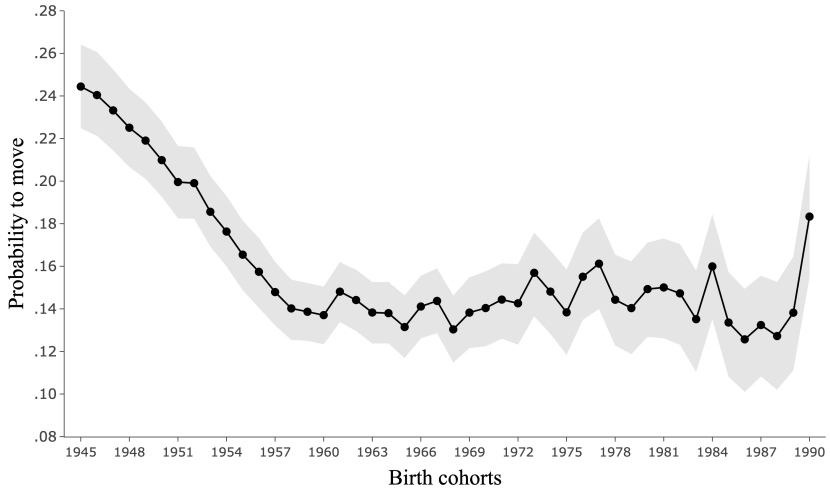
Notes: This figure plots the log-multiplicative layer effect across birth cohorts using 5-year bins. The vertical bars represent 95% confidence intervals.

Figure B.13: Measures of movement at generation $t = 1$ based on Erikson and Goldthorpe (2010) typology

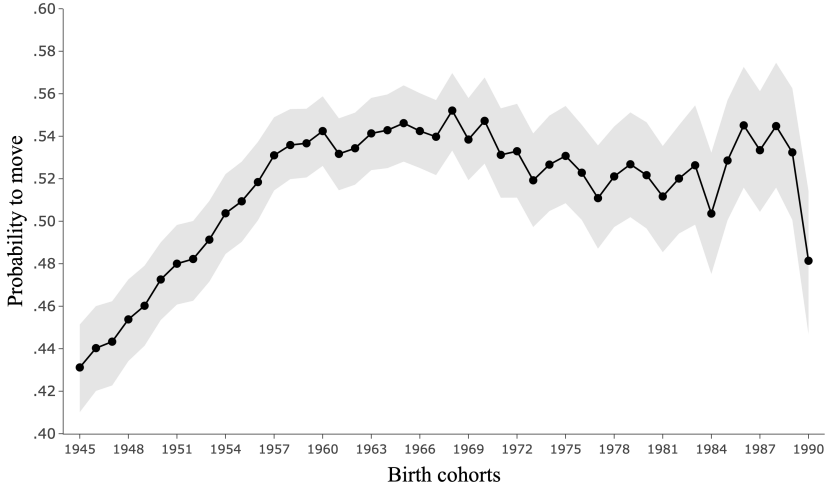
(A) Overall mobility (OM_1)



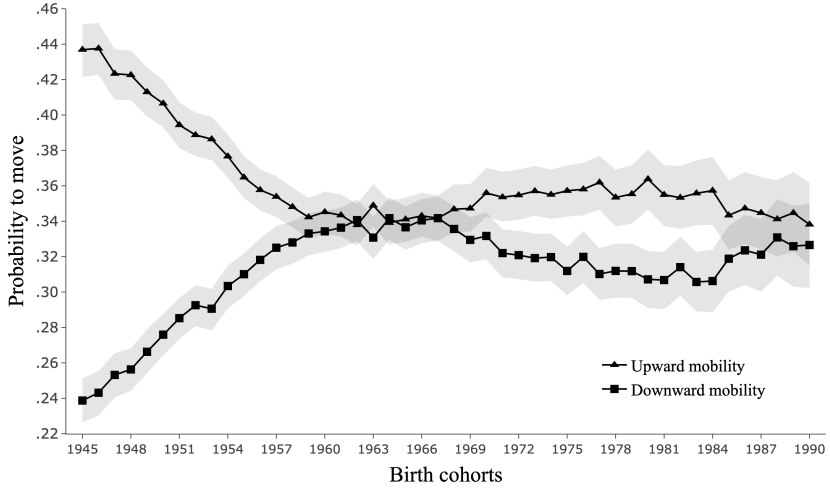
(B) Structural mobility (SM_1)



(C) Exchange mobility (EM_1)

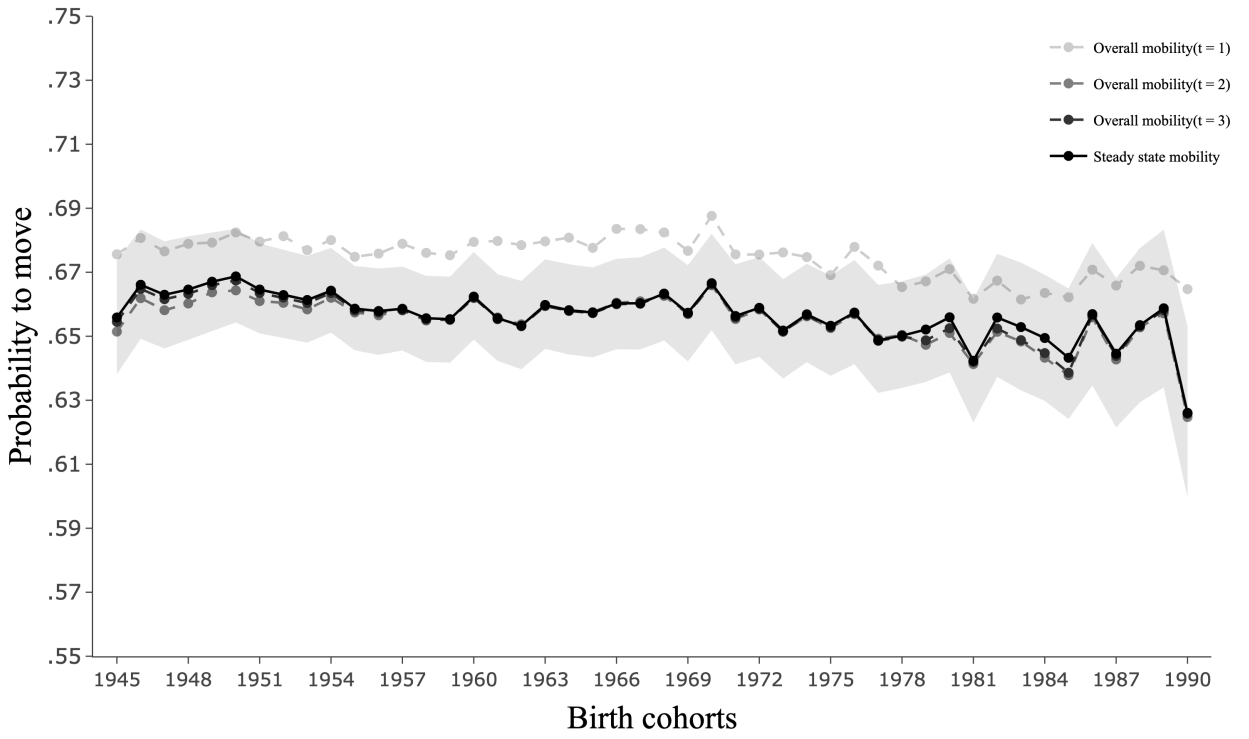


(D) Upward and downward mobility



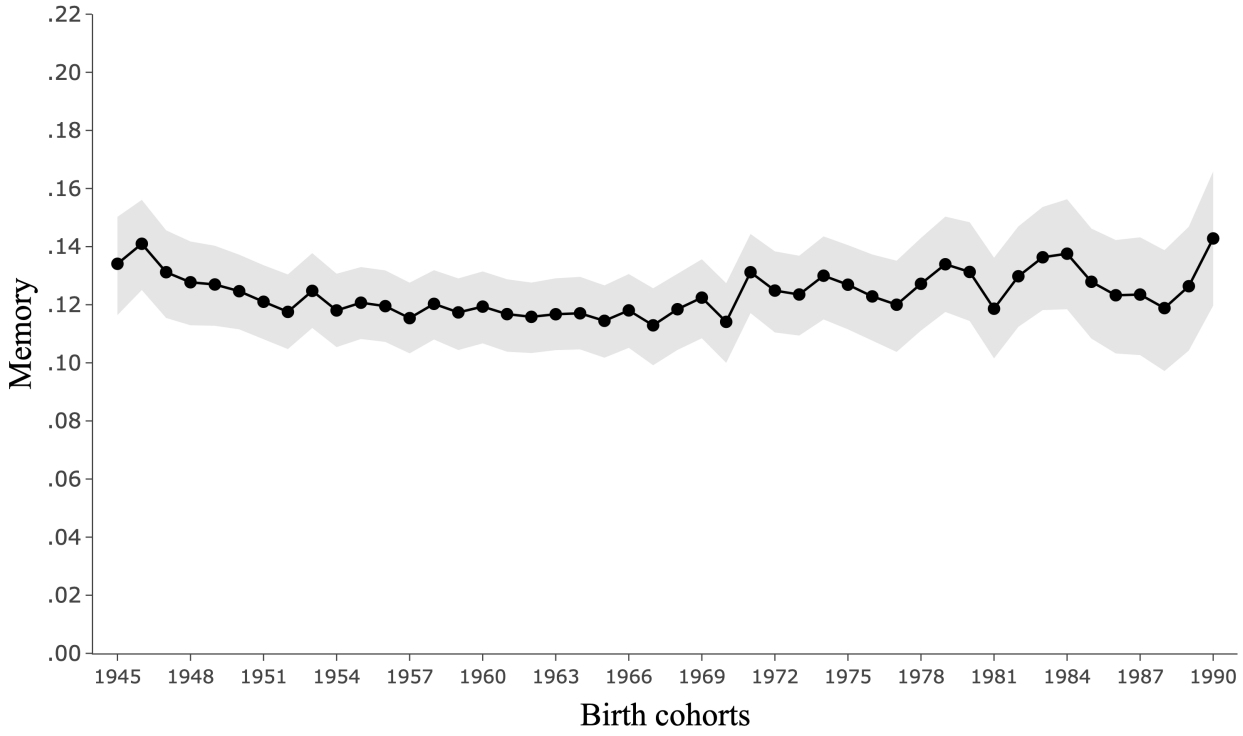
Notes: Shaded areas represent 95% confidence intervals.

Figure B.14: Overall mobility (OM_t) across synthetic generations based on Erikson and Goldthorpe (2010) typology



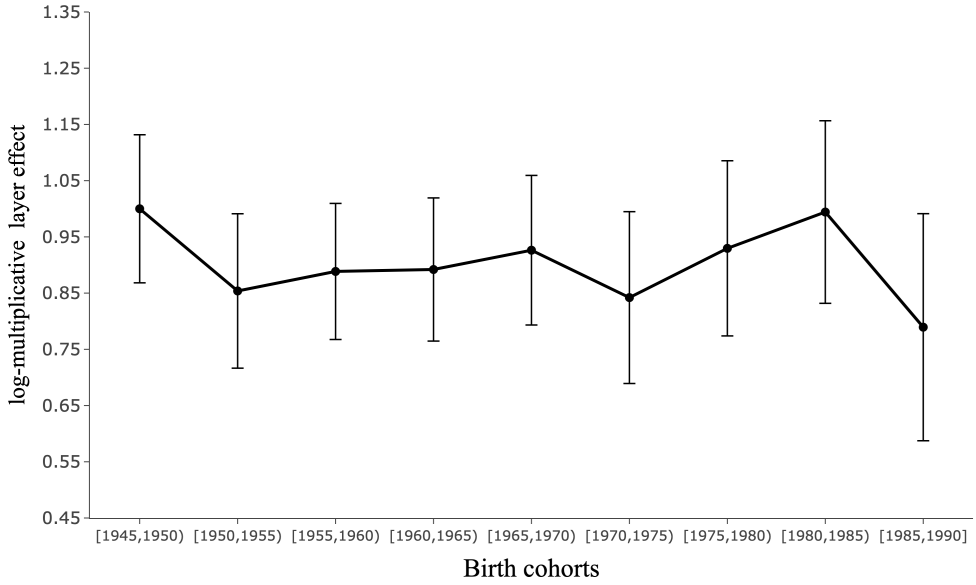
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure B.15: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on Erikson and Goldthorpe (2010) typology



Notes: Shaded areas represent 95% confidence intervals.

Figure B.16: Log-multiplicative layer effects based on Erikson and Goldthorpe (2010) typology

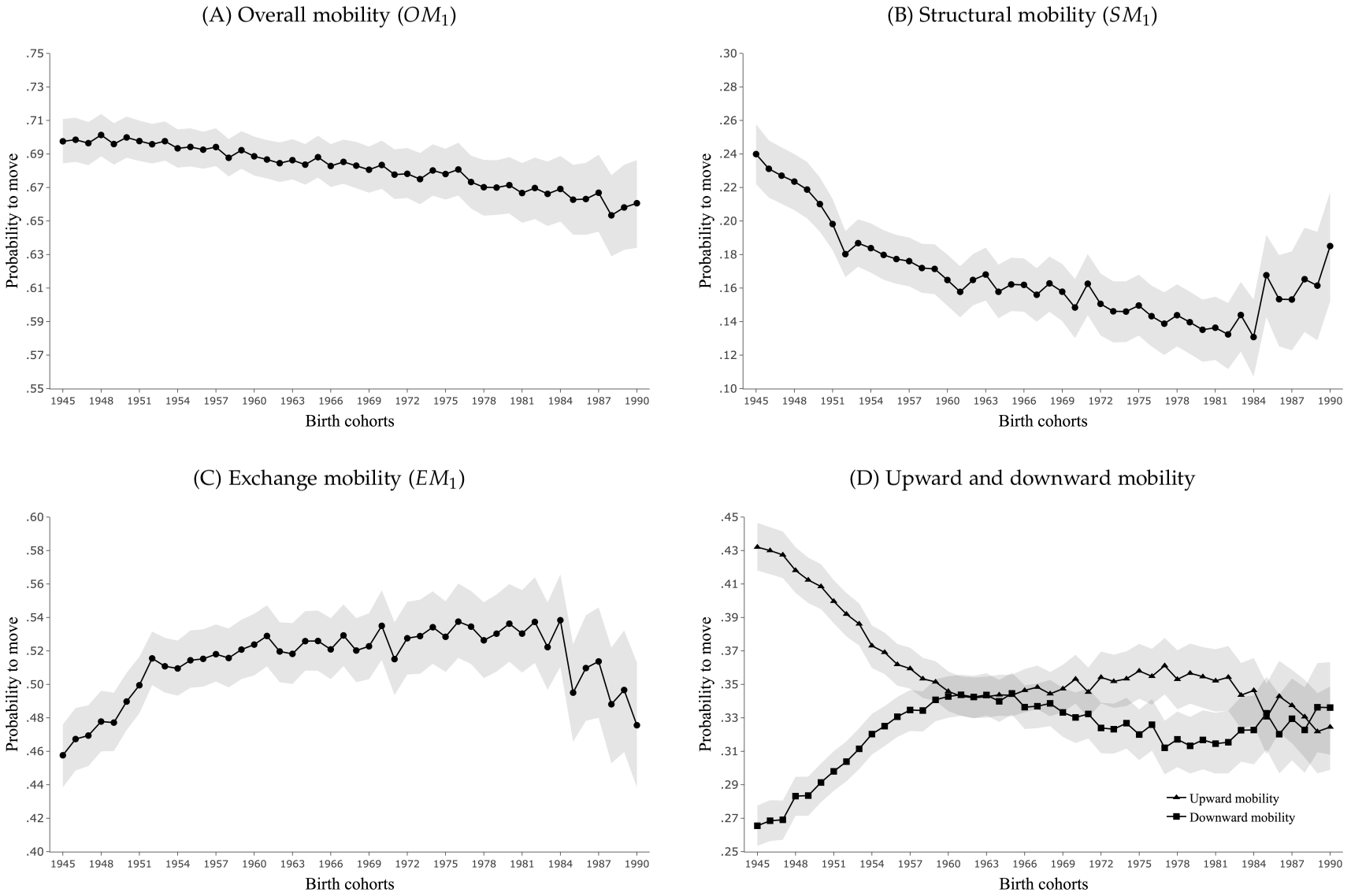


Notes: This figure plots the log-multiplicative layer effect across birth cohorts using 5-year bins. The vertical bars represent 95% confidence intervals.

C Weighted Estimates

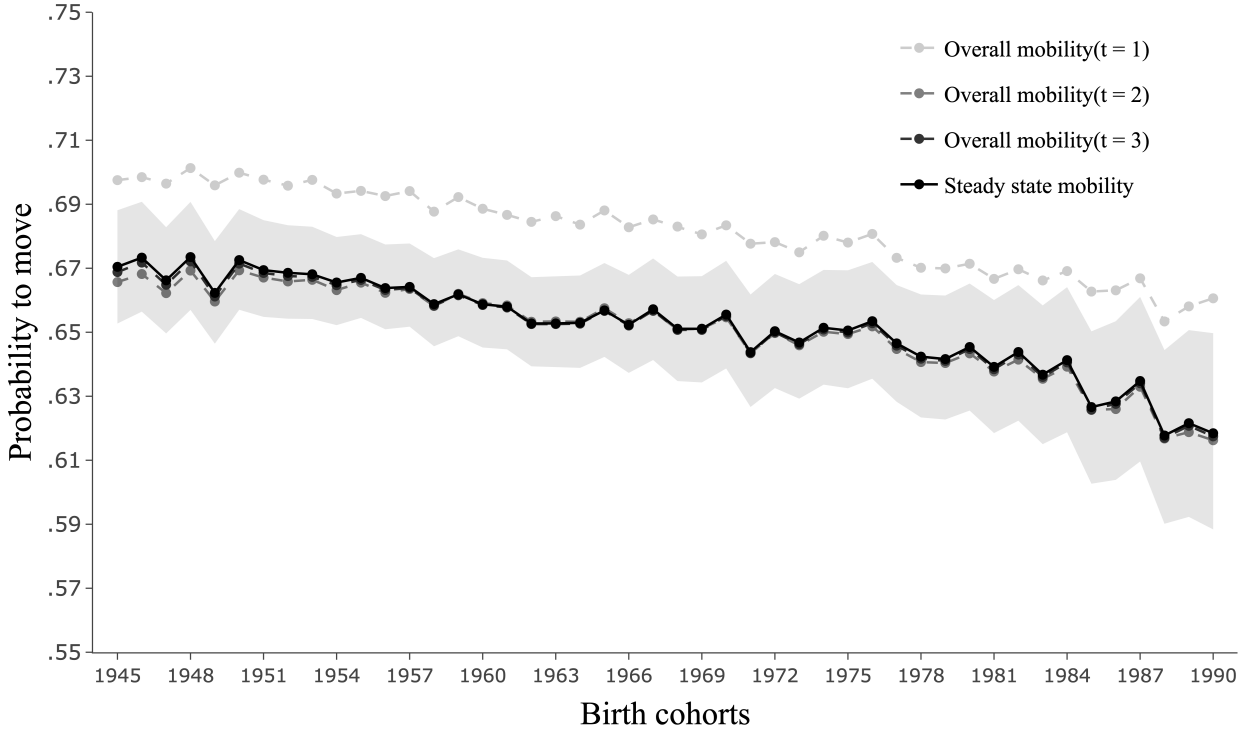
We conducted a parallel analysis using the GSS post-stratification weights, which adjust for unequal probabilities of sample selection, ballot and form assignment errors, and the Black oversamples in 1982 and 1987. The weighted results closely mirror our unweighted estimates. All measures of memory and association exhibit nearly identical patterns, and the weighted cell counts generally fluctuate only a little around the raw counts in the mobility tables. The only noteworthy difference involves our measures of movement, where we observe a slight downward trend in overall and steady-state mobility beginning with cohorts born in the 1950s.

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



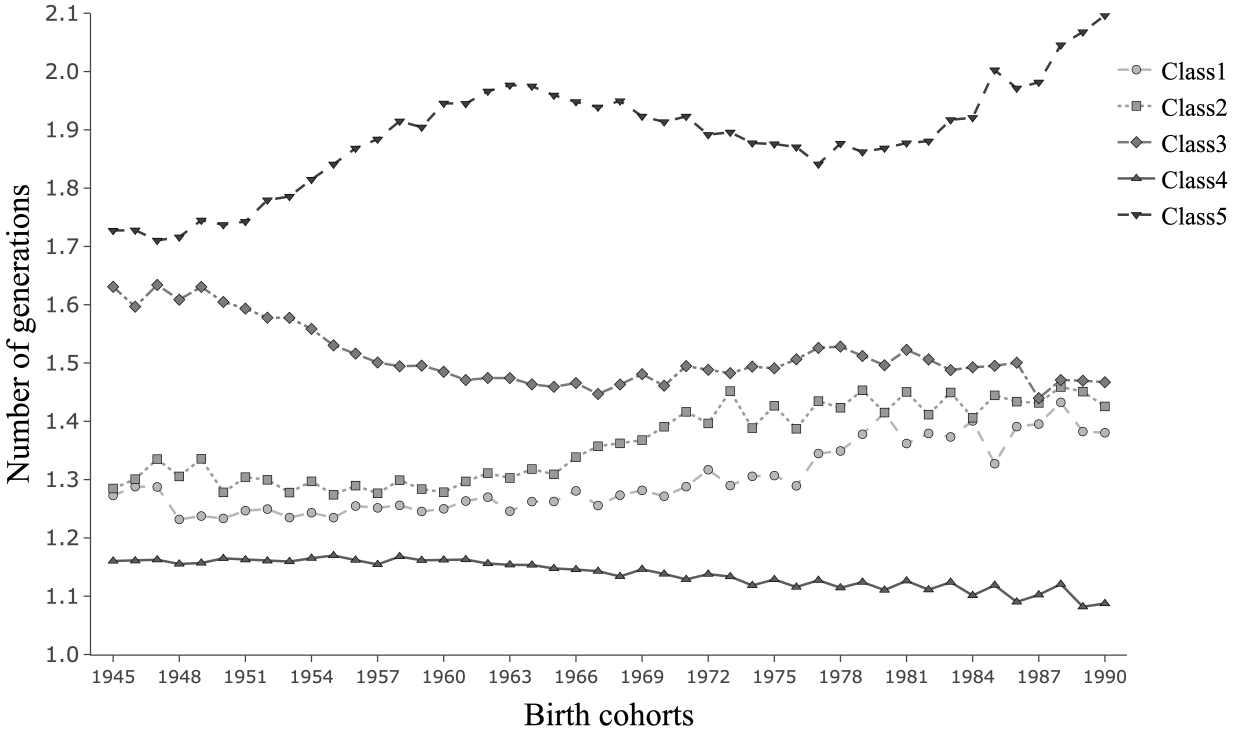
Notes: Shaded areas represent 95% confidence intervals.

Figure C.2: Overall mobility (OM_t) across synthetic generations



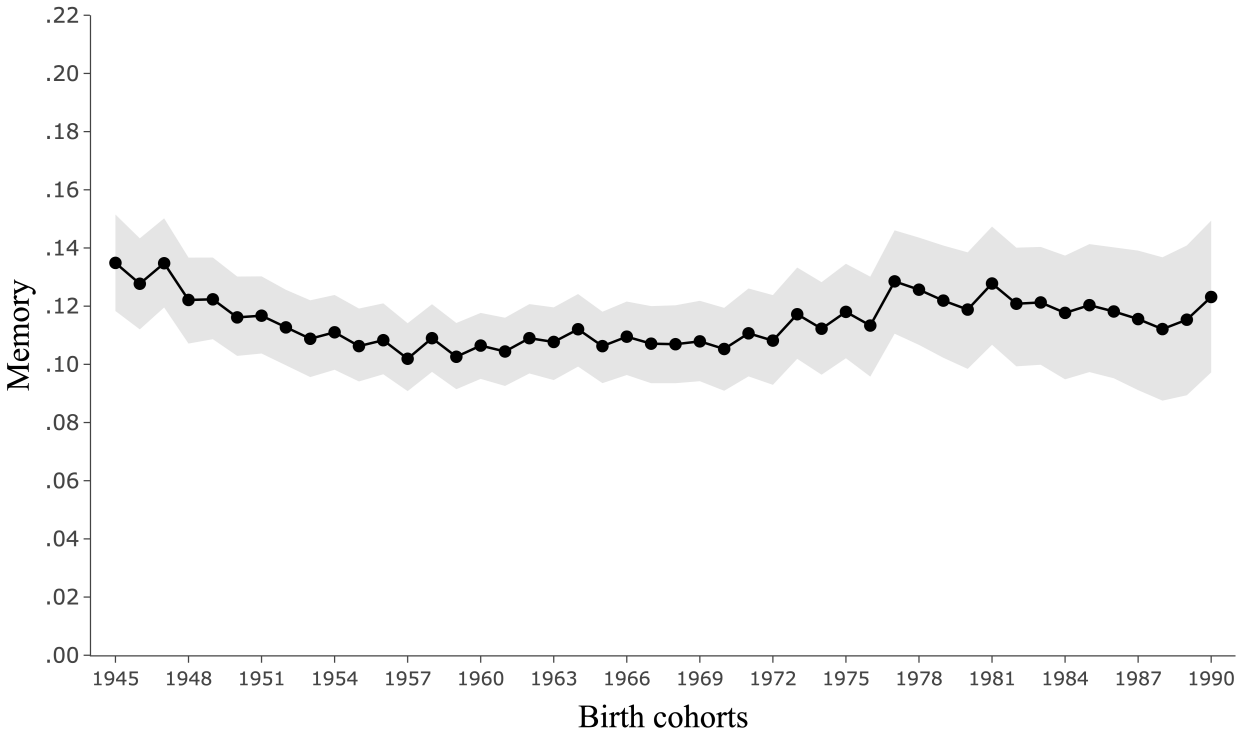
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for all cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure C.3: Mean time to exit from each origin class (MTE_i)



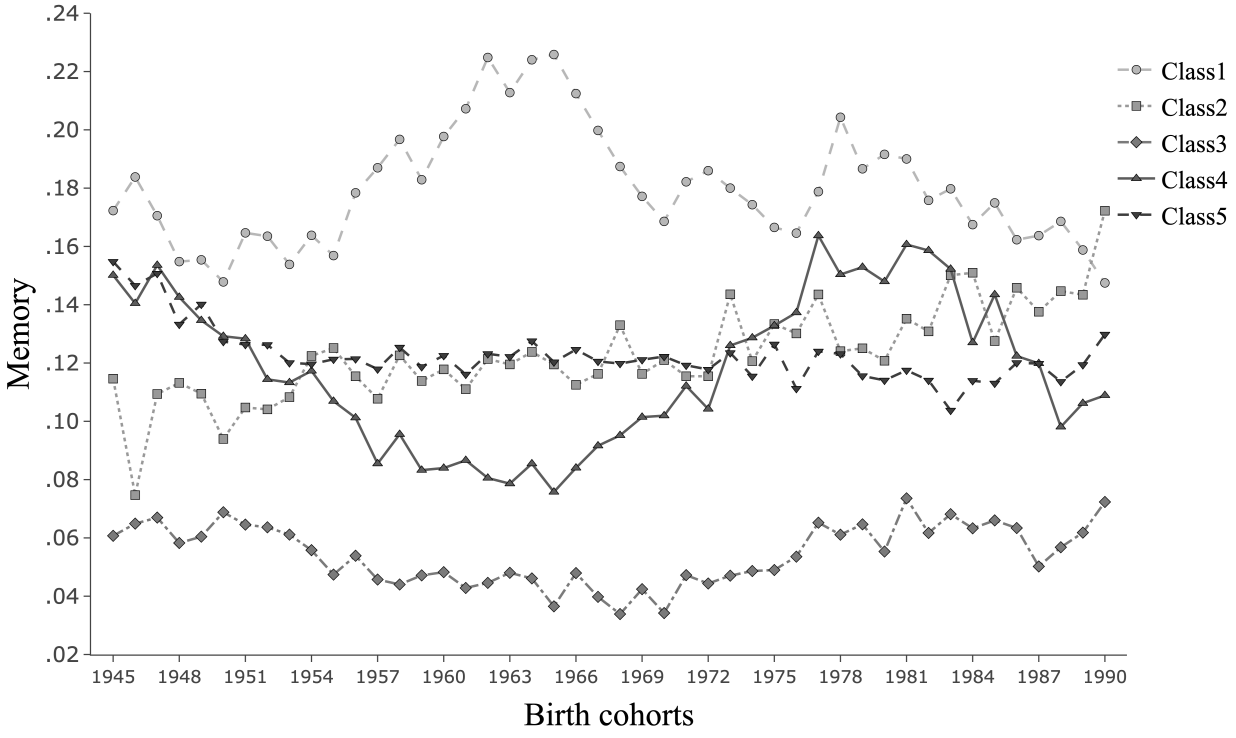
Notes: This figure plots the mean time to exit from each origin class (MTE_i), separately by cohort. Class 1 refers to higher-grade professionals, administrators, and managers; class 2 refers to lower-grade professionals, administrators, and managers; class 3 includes higher-grade routine non-manual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

Figure C.4: Aggregate intergenerational memory at generation $t = 1$ (AIM_1)



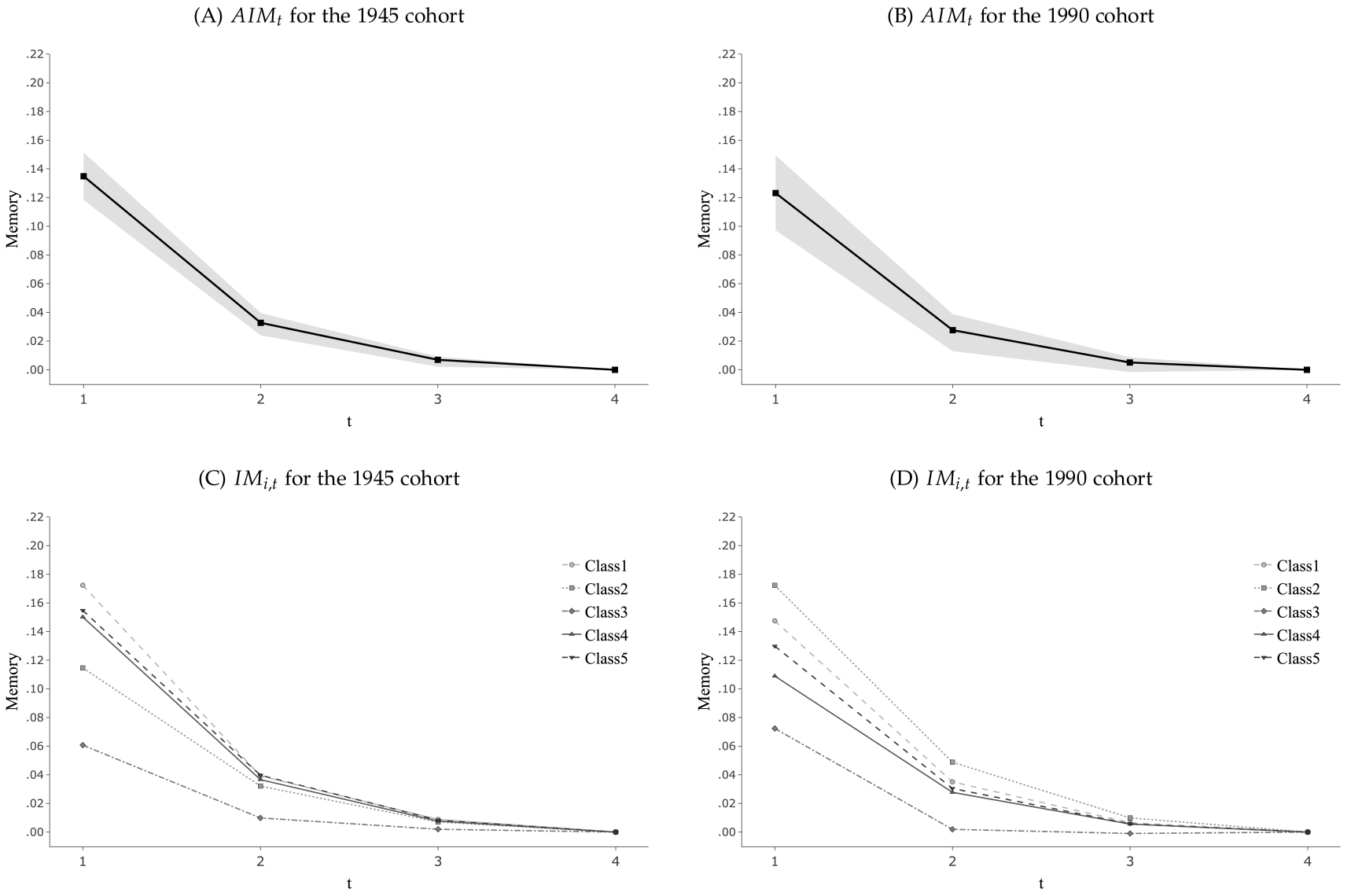
Notes: Shaded areas represent 95% confidence intervals.

Figure C.5: 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.

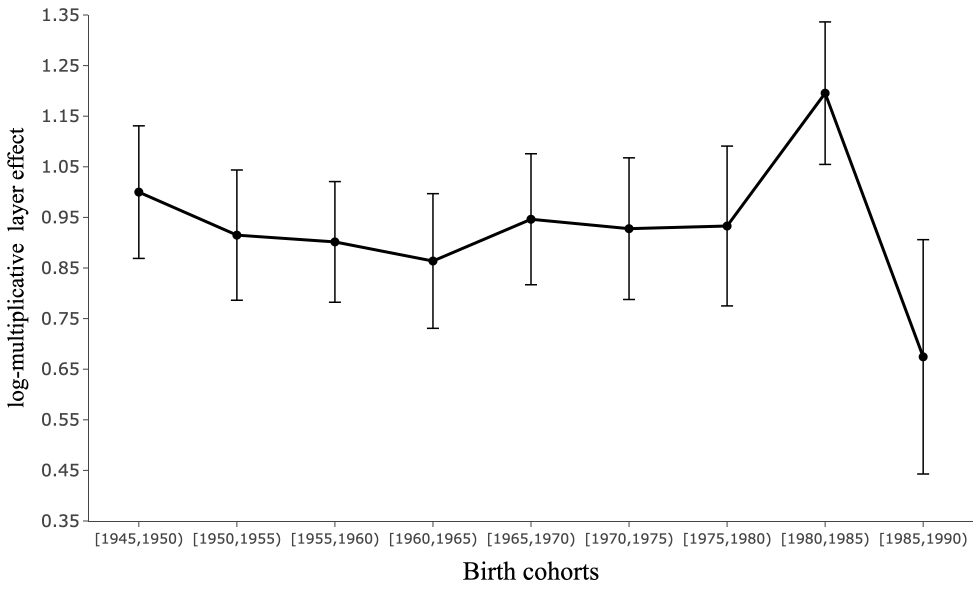
Figure C.6: Memory across synthetic generations in the 1945 and 1990 birth cohorts



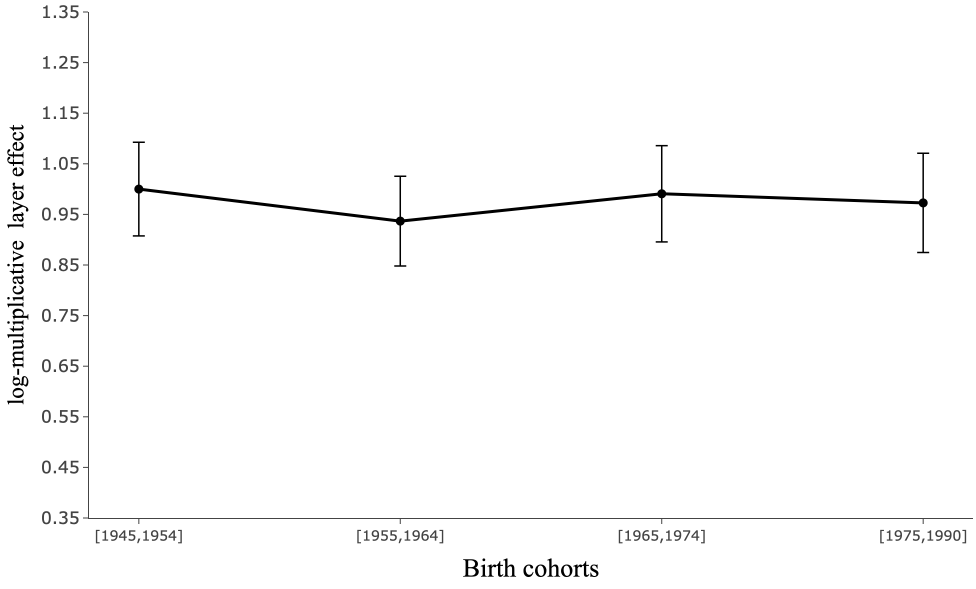
Notes: This figure illustrates the evolution of AIM_t and $IM_{i,t}$ across generations in a stationary Markov chain, separately for the 1945 and 1985 cohorts. By $t = 4$, both transition matrices have converged to the steady state, implying zero memory of class origins. Shaded areas represent 95% confidence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

Figure C.7: 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.

D Alternative Measures of Mobility

In this section, we report estimates from several alternative measures of movement, memory, and association. We begin with an alternative measure of movement—class outflows—computed from both the observed transition matrices and the Markov steady state. Specifically, we estimate and report the follow quantity:

$$O_{i,t} = \sum_{j \neq i} P_{ij}^{t},$$

for $t = 1$ and for $t = \infty$. These results are presented in Figure D.1. The outflow patterns capture movement out of each origin class separately and thus tend to mirror the patterns in our measure of mean time to exit. They too indicate that movement is declining for both the upper and lower classes but rising in the middle, particularly for class 3 (higher-grade routine non-manual workers, technicians, and supervisors).

We next turn to mean first passage time (MFPT; Grinstead and Snell 1997; Kemeny and Snell 1976). MFPT characterizes movement between specific pairs of classes across generations of synthetic dynasties. The MFPT estimates the expected number of generations it would take to reach destination class j when starting from origin class i in the founding generation of a dynasty. We follow the logic for computing this measure as outlined in Grinstead and Snell (1997). Consider an ergodic Markov chain, and let $MFPT_{ij}$ denote the expected number of generations needed to reach class j from class i (for $i \neq j$). If the process reaches j in the first generation, then the transition occurs with probability 1, and thus $MFPT_{ij} = 1$. However, if this direct transition does not occur, the process instead moves to some intermediate state k in the first generation. In this case, one generation has already passed, and the expected number of additional generations to reach j from k is given by $MFPT_{kj}$. The total expected number of generations from i to j can therefore be formally defined as follows:

$$MFPT_{ij} = P_{ij} + \sum_{k \neq j} P_{ik} \cdot (MFPT_{kj} + 1), \tag{D1}$$

or since $\sum_k P_{ik} = 1$,

$$MFPT_{ij} = 1 + \sum_{k \neq j} P_{ik} \cdot MFPT_{kj}. \tag{D2}$$

Therefore, $MFPT_{ij}$ can be computed from Equation (D2) by solving, in our case, a system of 20 equations. Since we are using a 5×5 transition matrix, there are 25 possible (i, j) class combinations. Excluding the 5 diagonal elements where $i = j$, we are left

with 20 off-diagonal unknowns, each corresponding to a distinct $MFPT_{ij}$, to be solved simultaneously.

Figure D.2 shows estimates of the MFPT from origin class i to destination class j, separately by cohort. Downward transitions appear in the top panel, while upward transitions are shown in the bottom panel. Except for class 4 (higher-grade manual workers, lower-grade technicians, and farmers), which is a rare destination for all origins, we generally observe longer times for upward than for downward transitions. Among the upward transitions, class 3 is the most readily attainable destination for classes 4 and 5. For downward transitions, class 3 is again the most common destination for the top two classes. These patterns change little across cohorts.

Next, we examine alternative measures of intergenerational memory, including the maximum distance to stationarity (Blume et al., 2025; Levin et al., 2009) and the second-largest eigenvalue of the transition matrix (Sommers and Conlisk, 1979; Conlisk and Sommers, 1979; Shorrocks, 1978). These measures respectively quantify the distance from the steady state, and the speed at which the Markov process converges to it. The maximum distance to stationarity can be formally defined as follows:

$$d_t = \max_i \sum_j |P_{ij}^t - \mu_{j,\infty}|, \tag{D3}$$

which represents the largest difference between any row of the observed transition matrix and the steady-state distribution μ_∞. The magnitude of d_t represents the worst-case distance of the Markov process from its steady state——the largest deviation from equality of opportunity across all class origins at generation t. Conceptually, it is analogous to aggregate intergenerational memory AIM_t defined in Equation (6), but with a key distinction: while AIM_t reflects the average distance to the steady state across all origin classes, d_t captures the maximal deviation. Equivalently, d_t can be interpreted as the maximum value of the individual memory metric $IM_{i,t}$ from Equation (7), taken across all origin classes i, thereby highlighting the "worst-case class origin" with respect to its distance from multi-generational equality of opportunity.

To provide an intuitive explanation of the second-largest eigenvalue as a measure of memory, recall the standard spectral theorem for diagonalizable matrices (Meyer, 2000, pp. 517–518; Bhatia, 1997, pp. 4–5):

$$P = V\Lambda V^{-1} = V\Lambda U = \sum_i \lambda_i \mathbf{v}_i \mathbf{u}_i, \tag{D4}$$

where V is the matrix whose columns are the right eigenvectors $\mathbf{v}_i$, Λ is the diagonal

matrix of eigenvalues λ_i, and $\mathbf{U}$ is the matrix whose rows are the left eigenvectors $\mathbf{u}_i$. Recall that a vector $\mathbf{v}$ is a right eigenvector if $P\mathbf{v} = \lambda\mathbf{v}$, while a vector $\mathbf{u}$ is called left eigenvector if $\mathbf{u}P = \lambda\mathbf{u}$.

Then, for the t-th generation in our setting, the expression can be written as:

$$P^t = \sum_i \lambda_i^t \mathbf{v}_i \mathbf{u}_i. \tag{D5}$$

To derive the expression for the distribution of classes in generation t, we apply the matrix P^t to the initial distribution μ_0:

$$\mu_t = \mu_0 P^t = \mu_0 \sum_i \lambda_i^t \mathbf{v}_i \mathbf{u}_i = \sum_i \lambda_i^t (\mu_0 \mathbf{u}_i)\mathbf{v}_i = \sum_i \lambda_i^t \alpha_i \mathbf{v}_i, \tag{D6}$$

where $\alpha_i = (\mu_0 \mathbf{u}_i)$ denotes the scalar obtained from the inner product between the initial class distribution and the left eigenvector $\mathbf{u}_i$. Recall that the eigenvalues of P are ordered such that $|\lambda_1| > |\lambda_2| ... > |\lambda_n|$, and that the dominant eigenvalue λ_1 equals 1. The corresponding right eigenvector $\mathbf{v}_1$ represents the steady-state distribution μ_∞ (Sommers and Conlisk, 1979).

Using this ordering, we can rewrite Equation (D6) in a form that is more intuitive for our analysis:

$$\mu_t = \mu_\infty + \lambda_2^t \alpha_2 \mathbf{v}_2 + \cdots + \lambda_n^t \alpha_n \mathbf{v}_n, \tag{D7}$$

where, for the purpose of studying intergenerational mobility, the n eigenvectors $\mathbf{v}_i$ can be interpreted as the principal directions of mobility flows. Each $\mathbf{v}_i$ identifies a "barrier" that slows the evolution of the current distribution μ_t toward the steady-state distribution μ_∞, and the elements of $\mathbf{v}_i$ correspond to class-specific coordinates along each direction. The scalar coefficients α_i measure the weight or relative importance of each barrier in this decomposition, while the eigenvalues λ_i indicate the persistence of the corresponding barrier over generations t. Since $0 \leq |\lambda_i| \leq 1$, as $t \to \infty$, all terms multiplied by λ_i^t converge to 0. Convergence occurs fastest along the n-th eigenvector $\mathbf{v}_n$ and slowest along the second-largest eigenvector $\mathbf{v}_2$. Consequently, $\mathbf{v}_2$ can be interpreted as the dominant (most persistent) pattern that constrains intergenerational mobility, and $|\lambda_2|$ represents the upper bound on persistence in the system. Larger values of $|\lambda_2|$ correspond to slower convergence and, therefore, lower mobility conceptualized as memory. Formally, the convergence rate can be bounded as

$$\|\mu_\infty - \mu_t\| \leq c\,|\lambda_2|^t, \quad \text{where} \quad c = \sum_{i=2}^{n} |\alpha_i|\,\|\mathbf{v}_i\|, \tag{D8}$$

with c a constant depending on the initial distribution and the eigenvectors.

Figure D.3 plots trends in d_t and $|\lambda_2|$ across cohorts. These trends align closely with our results from the main text, showing a fairly stable pattern over time. Overall, the weight of the evidence suggests there has been little change in intergenerational memory.

Finally, we consider several alternative measures of association that are based on the joint distribution of parental and child occupations, in contrast to the conditional probabilities represented by the transition matrix. These include the Altham index (Altham, 1970) and the Hellinger dependence index (Coleman and Lukina, 2025; Geenens and Lafaye de Micheaux, 2022). Both summarize the degree of dependence in the joint probability distribution of parental origins and child destinations.

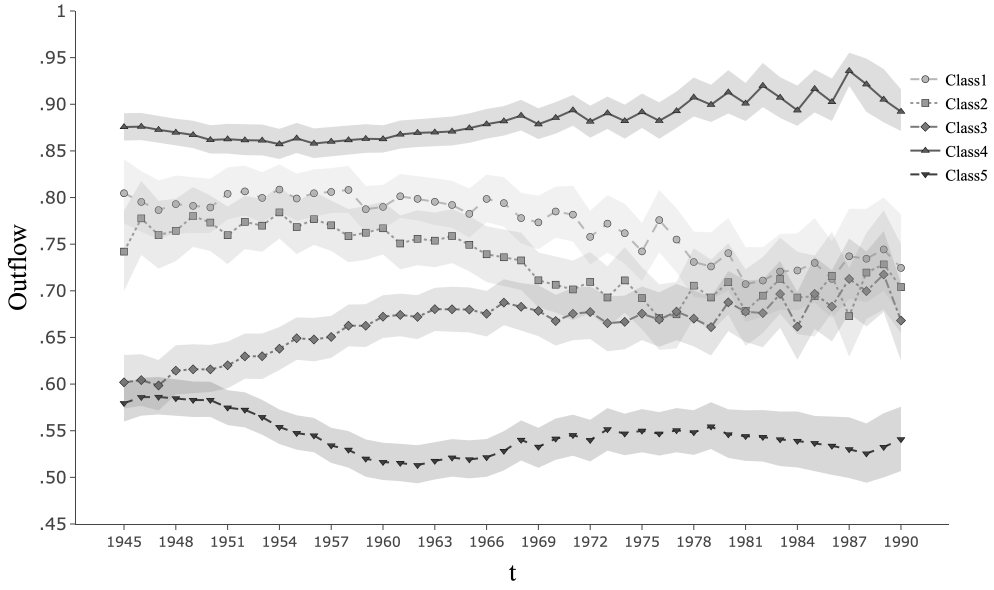
The Altham index provides a summary measure of dependence in a contingency table by quantifying the deviation of an observed probability matrix from the independence matrix. Formally, it is defined as the square root of the sum of squared deviations of all log-odds ratios from zero. Recall that, under perfect independence, all odds ratios equal one, and their logarithms equal zero. The index ranges from 0 to ∞, where 0 indicates no association, and higher values signify stronger dependence between origins and destinations, corresponding to lower mobility. The index has no finite upper bound because, in theory, the odds ratios can become arbitrarily large, reflecting extreme persistence of status across generations.

The Hellinger index uses iterative proportional fitting to transform the marginal proportions of the probability matrix to a uniform distribution while preserving the underlying dependence structure (i.e., the odds ratios). The transformed matrices with uniform marginals are then contrasted with the independence matrix under uniform marginals. The measure ranges from 0 to 1, where 0 indicates complete independence between origins and destinations and 1 indicates perfect dependence.

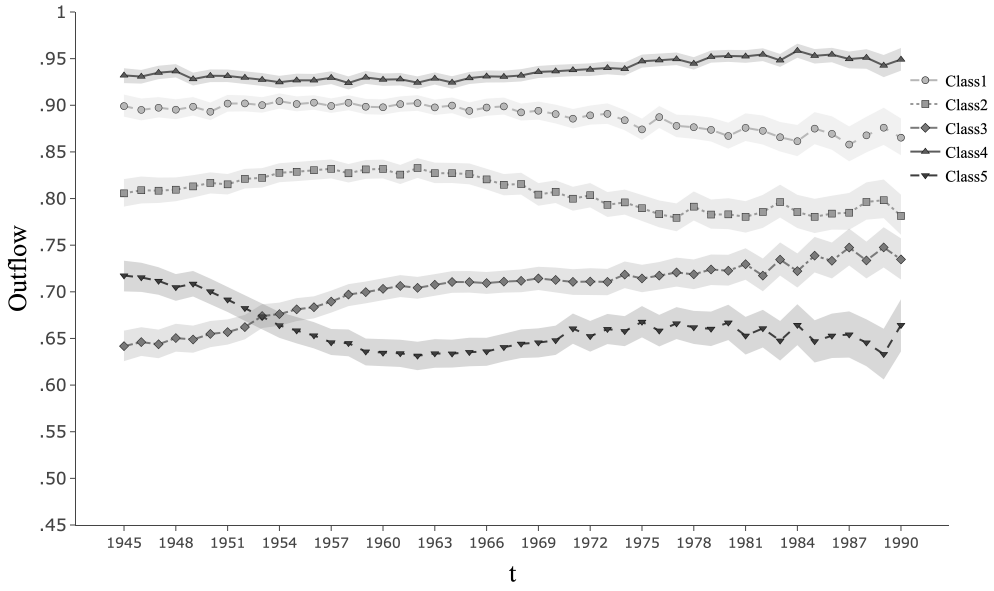
Figure D.4 displays estimates of the Altham and Hellinger indices computed from the smoothed mobility tables. As with our other measures of association—in particular, the log-multiplicative layer effects from the model in Equation 9—these trends provide little evidence of an upward or downward shift. The point estimates fluctuate in no clear direction, especially among more recent cohorts, but these changes generally cannot be statistically distinguished from the levels observed among earlier cohorts.

Figure D.1: Class outflows at generation $t = 1$ and at the steady state

(A) Outflows at generation $t = 1$

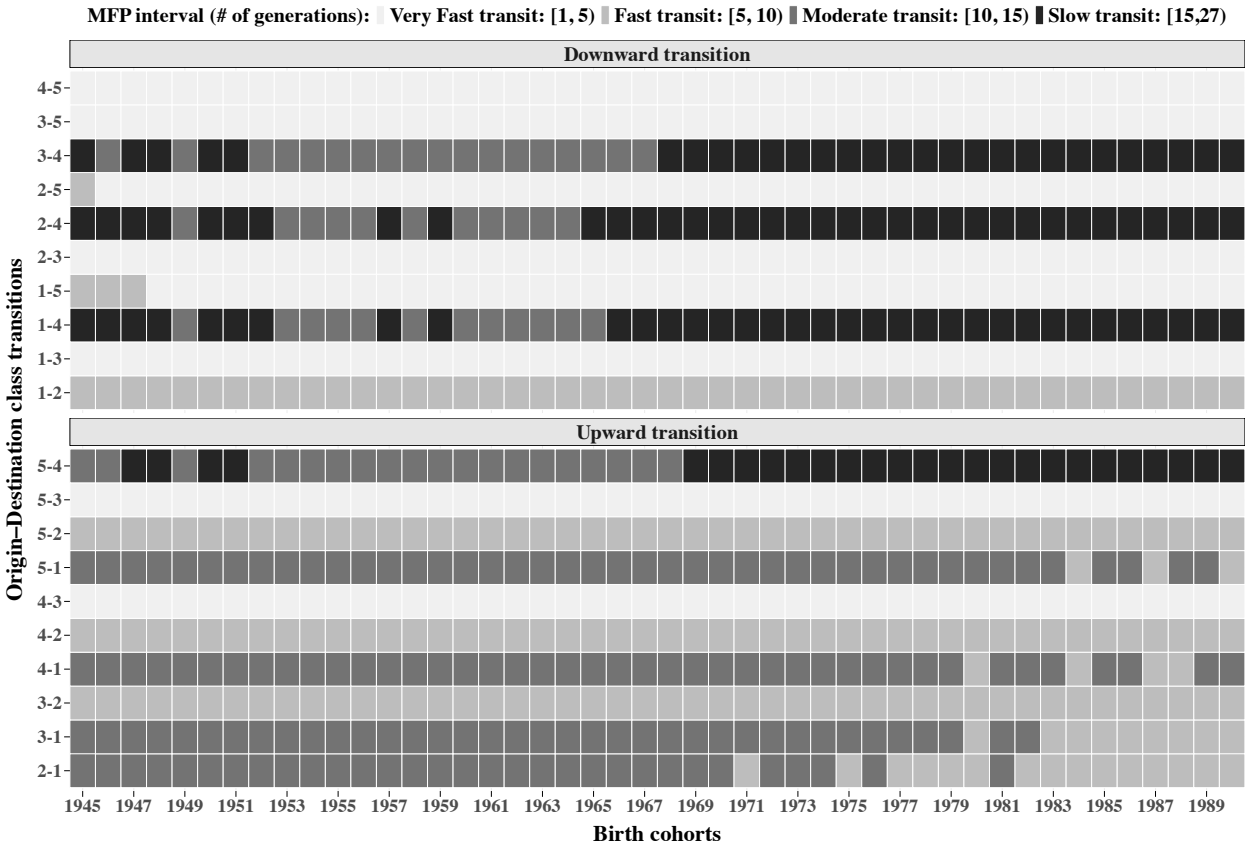


(B) Outflows at the steady state



Notes: Shaded areas represent 95% confidence intervals. 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.

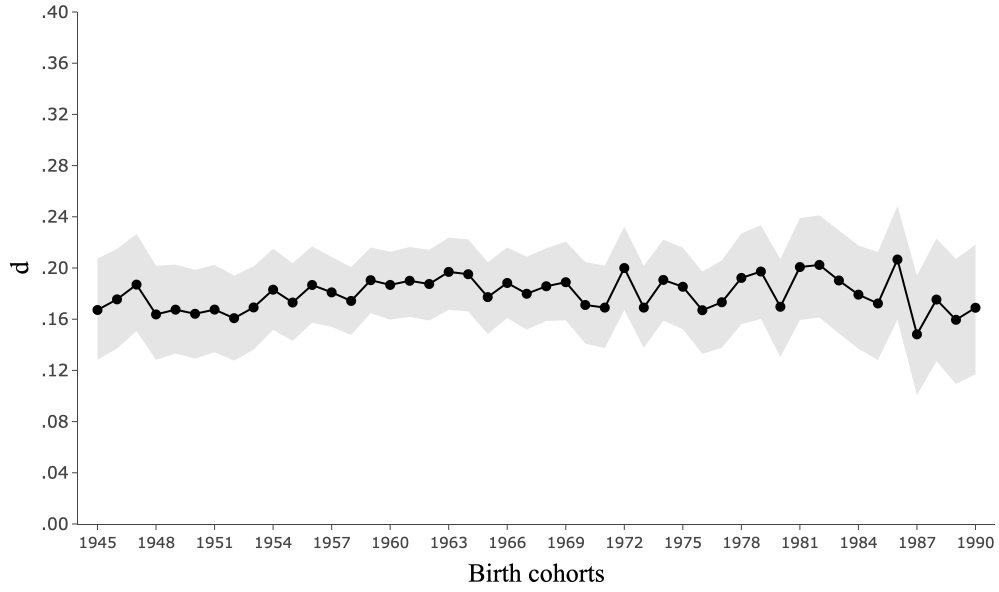
Figure D.2: Mean first passage time



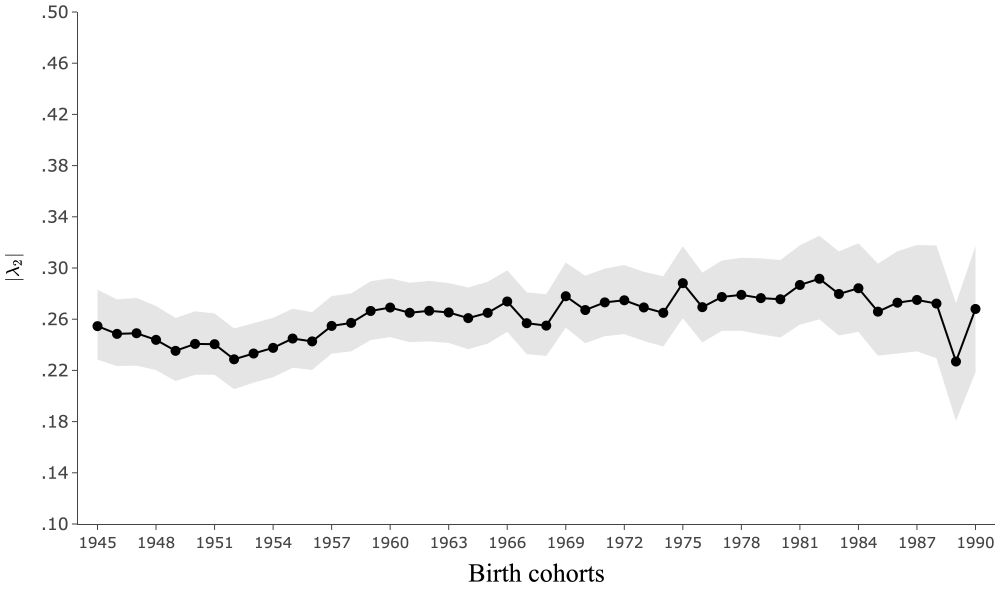
Notes: Class 1 refers to higher-grade professionals, administrators, and managers; class 2 refers to lower-grade professionals, administrators, and managers; class 3 includes higher-grade routine non-manual workers, technicians, and supervisors; class 4 comprises higher-grade manual workers, lower-grade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

Figure D.3: Alternative measures of memory

(A) Maximum distance to stationarity (d_t)



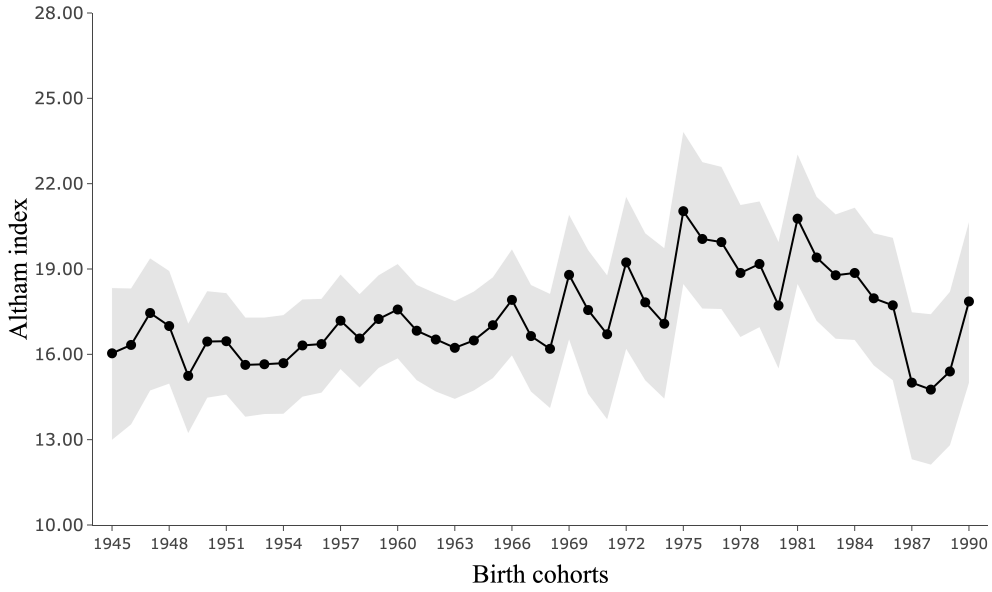
(B) Second largest eigenvalue modulus ($|\lambda_2|$)



Notes: Shaded areas represent 95% confidence intervals.

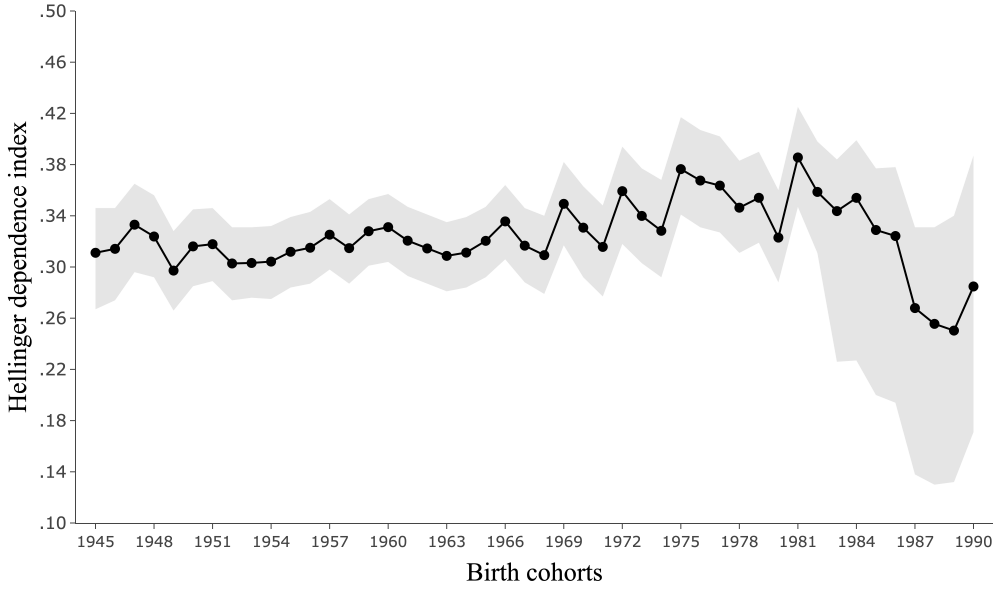
Figure D.4: Alternative measures of dependence

(A) Altham index



Notes: Shaded areas represent 95% confidence intervals.

(B) Hellinger dependence index



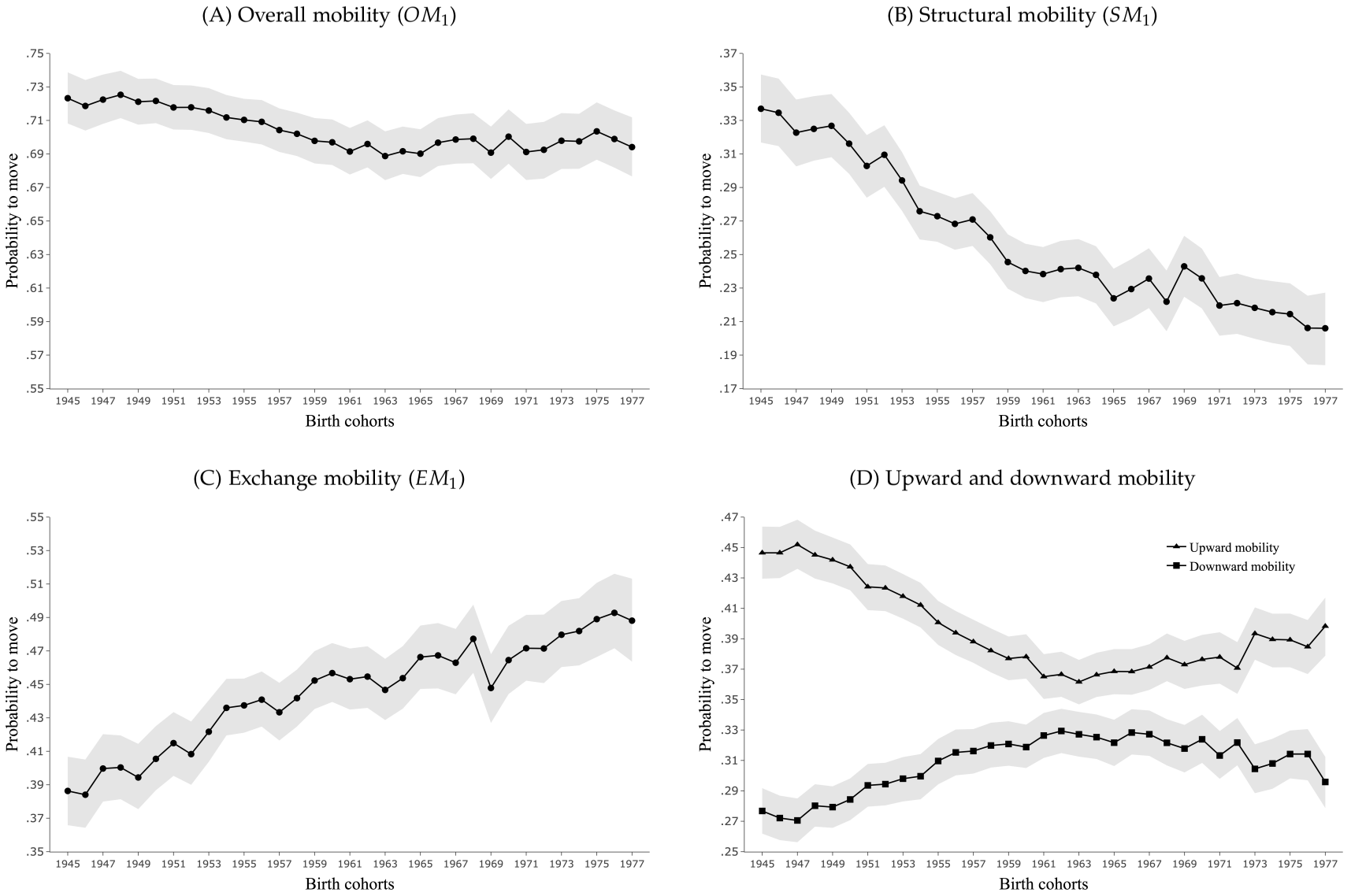
Notes: Shaded areas represent 95% confidence intervals.

E Trends by Gender

In this section, we examine potential gender differences in mobility patterns across cohorts. Specifically, we replicate our main analyses using transition matrices constructed separately from father–daughter, father–son, and mother-child pairs, rather than from the combined father-child pairs as in the main text. We also construct transition matrices based on the highest-ranked class of either the mother or father. Trend estimates based on father-daughter pairs are presented in Figures E.1 to E.4, while those based on father-son pairs appear in Figures E.5 to E.8. Estimates based on mother-child pairs are shown in Figures E.9 to E.12. And estimates based on the highest-ranked class of either parent are presented in Figures E.13 to E.16. Due to sample size limitations—particularly the small number of female observations in class 4—we are only able to replicate our main analyses using 15,560 mother–child pairs (respondents aged 25–55, born between 1948 and 1990), 11,046 father–daughter pairs (respondents aged 25–55, born between 1945 and 1977), and 11,879 higher-status-parent–child pairs (respondents aged 25–55, born between 1945 and 1990). A narrower range of cohorts is considered in some of these ancillary analyses because we exclude cohorts for which more than 5% of the bootstrap replications yield non-primitive transition matrices.

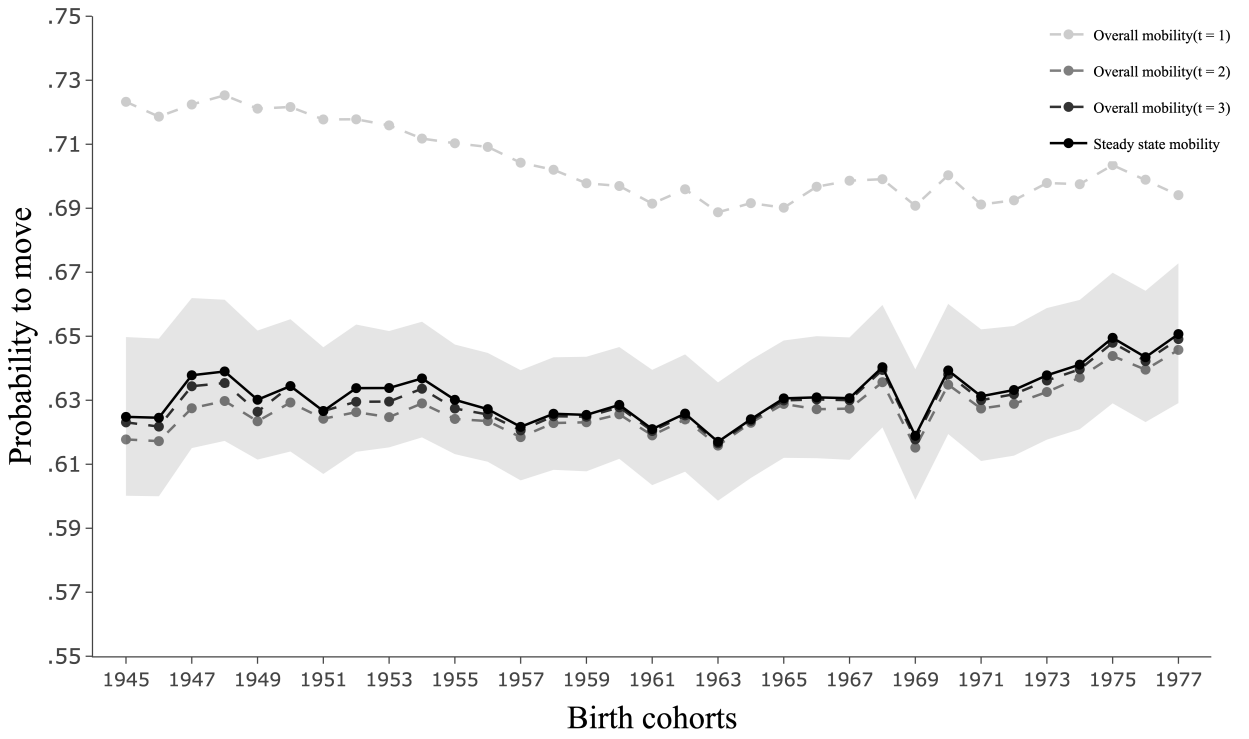
Overall, we find few major differences in trends when comparing results based on father-son versus father-daughter transitions. Incorporating mothers' occupational class also suggests a broadly stable pattern of movement and memory during this period. Across all these different sets of estimates, our focal measures of movement, memory, and association generally provide little evidence of a clear upward or downward trend in mobility.

Figure E.1: Measures of movement at generation $t = 1$ based on father-daughter pairs



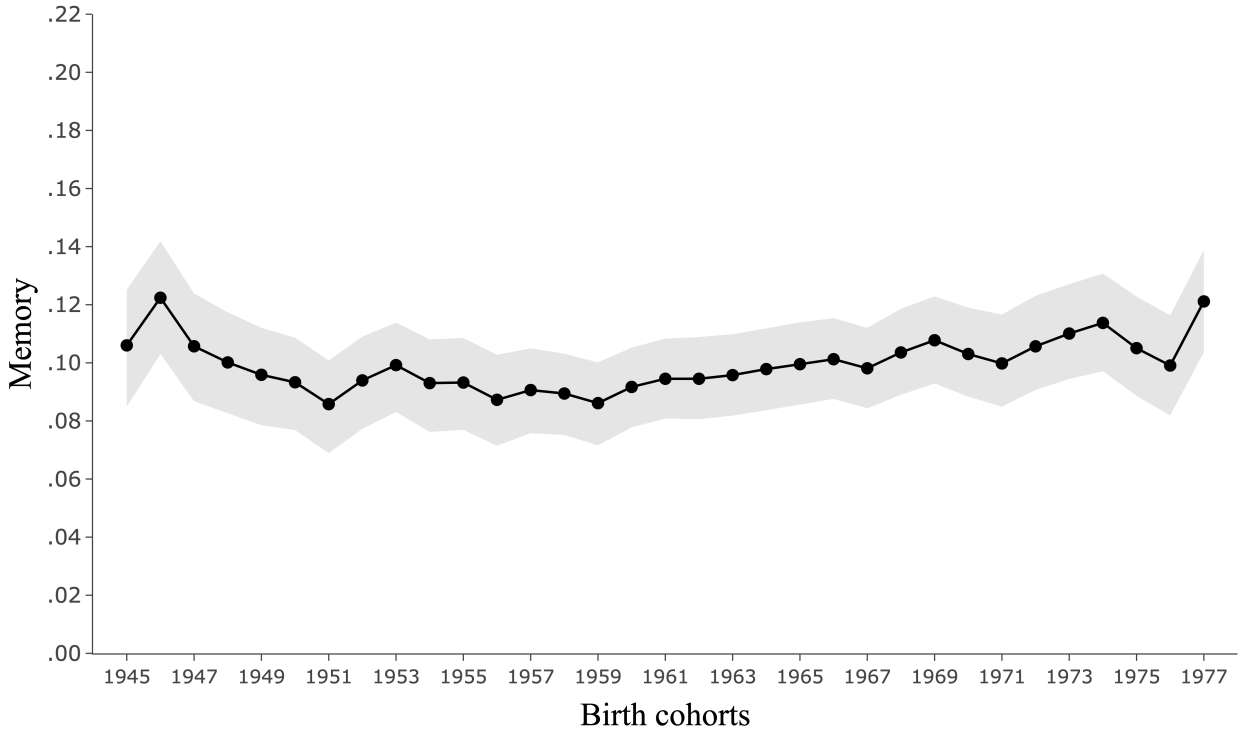
Notes: Shaded areas represent 95% confidence intervals.

Figure E.2: Overall mobility (OM_t) across synthetic generations based on father-daughter pairs



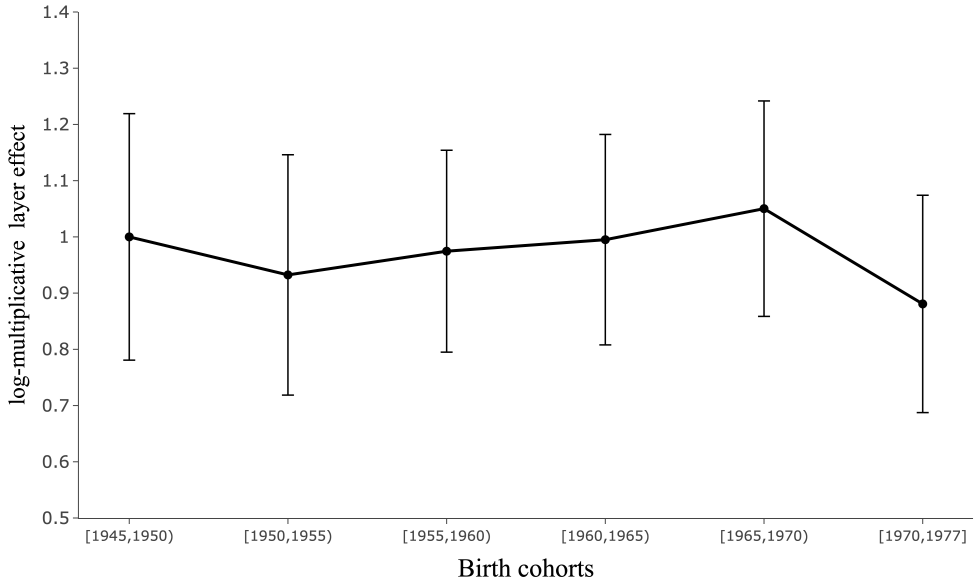
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure E.3: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on father-daughter pairs



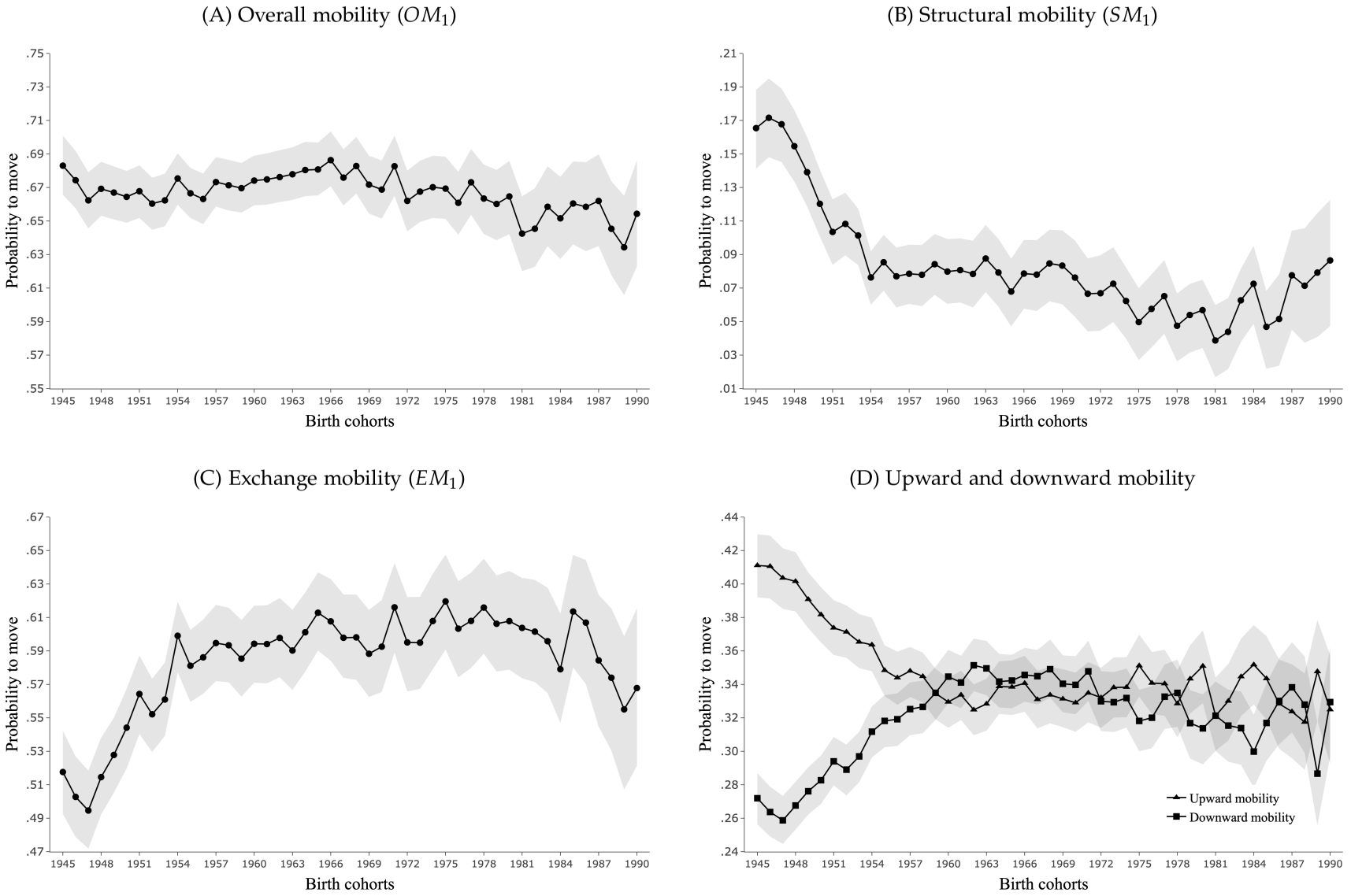
Notes: Shaded areas represent 95% confidence intervals.

Figure E.4: Log-multiplicative layer effects based on father-daughter pairs



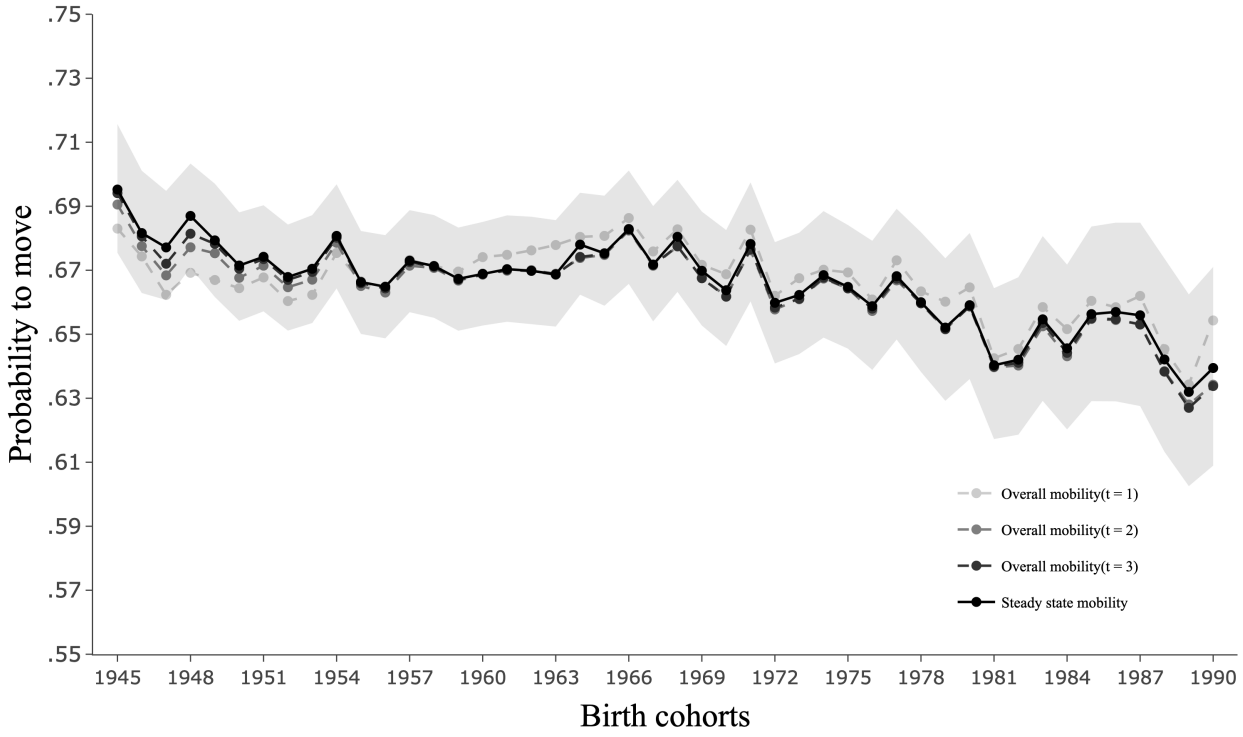
Notes: This figure plots the log-multiplicative layer effect across birth cohorts using ∼5-year bins. The vertical bars represent 95% confidence intervals.

Figure E.5: Measures of movement at generation $t = 1$ based on father-son pairs



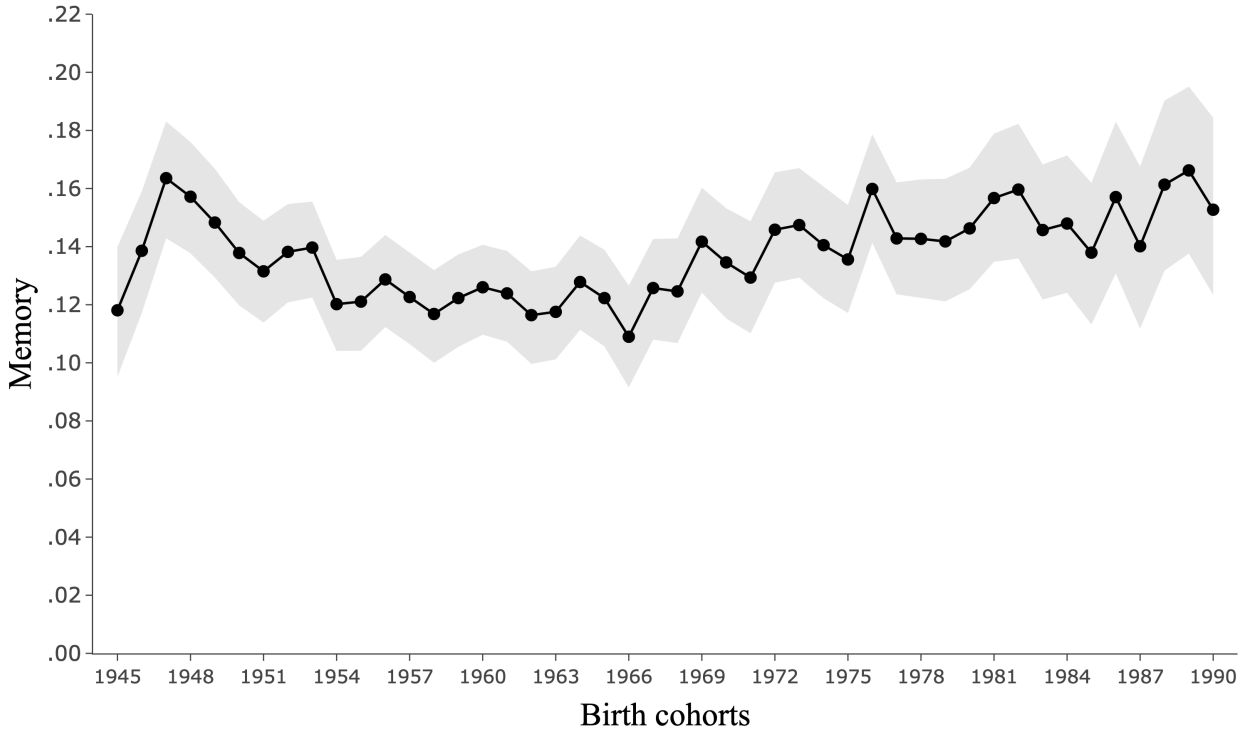
Notes: Shaded areas represent 95% confidence intervals.

Figure E.6: Overall mobility (OM_t) across synthetic generations based on father-son pairs



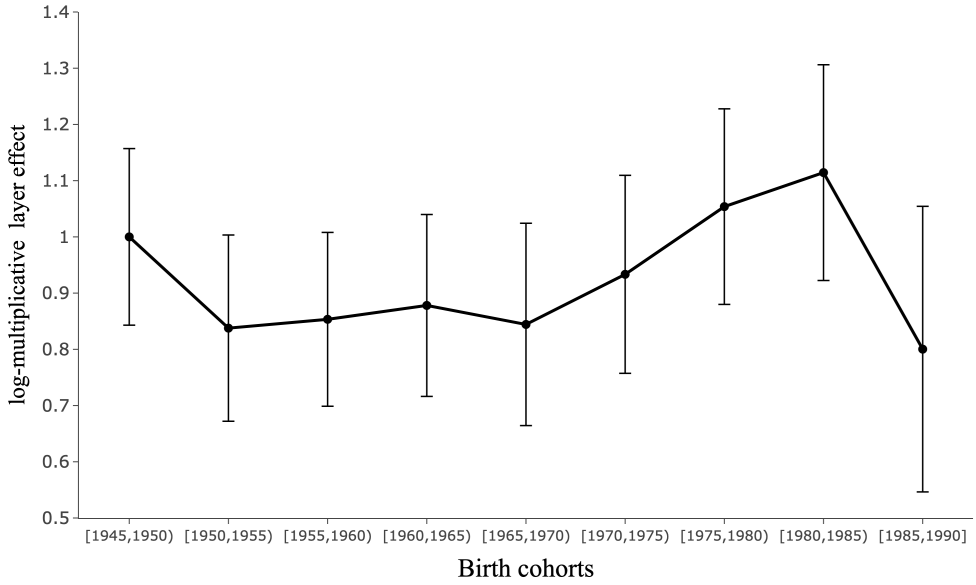
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure E.7: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on father-son pairs



Notes: Shaded areas represent 95% confidence intervals.

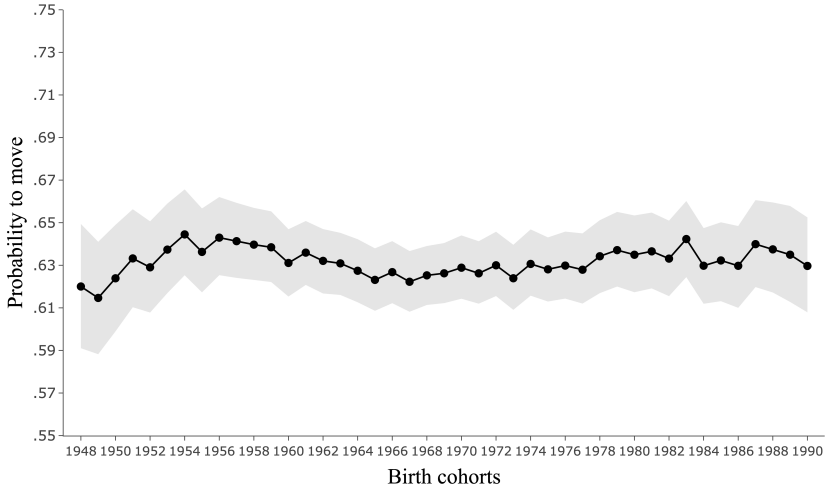
Figure E.8: Log-multiplicative layer effects based on father-son pairs



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

Figure E.9: Measures of movement at generation $t = 1$ based on mother-child pairs

(A) Overall mobility (OM_1)



(B) Structural mobility (SM_1)



(C) Exchange mobility (EM_1)

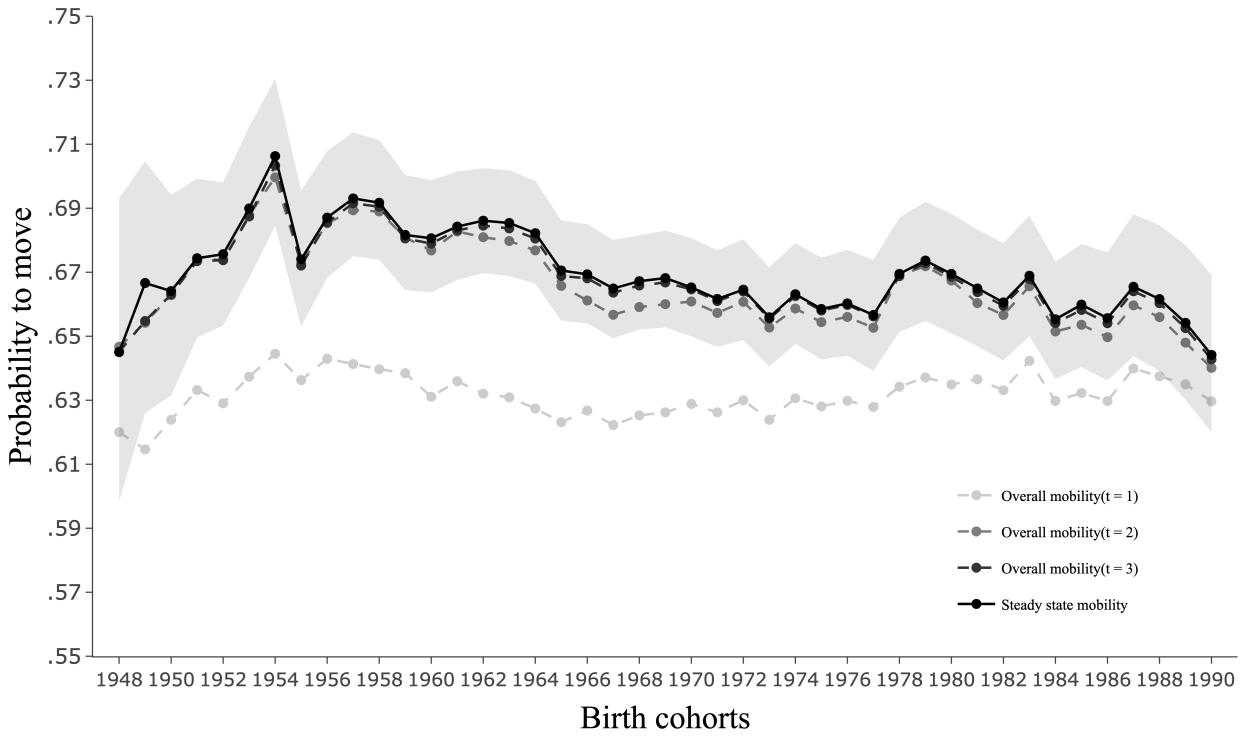


(D) Upward and downward mobility



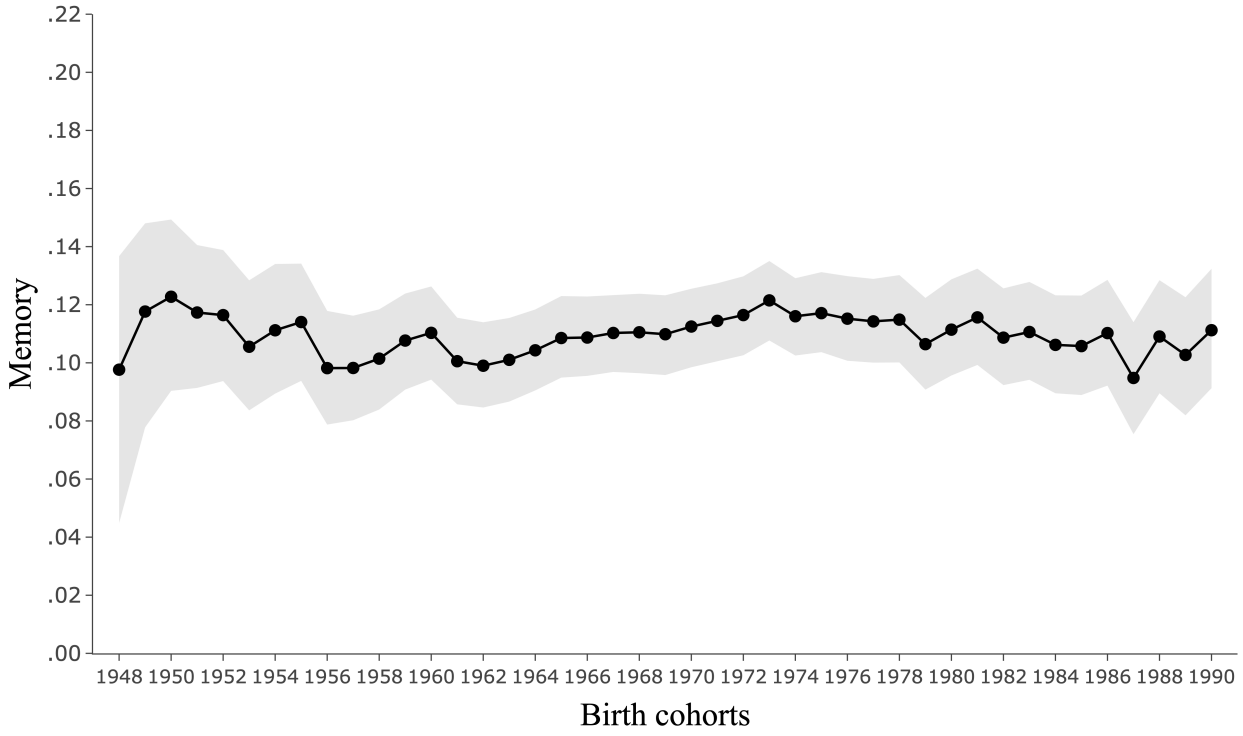
Notes: Shaded areas represent 95% confidence intervals.

Figure E.10: Overall mobility (OM_t) across synthetic generations based on mother-child pairs



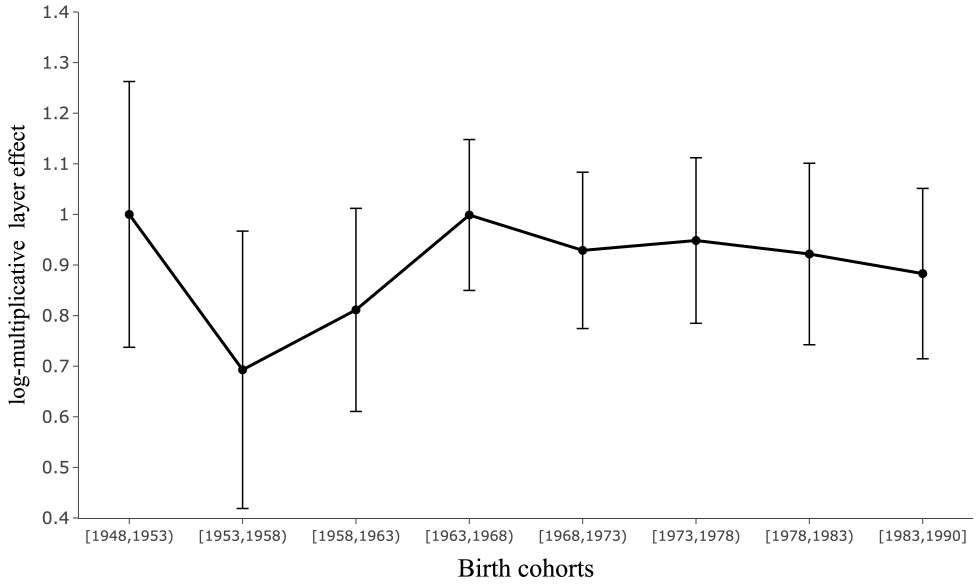
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure E.11: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on mother-child pairs



Notes: Shaded areas represent 95% confidence intervals.

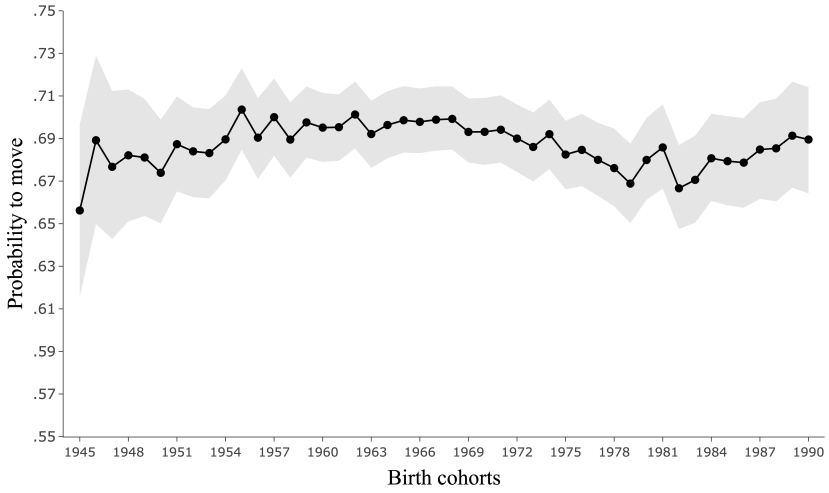
Figure E.12: Log-multiplicative layer effects based on mother-child pairs



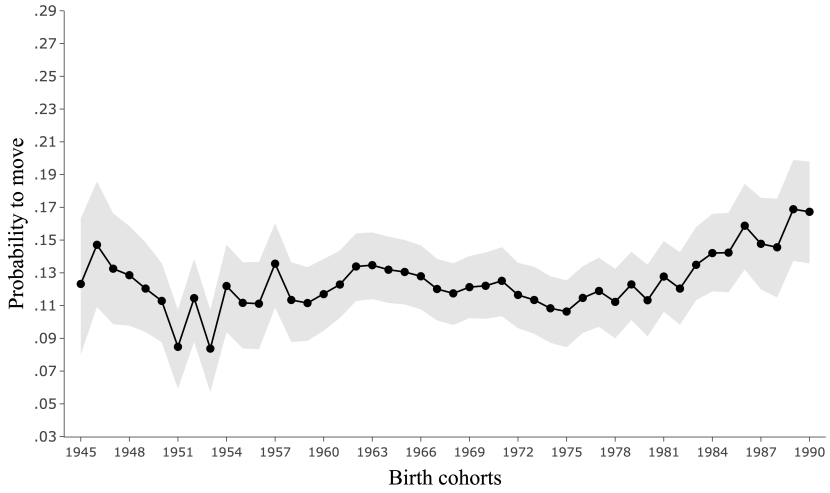
Notes: This figure plots the log-multiplicative layer effect across birth cohorts using 5-year bins. The vertical bars represent 95% confidence intervals.

Figure E.13: Measures of movement at generation $t = 1$ based on parent with higher status-child pairs

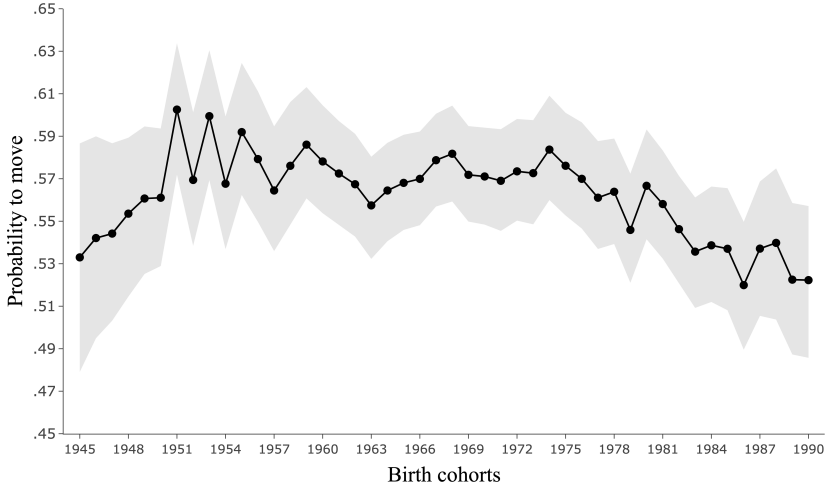
(A) Overall mobility (OM_1)



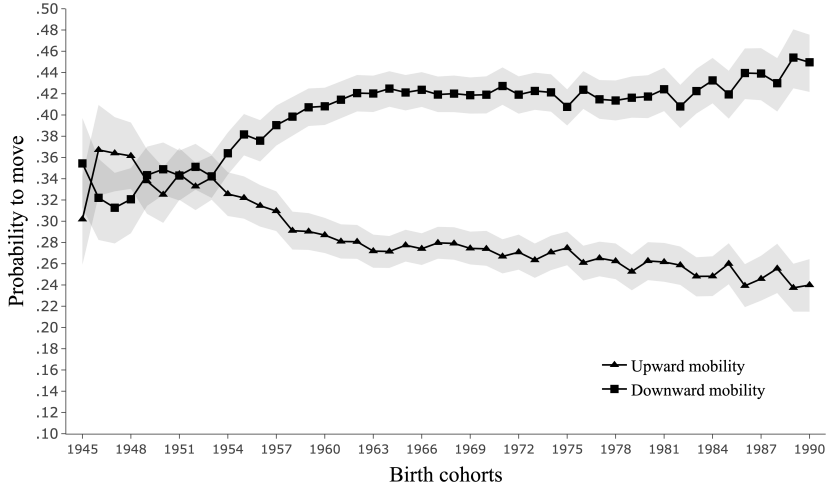
(B) Structural mobility (SM_1)



(C) Exchange mobility (EM_1)

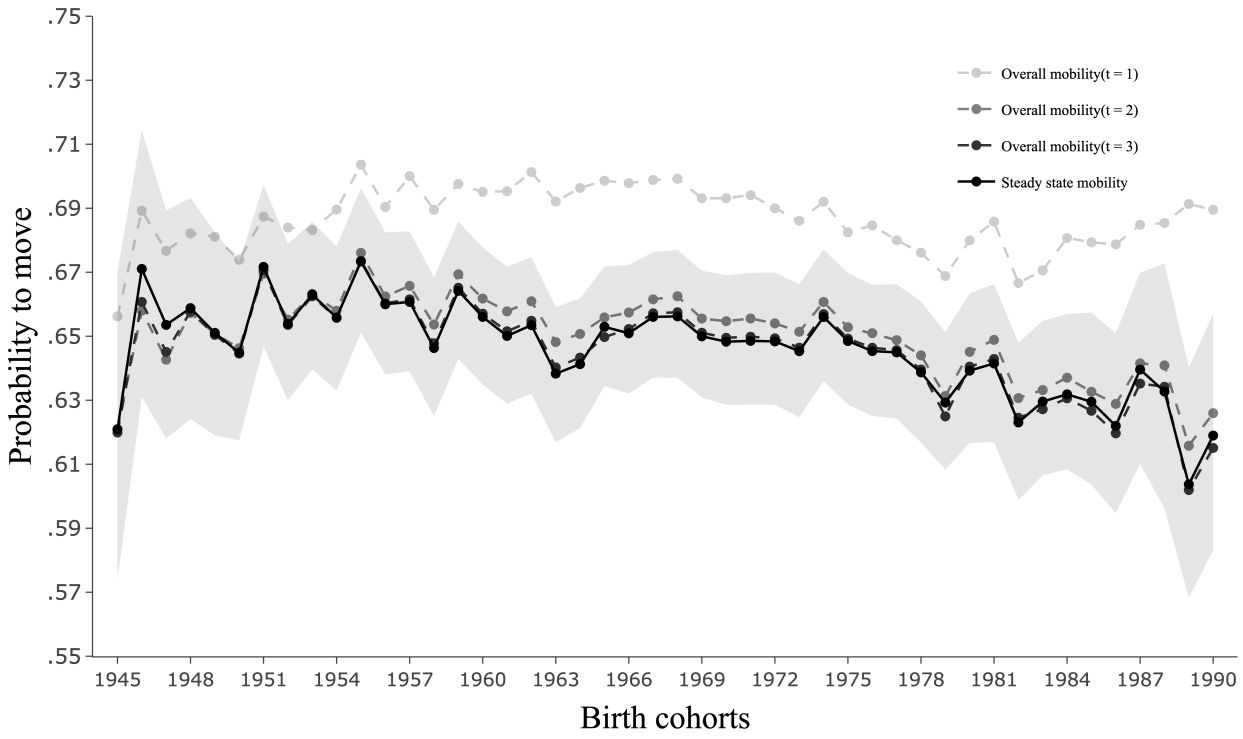


(D) Upward and downward mobility



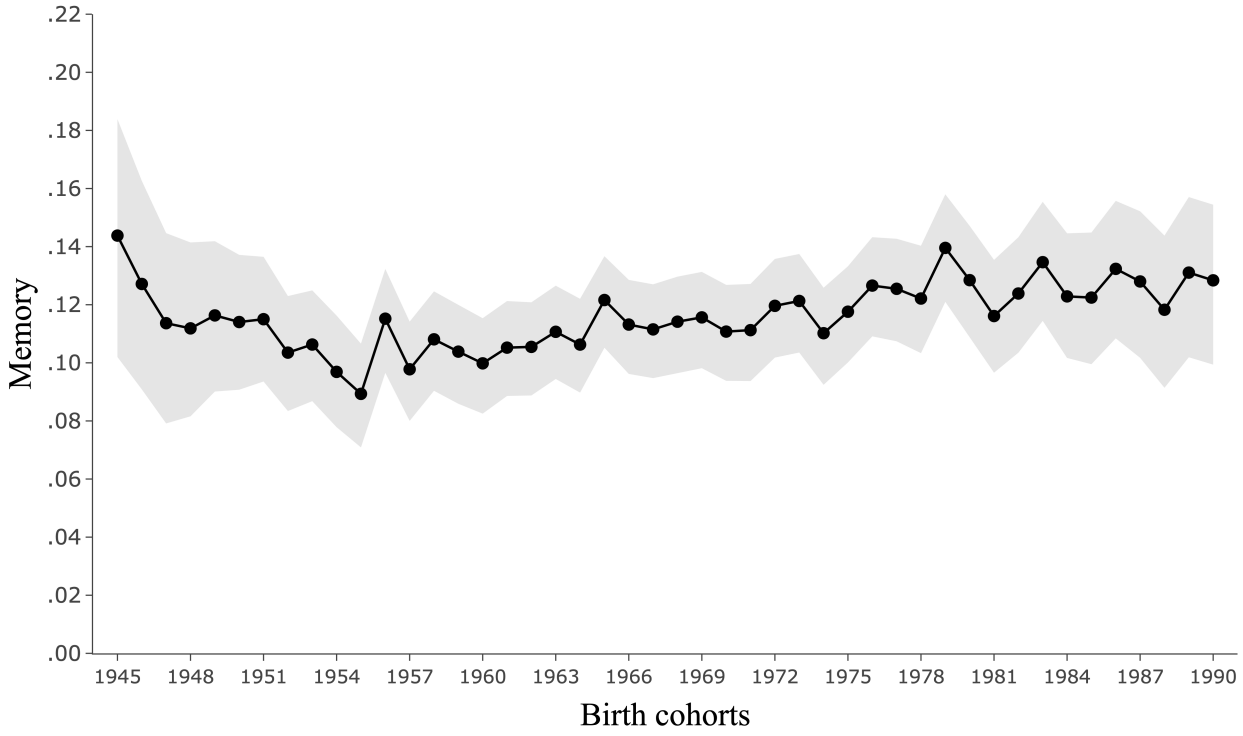
Notes: Shaded areas represent 95% confidence intervals.

Figure E.14: Overall mobility (OM_t) across synthetic generations based on parent with higher status-child pairs



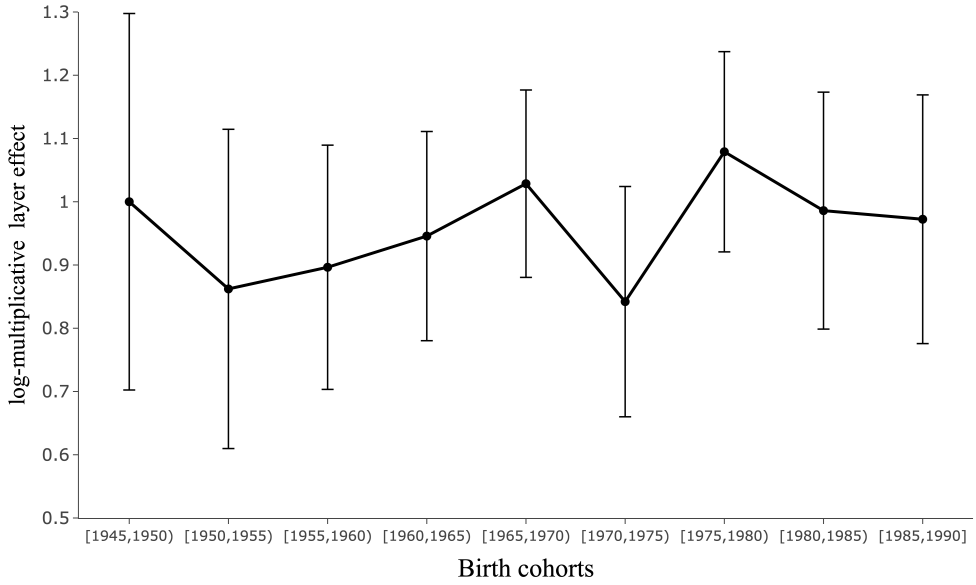
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure E.15: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on parent with higher status-child pairs



Notes: Shaded areas represent 95% confidence intervals.

Figure E.16: Log-multiplicative layer effects based on parent with higher status-child pairs

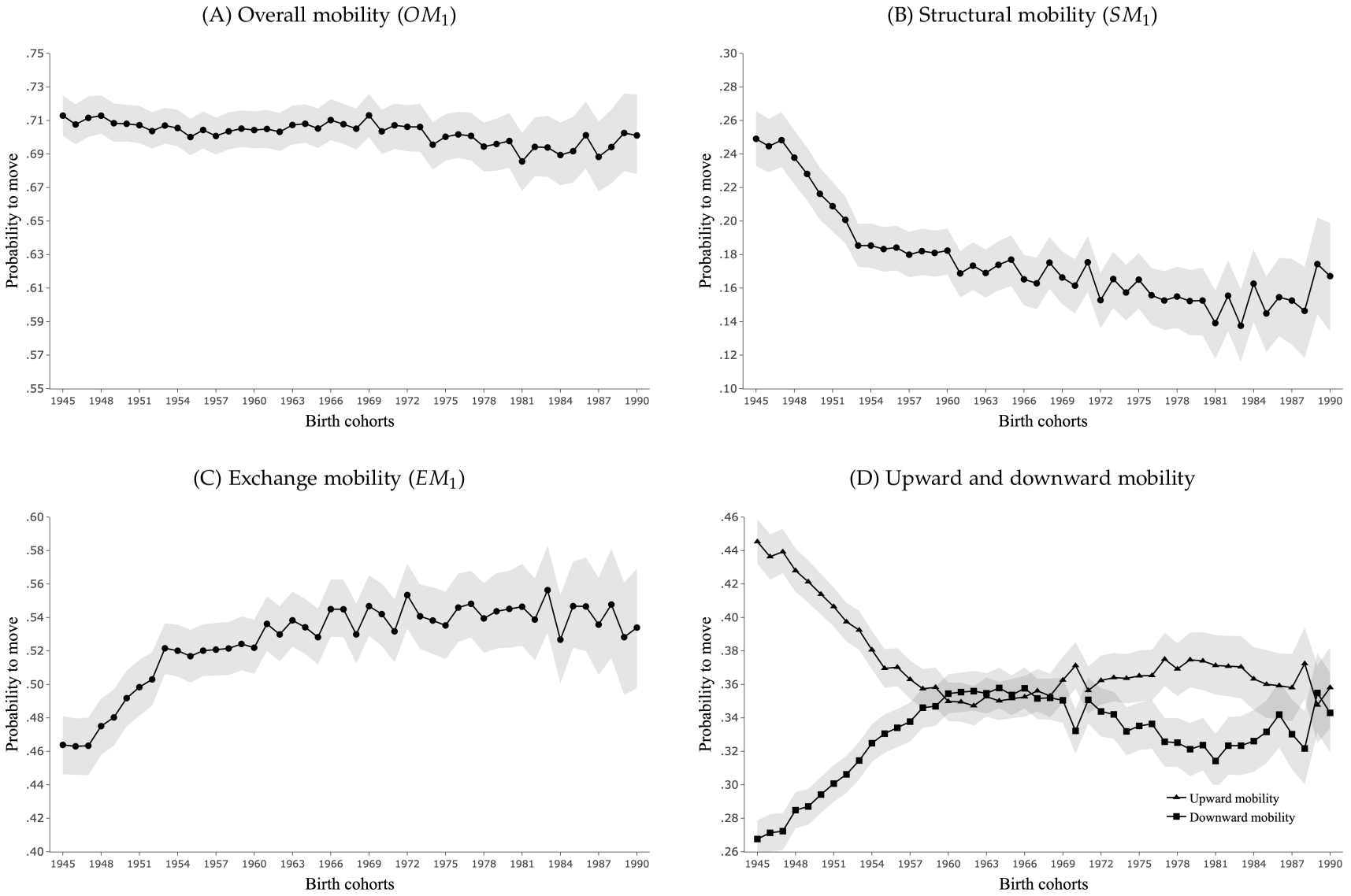


Notes: This figure plots the log-multiplicative layer effect across birth cohorts using ∼5-year bins. The vertical bars represent 95% confidence intervals.

F Trends by Race

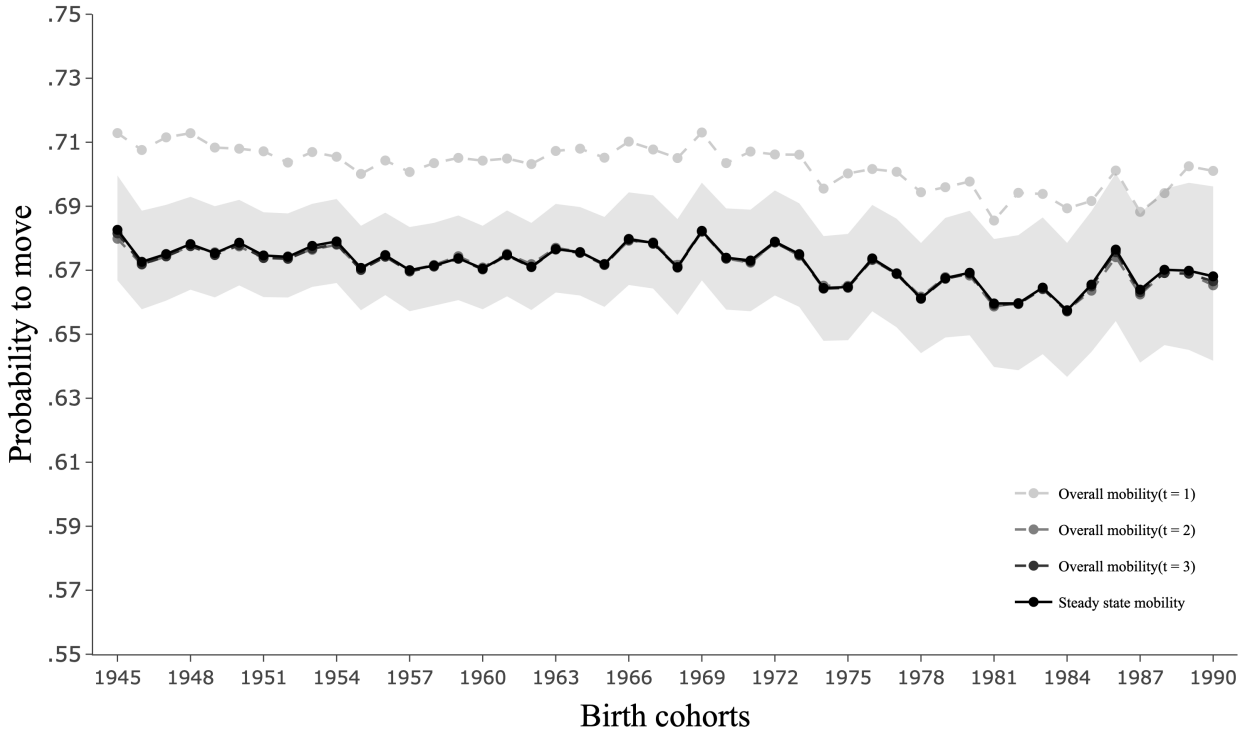
Due to sample limitations, our data include only 4,831 non-White father–child pairs among cohorts born between 1945 and 1990 who were age 25-55 at the time of their GSS interview. To examine potential heterogeneity by race, we therefore replicate our main analysis after excluding non-White pairs and focusing solely on White father–child pairs, which yields 19,395 observations. Because these cases constitute the majority of our sample in the main text, all key trends are largely unchanged when restricted to White father-child pairs.

Figure F.1: Measures of movement at generation $t = 1$ based on White father-child pairs



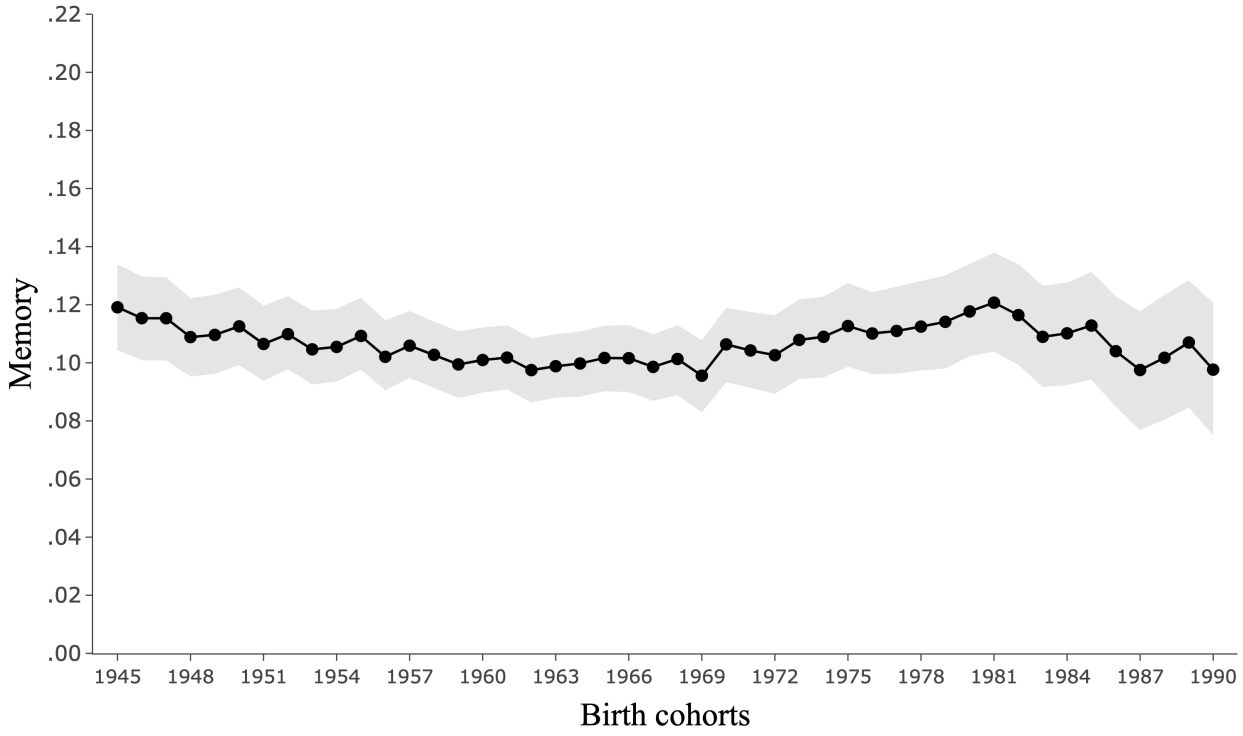
Notes: Shaded areas represent 95% confidence intervals.

Figure F.2: Overall mobility (OM_t) across synthetic generations based on White father-child pairs



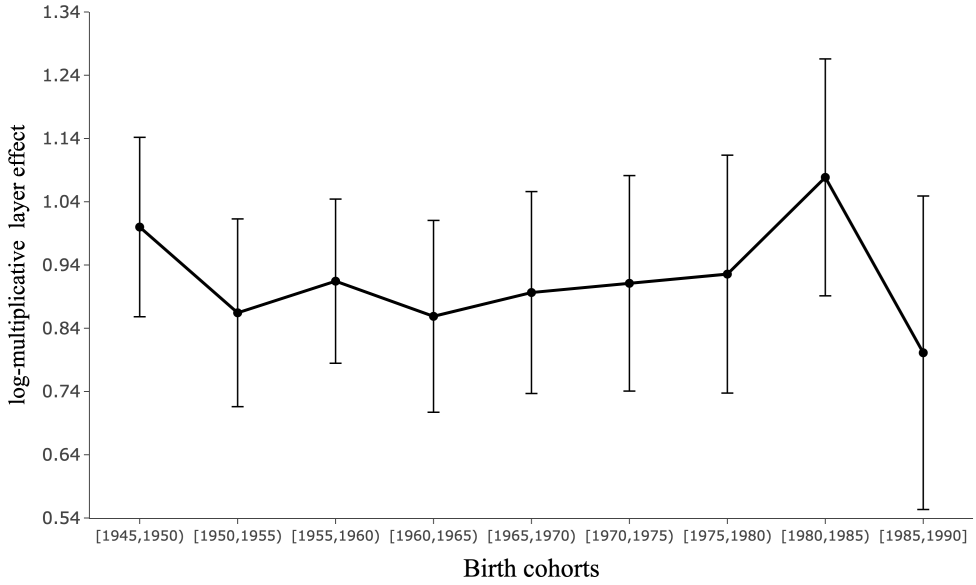
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure F.3: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on White father-child pairs



Notes: Shaded areas represent 95% confidence intervals.

Figure F.4: Log-multiplicative layer effects based on White father-child pairs



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

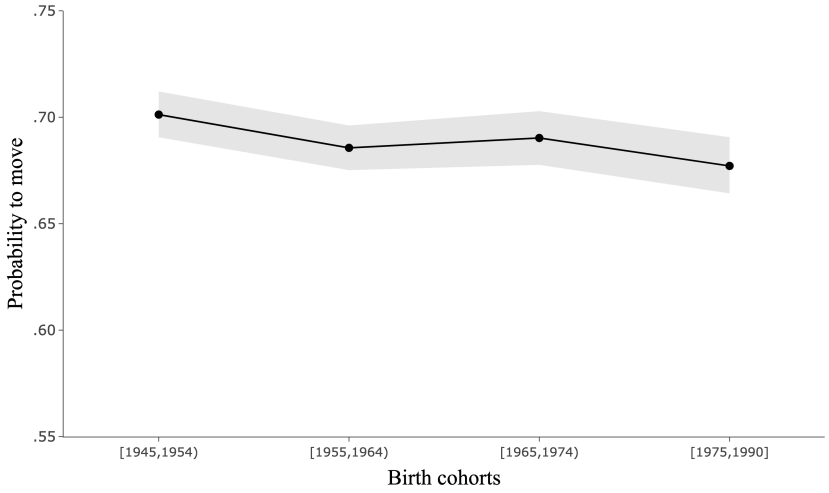
G Alternative Approaches to Smoothing

In this section, we replicate our main analyses using alternative methods for addressing sparsity in the origin-by-destination-by-cohort mobility tables. Instead of smoothing these tables with penalized splines, as in Equation 8, we construct transition matrices based on binned cohorts with 5- and ∼10-year bin widths. We then compute our measures of movement and memory from these binned matrices. The resulting estimates—presented in Figures G.1 to G.6—are broadly consistent with the findings reported in the main text.

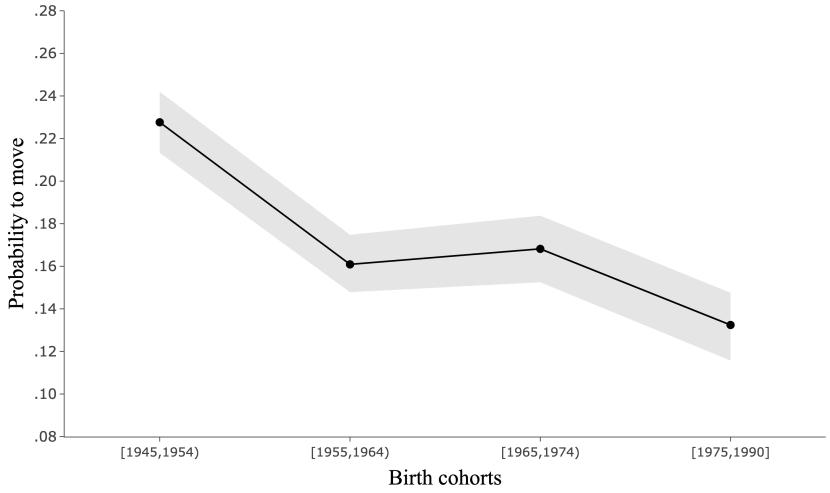
For comparison, we also present results obtained without any binning or smoothing. These estimates are shown in Figures G.7 to G.9. As expected, the unsmoothed transition matrices yield estimates that are much less precise and exhibit far more year-to-year volatility. Nevertheless, aside from this added noise, the trends appear broadly similar in that our key measures of movement and memory shown no indication of a consistent increase or decrease across cohorts.

Figure G.1: Measures of movement at generation $t = 1$ based on 10-year cohort bins

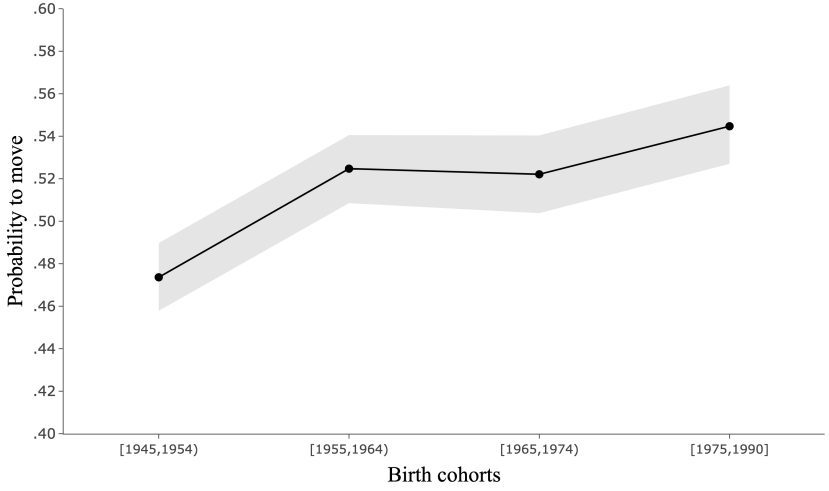
(A) Overall mobility (OM_1)



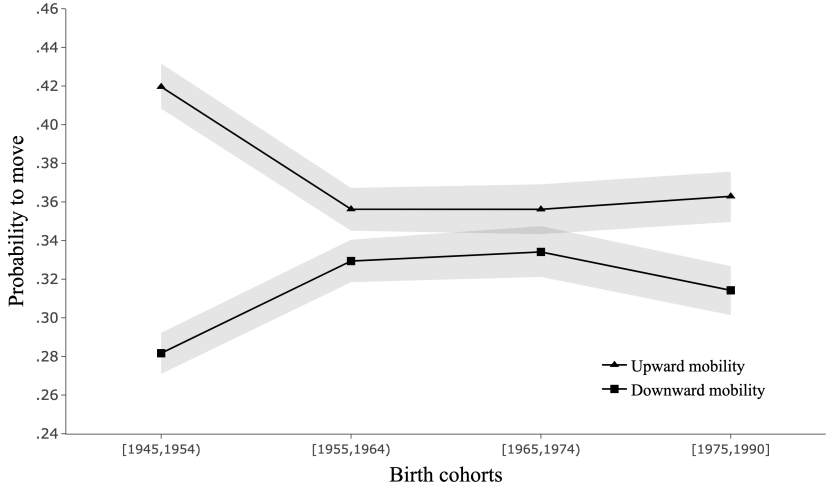
(B) Structural mobility (SM_1)



(C) Exchange mobility (EM_1)

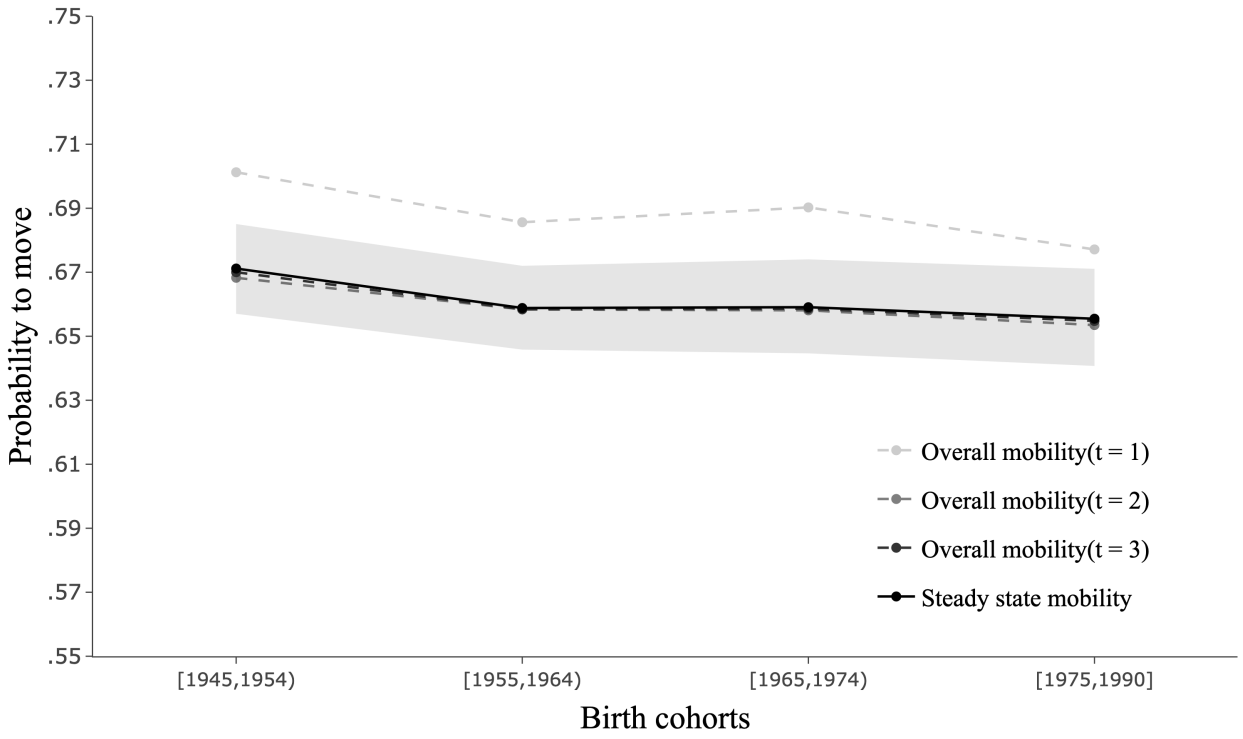


(D) Upward and downward mobility



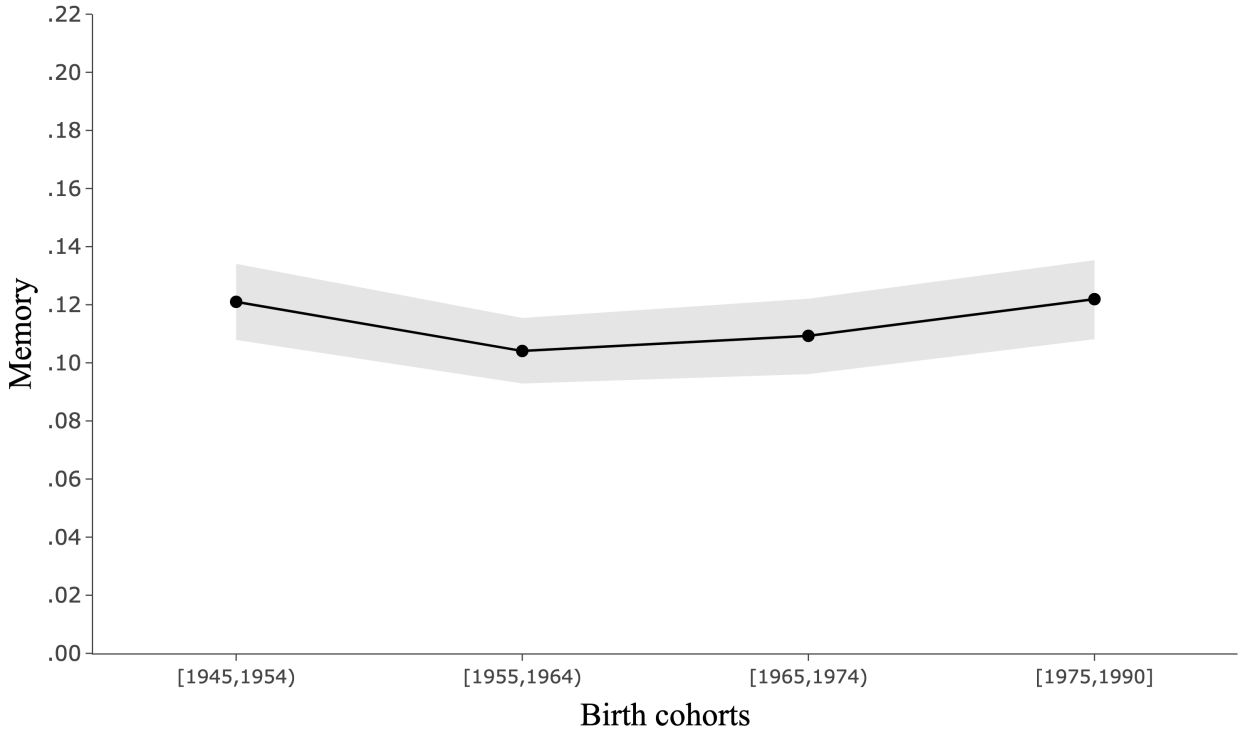
Notes: Shaded areas represent 95% confidence intervals.

Figure G.2: Overall mobility (OM_t) across synthetic generations based on 10-year cohort bins



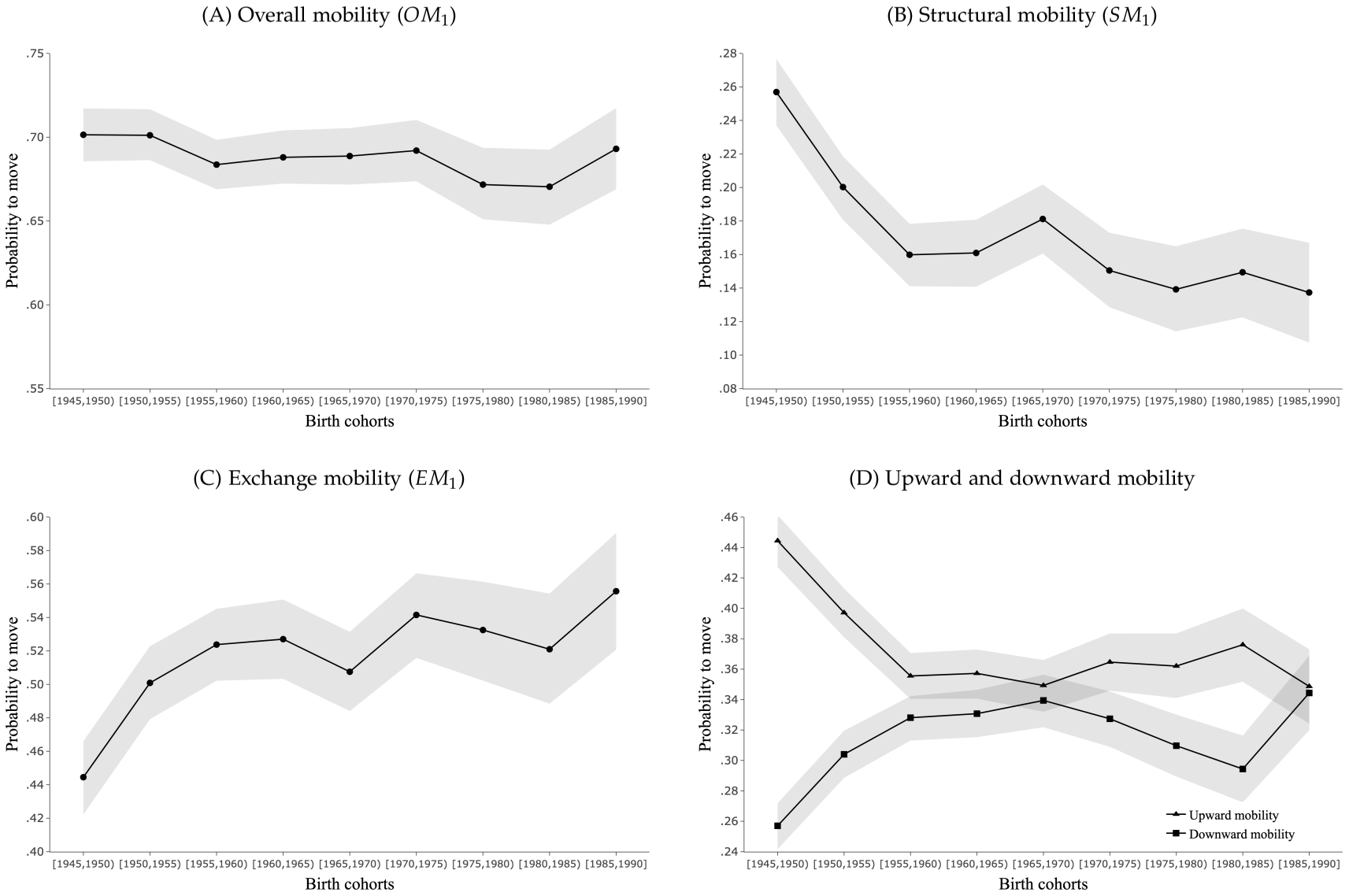
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chain. By $t = 4$, the Markov chains for most cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure G.3: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on 10-year cohort bins



Notes: Shaded areas represent 95% confidence intervals.

Figure G.4: Measures of movement at generation $t = 1$ based on 5-year cohort bins



Notes: Shaded areas represent 95% confidence intervals.

Figure G.5: Overall mobility (OM_t) across synthetic generations based on 5-year cohort bins



Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most 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.

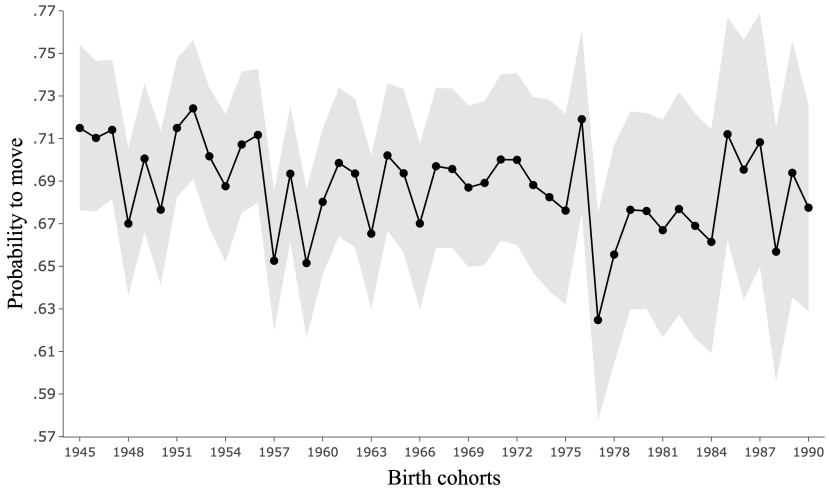
Figure G.6: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on 5-year cohort bins



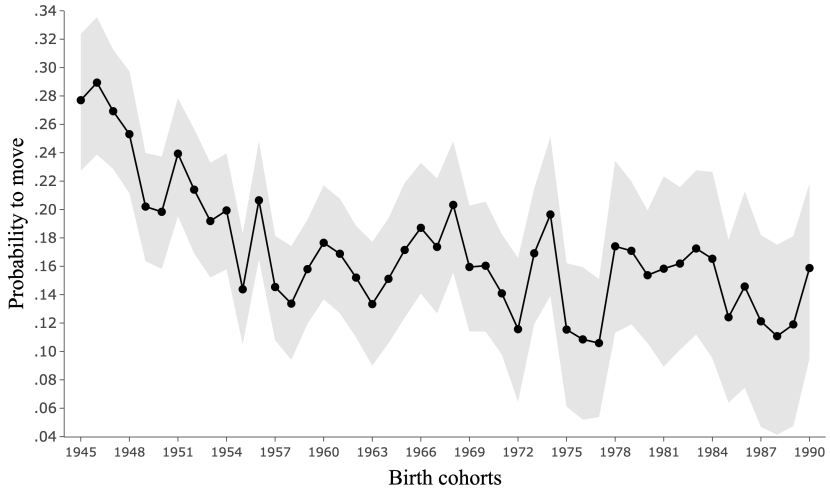
Notes: Shaded areas represent 95% confidence intervals.

Figure G.7: Measures of movement at generation $t = 1$ based on unsmoothed data

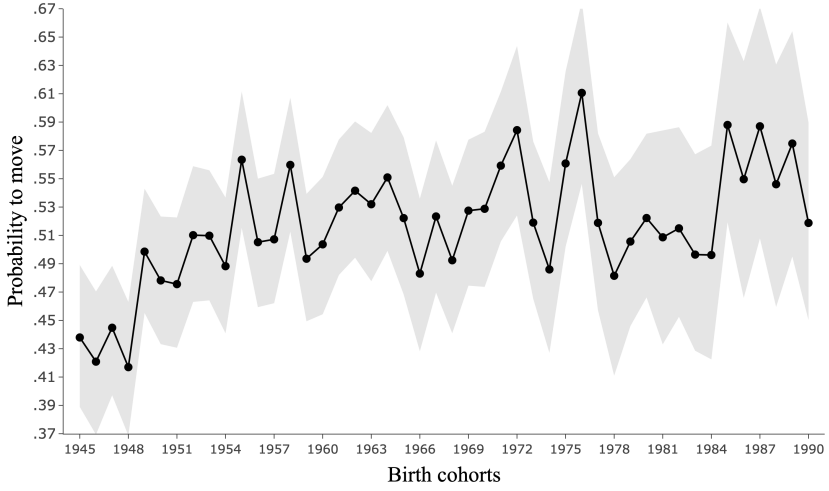
(A) Overall mobility (OM_1)



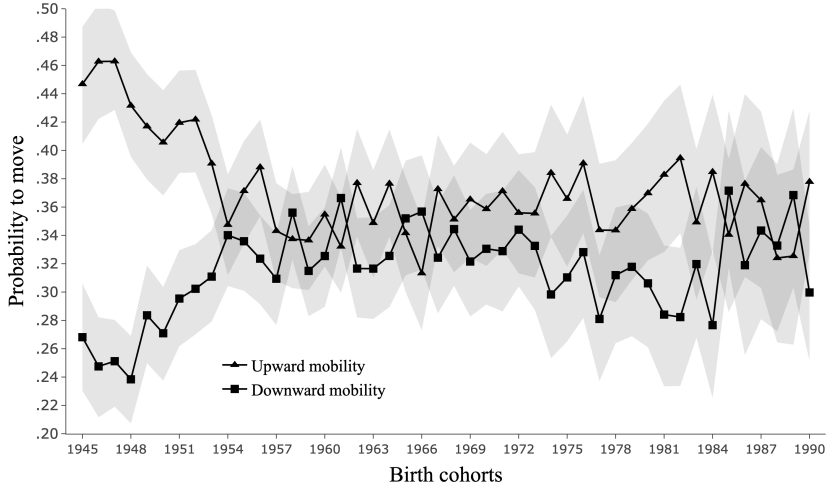
(B) Structural mobility (SM_1)



(C) Exchange mobility (EM_1)

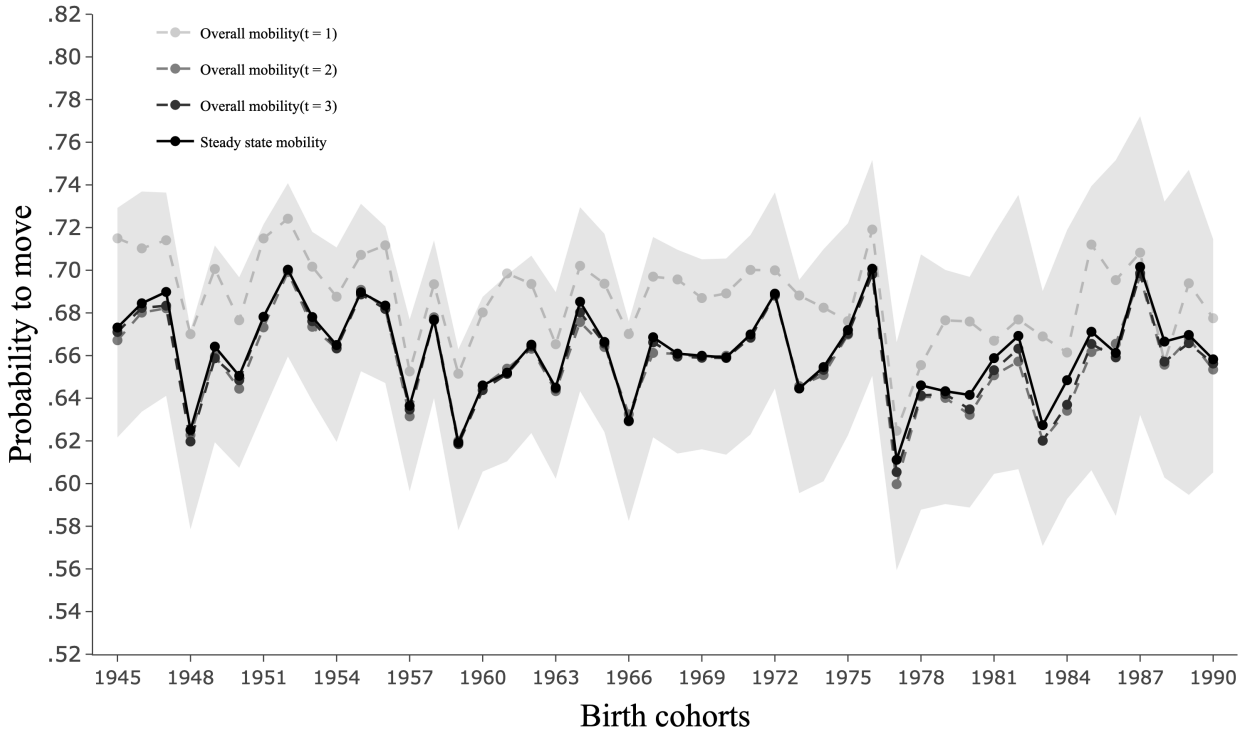


(D) Upward and downward mobility



Notes: Shaded areas represent 95% confidence intervals.

Figure G.8: Overall mobility (OM_t) across synthetic generations based on unsmoothed data



Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most 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.

Figure G.9: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on unsmoothed data

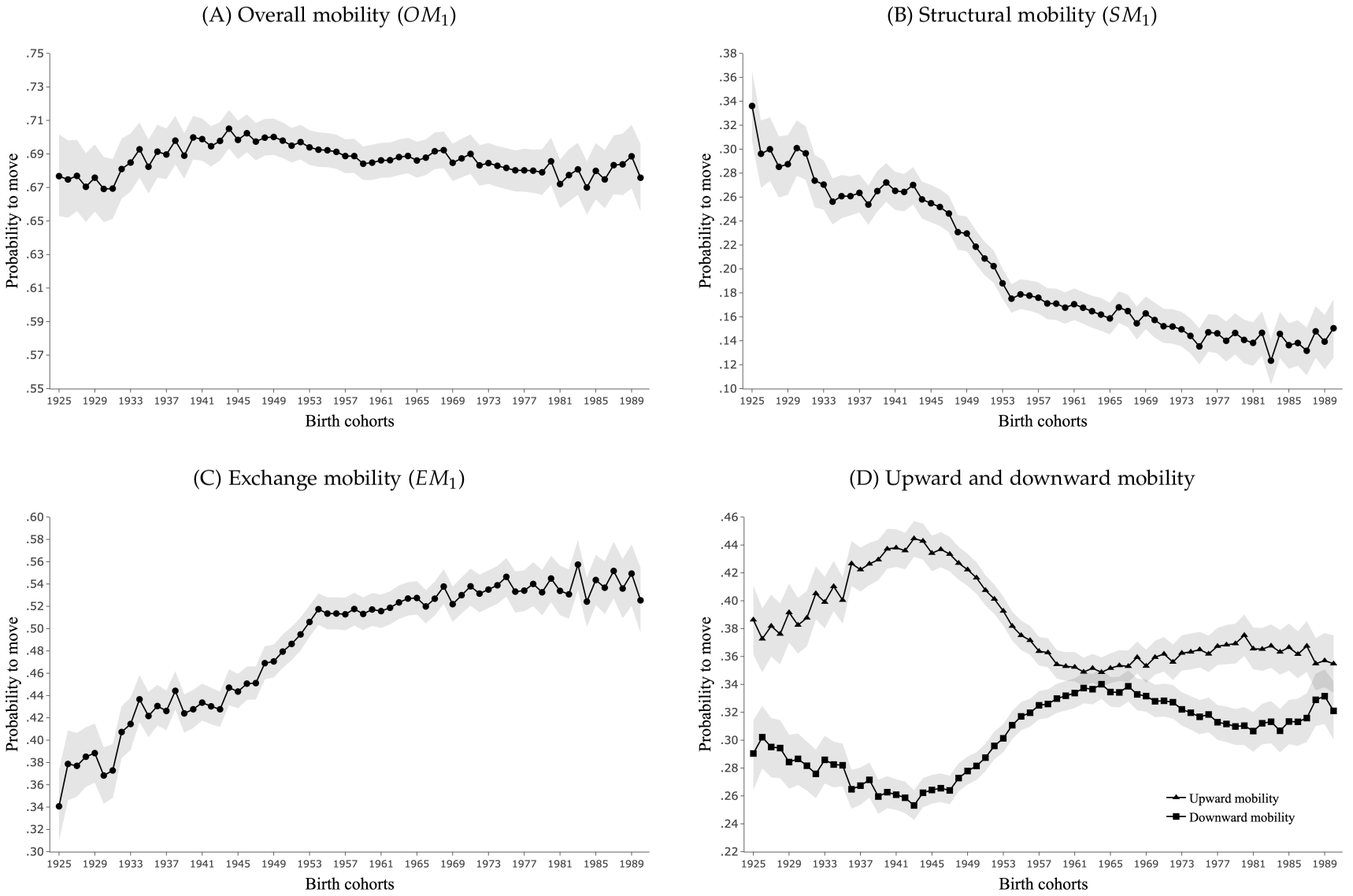


Notes: Shaded areas represent 95% confidence intervals.

H An Extended Series of Cohorts

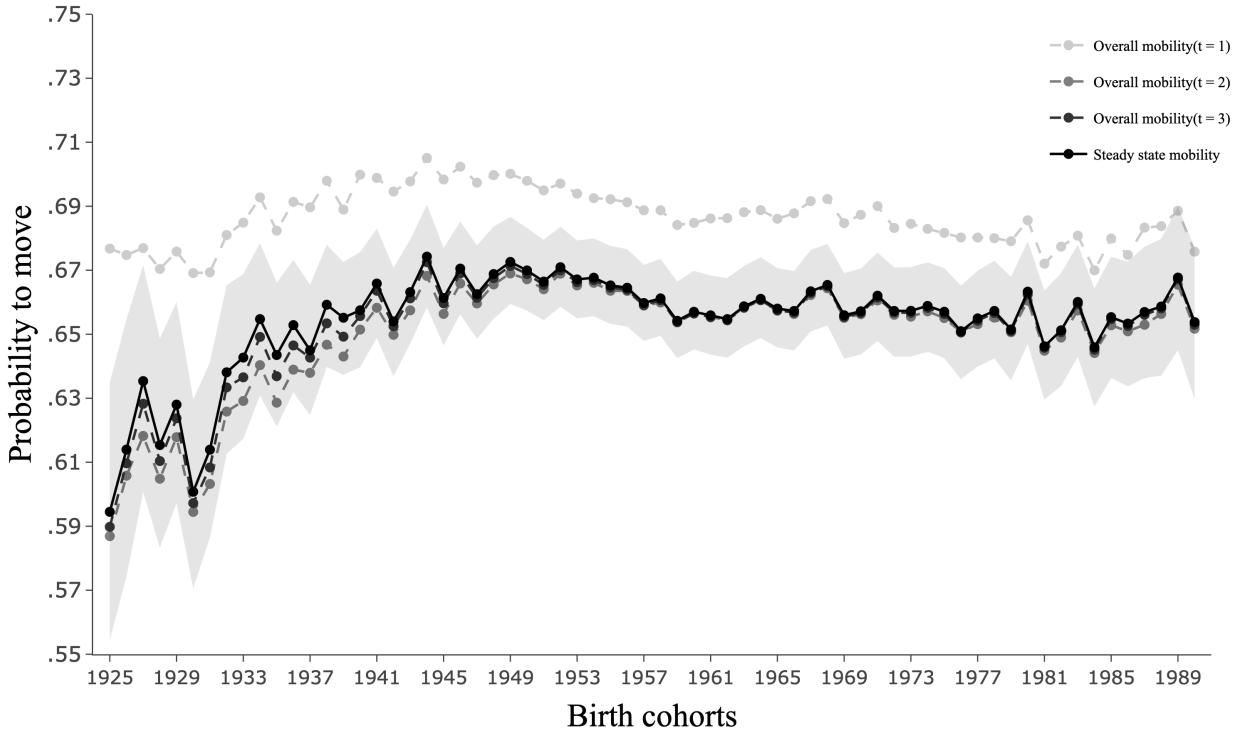
In this section, we examine mobility patterns among earlier cohorts in the GSS. Specifically, we replicate our main analysis using father-child pairs constructed for cohorts born between 1925 and 1990, applying the same age restriction of 25 to 55 at the time of the GSS interview. Including cohorts as early as 1925 reveals some distinct dynamics compared to later cohorts. Before 1945, we observe a clear upward trend in steady-state mobility, and a clear downward trend in memory and association. After 1945, however, these trends dissipate, and both movement and memory appear largely flat thereafter.

Figure H.1: Measures of movement at generation $t = 1$ based on cohorts born between 1925 and 1985



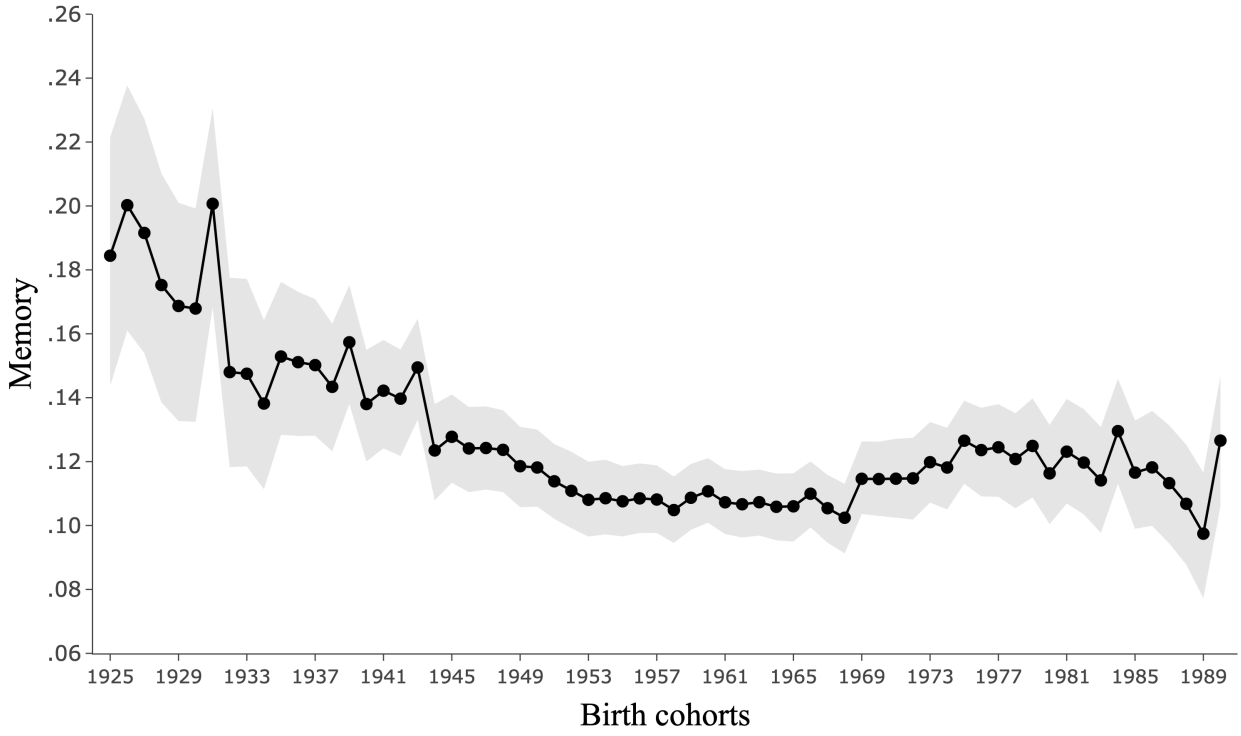
Notes: Shaded areas represent 95% confidence intervals.

Figure H.2: Overall mobility (OM_t) across synthetic generations based on cohorts born between 1925 and 1985



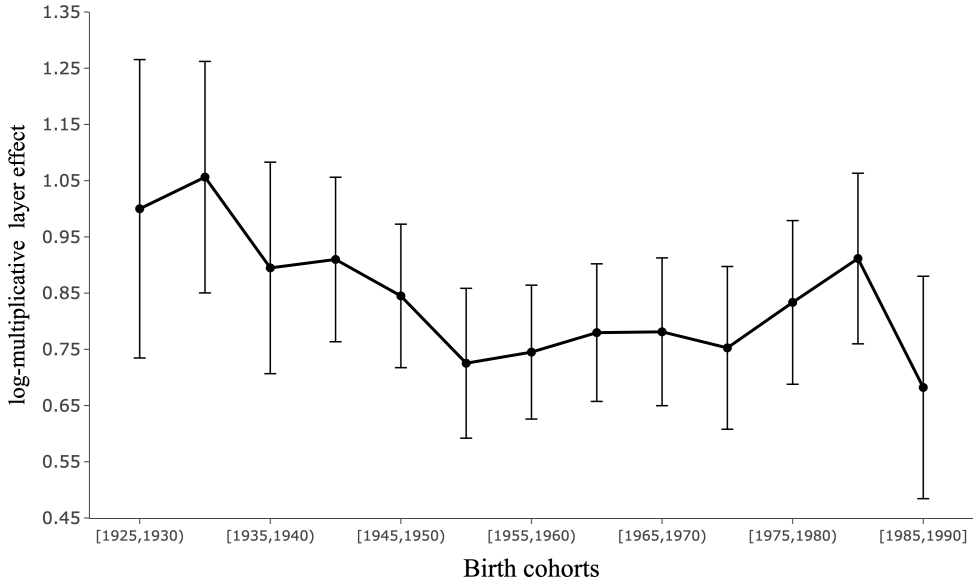
Notes: This figure illustrates the evolution of overall mobility across generations in a stationary Markov chains. By $t = 4$, the Markov chains for most of the cohorts have converged to their respective steady-state distributions, where there is no structural mobility. Shaded areas represent 95% confidence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

Figure H.3: Aggregate intergenerational memory at generation $t = 1$ (AIM_1) based on cohorts born between 1925 and 1985



Notes: Shaded areas represent 95% confidence intervals.

Figure H.4: Log-multiplicative layer effects based on cohorts born between 1925 and 1985



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