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Linked Lives, Linked Trajectories: Intergenerational Association of Intragenerational Income Mobility

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Abstract

Most intergenerational mobility studies rely on either snapshot or time-averaged measures of earnings, but have yet to examine resemblance of earnings trajectories over the life course of successive generations. We propose a linked trajectory mobility approach that decomposes the progression of economic status over two generations into associations in four life-cycle dimensions: initial position, growth rate, growth deceleration, and volatility. Using father-son dyad data from the Panel Study of Income Dynamics, we show that men resemble their fathers not only in the overall level of earnings but also in the pattern by which their earnings develop over time. The intergenerational persistence of earnings varies substantially across life stages of both generations; it is strongest for fathers' early-career and sons' mid-career, with an intergenerational elasticity (IGE) as high as .6. This result can be explained by the concurrence of the parent's early career and the offspring's early childhood. Our findings suggest the intergenerational economic association between parents and offspring is not age-constant but is contingent on the respective life stages of both generations and, most importantly, the period during which they overlap.

Keywords

intergenerational mobility, intragenerational mobility, income, life course

The recent takeoff of income inequality in the United States and worldwide has revitalized the study of social mobility in sociology, a topic of long-standing interest in the discipline (Blau and Duncan 1967; Erikson and Goldthorpe 1992; Featherman and Hauser 1978; for reviews, see Breen and Jonsson 2005; Hout and DiPrete 2006; Mitnik et al. 2015; Torche 2015b). The study of social mobility, and in particular income mobility, is also increasingly discussed and debated by economists, policymakers, and the public (Black and Devereux 2011; Chetty et al. 2014; Corak 2004; Ermisch, Jäntti, and Smeeding 2012; McCall 2013; Solon 1992, 1999). Social mobility, the movement of individuals between social positions or up and down the income ladder, can happen both within and between

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generations. Although the majority of work in the literature focuses on mobility between parents and offspring, mobility within the life course, such as changes in employment, jobs, organizations, wages, and income over an individual's working life, is an equally important form of social mobility (Bernhardt et al. 2001; Cheng 2014; Jarvis and Song 2017; Sørensen 1975; Spilerman 1977).

Both the inter- and intragenerational aspects of mobility have been extensively studied, but little research combines the two. Instead, most studies use a "snapshot" approach, which relies on the association in a point-in-time or multi-year average of socioeconomic status between parents and offspring to measure the intergenerational elasticity (IGE) of earnings (Mitnik, Cumberworth, and Grusky 2016; Solon 1992), rank-rank slope of income percentiles (Chetty et al. 2014), or odds ratios in occupational mobility tables (Hout 1983). These measures, despite serving as fundamental tools in social mobility research, do not represent the intergenerational association of socioeconomic status within an age-dependent framework. In his pioneering work on intragenerational mobility, Sørensen (1975) argues that studies on social mobility are often not comparable because "the positions of fathers and sons . . . are not fixed attributes of individuals over their lifetime." Ignoring life course changes in economic status may thus distort results about intergenerational mobility if individuals' statuses are age-specific or subject to year-to-year fluctuations.

In this article, we integrate the intra- and intergenerational approaches in the analysis of earnings mobility that play out over the course of generations and lives. Compared to occupations and other labor market outcomes, earnings are more variable within individual careers and thus a better indicator to show the link between "lineage" and "generational time" (Bengtson and Allen 2009). Motivated by life course theory, we argue that the strength of intergenerational association in socioeconomic status depends on parents' and offspring's respective life cycles, and most importantly, the period during which the parent's career and the offspring's childhood overlap.

Parents' socioeconomic status has a persistent and profound influence on offspring's development from birth to adolescence and on subsequent socioeconomic attainment in adulthood (Blau and Duncan 1967; Coleman et al. 1966; Jencks et al. 1979; Sewell and Hauser 1975). Given that parents' status may change across their own as well as their offspring's life course, the intergenerational effect should be considered as cumulative, dynamic, and contingent on their children's concurrent developmental stage. For example, prior studies show that the effect of family background varies by the timing, magnitude, and duration of childhood family wealth or poverty (Brooks-Gunn and Duncan 1997; Wodtke 2013). In particular, social inequality between children from poor and rich families may emerge as early as infancy through age 5 and continue to grow (Hanson et al. 2013; Heckman, Pinto, and Savelyev 2013), eventually leading to long-term diverging destinies for individuals born into different economic classes (DiPrete and Eirich 2006; McLanahan 2004). This life course perspective on human development has increasingly gained influence in studies on social inequality and mobility (e.g., Bloome 2017; Duncan, Ziol-Guest, and Kalil 2010; Killewald and Bryan 2018; Pfeffer and Killewald 2017; Warren, Sheridan, and Hauser 2002), but most studies focus on the age trajectory of only one generation or the intergenerational association for discrete age groups, rather than simultaneously investigating the entire intragenerational economic trajectories of *both* generations.

We propose a linked trajectory mobility model (LTMM), characterizing the time-varying features of parents' and offspring's working-life earnings trajectories by their initial positions, growth rates, growth deceleration, and earnings volatility. The model, technically known as the bivariate growth curve location-scale model, builds on recent developments in bivariate growth curve models (Kenny and Kashy 2011; Pugach, Hedecker, and Mermelstein 2014), variance function regressions (Hedeker, Mermelstein, and Demirtas 2012; Western and Bloome 2009), and the Bayesian approach to hierarchical model estimation (Gelman et al. 2014). The model parameters allow us to derive a variety of IGE estimates by measuring parents' and offspring's earnings at different ages or by averaging them over varying lengths of years. Previous IGE estimates typically fall in the range of .4 to .6, suggesting that a 1 percent income difference in the parent generation translates into a .4 to .6 percent difference in the offspring generation (Chetty et al. 2014; Mazumder 2005). Yet, to date, variation of IGE by age is mostly considered a methodological issue or the result of biases arising from measurement error, transitory fluctuations, or life-cycle income variations (Haider and Solon 2006; Mazumder 2016; Torche 2015b), rather than a theoretically relevant issue revealing shared life experiences among family members in the cross-generational reproduction of inequality.

Drawing on data from the 1968 to 2017 waves of the Panel Study of Income Dynamics, we apply the LTMM to analyze annual labor earnings from 47,348 person-years between ages 25 and 55 among 2,323 father-son dyads. Our results show that initial earnings, earnings growth rate, and earnings volatility between parents and offspring are all positively correlated. The associations lessen, but remain substantial, after controlling for education, race, and other covariates of the two generations. Thus, offspring resemble their parents not only in levels of earnings but also in the pattern by which their earnings develop over time.

To compare our results with previous studies on intergenerational earnings mobility, we derive age-specific IGE estimates from the trajectory parameters. The results show variations in IGE over the full working lives of both fathers and sons. Contrary to the common perception that intergenerational resemblance in earnings peaks when individuals are at their career prime (in their 40s for most adult workers), we find the highest IGE between fathers' early-career earnings and sons' mid-career earnings. The peaking IGE estimate is approximately equal to .6. Two further analyses—one dividing the sample into early-childbearing and late-childbearing fathers and the other modeling associations in the son's childhood and adulthood family income—consistently reveal that the earlier-than-expected peaking of IGE by father's age is likely due to the concurrence of the father's early career and the son's early childhood.

The results are consistent with a large body of early childhood literature emphasizing the importance of the early-life family environment for later-life outcomes (e.g., Duncan, Brooks-Gunn, and Klebanov 1994; Heckman 2006; Heckman et al. 2013; Jencks et al. 1979; Sewell and Hauser 1975). The IGE based on family income during individuals' childhood and adulthood is higher than that between fathers and sons at similar ages. With the growing concern that rising economic inequality may lead to reduced social mobility (Chetty et al. 2014; Corak 2013; Grusky et al. 2013; Jerrim and Macmillan 2015; Mitnik et al. 2016), policies and programs that target the early years of parenthood to promote intergenerational mobility would seem to have the greatest promise. The complex link between within-generation changes in economic circumstances and between-generation transmission of economic statuses warrants careful consideration in future research on social mobility.

THEORIZING LIFE COURSE CHANGES IN INTERGENERATIONAL PROCESSES

Prior Work on Social Mobility: The Snapshot Approach

Previous studies on mobility typically rely on IGE based on individual or household earnings to measure intergenerational associations in economic status (for a review, see Mitnik et al. 2015). This measure (β_1 in the following equations) reflects the percent difference in earnings in the son's generation associated with a 1 percent difference in fathers' earnings.[1]

$$\log\left(Y_i^s\right) = \beta_0 + \beta_1 \log\left(Y_i^f\right) + \epsilon_i \quad \text{Single-year} \tag{1}$$

$$\log\left(\bar{Y}_{it}^s\right) = \beta_0 + \beta_1 \log\left(\bar{Y}_{it}^f\right) + \epsilon_i \quad \text{Multi-year averages} \tag{2}$$

We refer to this type of research as the *snapshot approach* or *short panel approach* (Mazumder 2016, 2018), representing intergenerational mobility as a point-to-point association in earnings while ignoring individuals' earnings dynamics across the life course. Estimates from these studies show that IGE increased from around .2 in the 1970s (Behrman and Taubman 1985; Bowles 1972; Sewell and Hauser 1975) to .4 in the 1990s (Corak 2006; Solon 1992; Zimmerman 1992), and to .5 to .6 in more recent years (Bratsberg et al. 2007; Dahl and DeLeire 2008; Gouskova, Chiteji, and Stafford 2010; Mazumder 2005). This increase, however, cannot simply be interpreted as a historical change in intergenerational mobility. As Hauser (2010:5) notes, "estimates of magnitude of intergenerational economic persistence have tended to rise in recent years along with improved—or at least fancier—measurement and estimation procedures in new bodies of data, and using new time-series observations." Although the field has experienced substantial growth in terms of scholarship and data, conceptual and analytical challenges remain (for reviews, see Black and Devereux 2011; Hauser 2010; Lee and Solon 2009; Mitnik et al. 2015; Solon 1999; Torche 2015a, 2015b). We will discuss three major issues that despite being recognized, have not been satisfactorily addressed in the literature: (1) the omission of transitory fluctuations around lifetime earnings; (2) attenuation bias caused by measurement error; and (3) life-cycle bias that results from age-graded earnings growth.

First, earnings of U.S. workers and households have become more volatile since the 1990s, with an increasing chance of both income gain and income loss across the income distribution (Gottschalk and Moffitt 2009; Hacker 2006; Lemieux 2010; Piketty and Saez 2003; Western, Bloome, and Percheski 2008). Yet despite the recent trend in economic instability, studies on intergenerational income mobility mostly focus on the association between the "permanent income" of parents and offspring (Friedman 1957), that is, the overall level of lifetime earnings. Transitory fluctuations around lifetime earnings are typically operationalized as a form of "statistical noise" that can be removed by averaging earnings over multiple years.

A potential limitation of this approach, however, is that inequality increasingly exists in "changes in economic status, rather than on its level" (Western et al. 2012:342). Year-to-year fluctuation in earnings reflects the unpredictability of economic life experienced by individuals over biographical, family, and historical time. The assumption that children's economic standing depends on the overall level—rather than the trajectory—of parents' economic status may be justifiable during times of prosperity and stability of the U.S. labor market, such as the 1960s and 1970s (Bernhardt et al. 2001), but it may have become increasingly untenable in light of the rising earnings volatility and unstable economic life of recent decades (Dahl, DeLeire, and Schwabish 2011; Gottschalk and Moffitt 2009; Hacker 2006; Haider 2001; Haider and Solon 2006; Shin and Solon 2011).

Second, previous empirical IGE estimates are susceptible to *attenuation bias*, the classical errors-in-variables problem caused by inaccurate measures in the right-hand-side variable (fathers' earnings in our case) that shrinks the estimated regression coefficient toward zero. In such estimates, use of multi-year averaged earnings instead of single-year measures yields a higher IGE by purging random errors in the data collection. The measurement problem presents practical difficulties in retrospective surveys in which offspring report parents' information (Treiman and Hauser 1977). However, this bias can be reduced with the increasing availability of prospective, longitudinal data that provide fathers' income over a period of successive years (Song and Mare 2015), as well as, ideally, administrative tax data that provide more reliable income estimates (Chetty et al. 2014). Mazumder (2005), for instance, used social security earnings data to show that when calculating fathers' earnings, the estimated IGE increases with the number of years averaged, reaching as high as .6 when using 16 years of fathers' earnings. Attenuation bias may still occur despite the expanded availability of administrative data, albeit to a lesser extent. However, these data do not provide complete lifetime earnings profiles for most workers, and they often underrepresent low-income populations that do not file federal tax returns (Slemrod 2016; for a discussion of the current limitations of tax data, see Mazumder 2016).

Finally, it is well documented that intergenerational associations vary by the ages of parents and offspring. The disparity between associations estimated from current and lifetime earnings is known as *life-cycle bias*. Specifically, when single-year measures are used as a proxy for lifetime earnings, IGE can be severely biased if the ages of fathers or sons are either too young or too old. IGE tends to be higher when earnings are measured in one's 40s, the optimal life stage at which point-in-time earnings associate strongly with lifetime earnings (Björklund 1993). Unlike the attenuation bias caused by measurement errors in fathers' earnings, life-cycle bias can happen to both the left- and right-hand-side variables in regression models. For example, Haider and Solon (2006) show that IGE estimates are downwardly biased if sons' earnings are measured at earlier ages (e.g., in their 20s) due to the substantial inconsistency between early-life and later-life earnings. Other work suggests these biases "are not consistently in one direction or the other" and depend on assumptions implied in the model specification and the underlying earnings processes (Jenkins 1987:1158). The amount of life-cycle bias reflects changes in age-earnings profiles in both generations and may persist even if earnings measures are error-free.

A growing body of work uses improved data, measures, and methods to assess biases in standard measures of income mobility (Gouskova et al. 2010; Nybom and Stuhler 2016, 2017). Despite increased consensus on the rising instability of U.S. earnings and potential limitations of the traditional IGE measures, to our knowledge, no research has developed a dynamic, processual, and developmental perspective on social mobility. We offer a new perspective incorporating *intragenerational* earnings growth and fluctuation into the *intergenerational* transmission of economic status. By illustrating the fundamental connection of mobility within generations, on the one hand, and mobility between generations, on the other, our approach shifts the focus from "how to obtain an unbiased IGE" to "how does IGE depend on the life stages of parents and offspring."

A Linked Trajectory Approach to Intergenerational Social Mobility

Motivated by the "linked lives" principle in *life course theory* (Elder 1985; Mortimer and Shanahan 2007; Settersten and Mayer 1997) and its application in studies on family and intergenerational relations (Bengtson and Allen 2009; Seltzer and Bianchi 2013; Swartz 2009), we propose a "linked trajectory" approach to analyzing intergenerational social mobility. Life course theory posits that family members' life trajectories and sequences of transitions, in terms of when and where to attend school, work, and reside, are intricately linked (Elder 1985; George 1993; Hogan 1978). The temporal process via which parents' career trajectories unfold over the life course influences not only offspring's life circumstances and chances during childhood, but also their socioeconomic status in adulthood—including the beginning, ending, and orderliness of their career development (Sørensen 1979; Warren et al. 2002). Thus, the transmission of economic advantage and disadvantage across generations may occur in lockstep with life-cycle changes in social positions within each generation.

The topic of intragenerational mobility is the subject of a large literature (DiPrete and

Eirich 2006; Elder 1985, 1998; Mayer 2009; Sørensen 1979; Spilerman 1977; Stier and Grusky 1990). Yet few studies have considered both intra and intergenerational mobility (for some notable exceptions, see Bloome 2017; Duncan et al. 2010; Pfeffer and Killewald 2017; Warren et al. 2002). From a social stratification perspective, the long-term, time-dependent process of status attainment typically varies substantially across the population (Rosenfeld 1992; Sørensen 1977; Spilerman 1977). Workers start with different economic positions in the workforce, and as careers progress, follow diverging paths in terms of jobs, occupations, and earnings (Bernhardt et al. 2001; Cheng 2014; Tomaskovic-Devey, Thomas, and Johnson 2005).

The stratification of workers over the career span in one generation may extend beyond that generation. According to Becker's (1991) theory on social mobility, although family endowment, such as genetic makeup and stock of human capital, is relatively stable in the parent generation, family investment in children's care and development often varies over time. A recent study by Kornrich and Furstenberg (2013) shows that driven by rising income inequality, parental investment has grown unequally since the 1990s, concentrating on children younger than 6 years old and young adults in their mid-20s. Such a change reflects a complex connection between parent's age-specific economic status, children's timing of exposure to various economic circumstances, and the play-out of children's economic status in their adulthood.

Our linked trajectory approach departs from the snapshot approach in considering discrepancies in IGE estimates as the product of several linked social processes governing variation in earnings within and between generations, not as a type of statistical bias. The snapshot approach treats both the parent's and the offspring's earnings as temporally static measures for studying patterns of intergenerational dependence in the population. The linked trajectory approach, in contrast, conceptualizes the economic attainment of the two generations as long-term career processes. Accordingly, the focus shifts to the intergenerational association in the pattern of the two earnings *trajectories*. The resemblance between parents and offspring may result from their similar life experiences with respect to family, work, and educational institutions, as well as the overlapping lifetimes that family members spend with one another, especially in the period before the offspring's transition to adulthood (Uhlenberg 1980). Considering the entirety of intragenerational trajectories allows us to incorporate processes pertaining to not only the labor market but also family and childhood experiences that influence economic attainment later in life.

Empirical Implications

The similarities in the life-cycle earnings profiles of parents and offspring, although conjectured and theorized in sociological literature, are rarely the focus of empirical research on intergenerational mobility. We do not intend to isolate the specific mechanisms underlying the transmission of earnings patterns across generations, such as education, but we speculate that these mechanisms may lead to positive intergenerational associations in both the baseline level of earnings and the shape of earnings trajectories:

> *Hypothesis 1 (baseline earnings association):* There is a positive association in the baseline level of earnings of parents and offspring.
>
> *Hypothesis 2 (growth rate association):* There is a positive association in the steepness or growth rate of the respective earnings trajectories of parents and offspring.

In addition to the starting point and shape of earnings trajectories, individual *heterogeneity* in earnings may also exist in the amount of year-to-year fluctuation. An emerging line of work suggests that earnings volatility has contributed to a substantial proportion of the growth in economic inequality in the U.S. labor market (Gottschalk and Moffitt 2009; Hacker 2006; Western et al. 2012). The rise in economic insecurity may be society-wide, but it may disproportionately influence individuals in some social groups more than others. We focus on the intergenerational linkage in earnings volatility. Because offspring tend to follow in their parents' footsteps, entering into the same or similar career tracks and being exposed to similar labor market risks, there should be a positive association in earnings instability between the two generations. Yet, it is also plausible that the growth of earnings volatility is exogenous, widespread, and related to recent structural changes in the labor market, so that the level of earnings volatility does not persist across generations.

We therefore propose the following hypothesis:

> *Hypothesis 3 (positive volatility association):* There is a positive association in the amount of earnings volatility of parents and offspring.

Prior research shows the intergenerational association in earnings tends to be higher in life stages at which snapshot earnings correlate strongly with lifetime earnings (Grawe 2006; Haider and Solon 2006). From this perspective, earnings attainment in early life stages may not be a good proxy for a person's economic status later in life. Young workers' earnings may be particularly unstable, given that they may have recently transitioned from school to work (Elman and O'Rand 2004; Mare, Winship, and Kubitschek 1984), may be juggling a full-time job with a new family life (Goldscheider and DaVanzo 1989; Oppenheimer 2003), or may still be trying to find the right career through trial and error and frequent job changes (Johnson 1978; Neal 1999). By contrast, most workers' earnings plateau after the age of 40, resulting in less fluctuation during mid-career (Mazumder 2005) and a stronger correlation between their levels of current and lifetime earnings (Haider and Solon 2006).

The age-dependence pattern of earnings leads us to hypothesize the following:

> *Hypothesis 4a (higher IGE at offspring's middle career):* IGE is larger when offspring's earnings are measured at mid-career rather than at early or late career.

> *Hypothesis 4b (higher IGE at parents' middle career):* IGE is larger when parents' earnings are measured at mid-career rather than at early or late career.

Recent work also provides evidence contrary to Hypothesis 4b by showing that estimated IGE tends to be higher during fathers' early-career (see Grawe 2006:Table 2, Figure 2; Mazumder and Acosta 2015:Table 3). This early peaking of IGE with regard to fathers' age appears puzzling at first glance. As Mazumder and Acosta (2015:184) note, "[W]e find the largest estimates are produced when we use fathers' income measured at age 30. This is somewhat surprising given previous evidence (e.g., Mazumder 2005) of a U-shaped pattern of the transitory variance in earnings that is lowest in the middle of the life cycle."

We propose that this puzzling pattern of IGE with respect to parents' age may be explained by a competing mechanism emphasizing parents' and offspring's *shared lifetimes*. On the one hand, the intergenerational association depends not only on the earnings trajectories of the two generations in their respective adulthood stage, but also on the particular stages of the life course at which the two generations overlap. To the extent that most fathers have children *before* they reach mid-career, we should expect childhood in the offspring's generation to largely overlap with parents' early careers.[2]

On the other hand, family resources during childhood are known to influence children's human capital development, skill formation, and physiological well-being (Becker 1962; Cunha and Heckman 2007), as well as their subsequent labor outcomes (Brooks-Gunn and Duncan 1997; Corak 2006; Yeung, Linver, and Brooks-Gunn 2002). Adverse events during early childhood, ranging from economic hardship and parental divorce to child abuse and neglect, may have far-reaching implications for later-life productivity, earnings, and status attainment (Belfield et al. 2006; Heckman et al. 2010; Lareau 2011; Mayer 1997; Pearlin et al. 1981). If parents' investment is most critical when children are young, we expect parents' earnings during early parenthood, compared to earnings later in life, to be more strongly linked to offspring's earnings.

We thus propose the following hypothesis:

Hypothesis 4c (higher IGE at parents' early career): IGE is higher when parents' earnings are measured at the early career stage rather than at mid- or late career.

DATA, SAMPLE, AND MEASURES

Data

The ideal data for estimating intergenerational mobility require income measured for both generations for full life-cycle coverage (see a discussion in Mazumder 2018). Yet none of the available survey or administrative data in the United States or elsewhere satisfy this condition. Data from the Panel Study of Income Dynamics (PSID) provide the best approximation of this ideal data source, except not all respondents in the sample have been followed throughout their working lives. Begun in 1968, the PSID started with more than 18,000 household members from roughly 5,000 families. The study followed these individuals annually until 1997 and biennially from 1999 to 2017. All respondents, as well as their offspring and descendants, are considered to carry the PSID "gene" and thus become permanent PSID respondents even if they no longer live in the original PSID households. Their demographic and income information is gathered in each wave of the PSID survey and can be linked across years. We use the Family Identification Mapping System (FIMS) tool to link family members across generations.

Sample

The PSID consists of two subsamples: a nationally representative sample of U.S. households as of 1967 designed by the Survey Research Center (SRC sample) and an oversample of low-income households as part of the Survey of Economic Opportunity (SEO sample). Following common practice in the income mobility literature (Shin and Solon 2011; Solon 1992), we restrict our analysis to the SRC sample. Brown (1996) discusses potential problems of using the SEO sample and the impact on model estimations.

Our main analytic sample includes 2,323 father-son dyads, with a total of 47,348 person-year observations (30,427 for fathers; 16,921 for sons) with nonmissing values of earnings and other covariates (shown in Table A in the online supplement). We focus on person-year observations of fathers and sons in their prime age (between 25 and 55 years). Excluding ages beyond 55 minimizes biases due to selective sample attrition and selectivity near retirement age. For most families, we do not observe the entire 30-year earnings trajectory of fathers or sons. The precision of our estimates of earnings trajectory parameters will be low if there are too few observations per person. We thus restrict our sample to cases with at least five nonmissing earnings records for the father and four earnings records for the son. We also focus on fathers born after 1920 and sons born before 1990. We generate multiple dyads for families in which a father has two or more sons, and we exclude families in which only the earnings trajectory of the father or the son is available. For individuals who have partial missing data in earnings history, we use a Bayesian approach, which allows us to model missing data as unknown parameters and to obtain estimates from the posterior distribution. On average, we obtain 13.10 years and 7.28 years of observed earnings data for the father's generation and the son's generation, respectively.[3]

In additional analyses, we extracted a sample of men who were born into a PSID household after 1968 and were followed up to 49 years in the last wave of the survey. We use this sample to analyze the association between household income throughout childhood from birth to age 17 and during adulthood from age 25 to 49. For example, for a boy born in 1970, we measure childhood household income from 1970 to 1987 and adult household income from 1995 to 2016 (the year prior to the last wave of the PSID). We further restrict

Table 1. Summary Statistics for Log Earnings by Ages of Fathers and Sons

	N	Mean	SD	P10	P50	P90
Father (*N* = 30,427)						
Log earnings age 25 to 29	4,114	10.396	.589	9.768	10.472	10.968
Log earnings age 30 to 34	4,849	10.537	.633	9.848	10.625	11.161
Log earnings age 35 to 39	5,426	10.629	.663	9.873	10.694	11.320
Log earnings age 40 to 44	5,741	10.689	.692	9.934	10.746	11.394
Log earnings age 45 to 49	5,345	10.671	.756	9.873	10.735	11.449
Log earnings age 50 to 55	4,952	10.674	.797	9.787	10.733	11.496
Son (*N* = 16,921)						
Log earnings age 25 to 29	4,704	10.307	.697	9.574	10.395	10.981
Log earnings age 30 to 34	4,262	10.507	.729	9.736	10.577	11.236
Log earnings age 35 to 39	3,223	10.620	.795	9.778	10.683	11.447
Log earnings age 40 to 44	2,310	10.695	.840	9.878	10.717	11.556
Log earnings age 45 to 49	1,433	10.699	.937	9.834	10.760	11.593
Log earnings age 50 to 55	989	10.706	.944	9.814	10.758	11.679

Data source: Panel Study of Income Dynamics (SRC Sample), 1968 to 2017.
Note: The numbers of observations are counted in person-year observations. The total number of father-son pairs is 2,323 and the number of father-son person-year pairs is 47,348. P10, P50, and P90 refer to the 10th, 50th, and 90th percentile of the earnings distribution within the respective age group.

the sample to men born between 1967 and 1981. This restriction ensures we observe fathers' or household income for sons who grew up in PSID households from birth to age 17 and at least 10 years of their adulthood income after age 25. The final sample for family income analysis includes 64,910 person-year observations for 3,166 individuals, with 48,237 person-year observations for childhood and 16,673 for adulthood.

We restrict our main analysis to father-son dyads for several reasons. First, the PSID has more consistent earnings measures for household heads, who are most often identified as husbands. We analyze only household heads with nonmissing salary and wage information. Second, we omit women because of the complex interactions between marriage, parenthood, and labor force participation for women. The gendered patterns of earnings dynamics and intergenerational transmission of status deserve further study. Third, restricting the sample to father-son dyads allows us to compare our results with estimates from previous studies, which either focus on males exclusively or, more rarely, conduct separate analyses for men and women.

Measures

Labor income. The key outcome variable is the annual labor income for fathers and sons during the years they were PSID household heads between ages 25 and 55. All income variables are converted to 2017 dollars using CPI-U-RS. We follow Card and DiNardo (2002) in replacing top-coded earnings with 1.4*$Y if the top value is $Y. Table 1 summarizes earnings by age group and generation. For both generations, individuals' logarithm earnings grow quadratically as a function of age and reach their peak around age 40 to 44.

Family income. Family income is measured as the sum of income from the household head and spouse's total taxable income and transfer income to the family.[4] We transformed the variable by taking the natural logarithm and bottom coded 182 non-positive observations of family income (.08 percent of total person-year observations) to $1. Childhood family income is measured between ages 0 and 17, and adulthood family income between 25 and 55. On average, we obtain

15.36 years and 7.40 years of family income for childhood and adulthood, respectively.[5]

Zero income and missing income. In keeping with recent work on intergenerational income mobility (e.g., Chetty et al. 2014; Mazumder 2005), we code zero income as missing. A visualization of the missing data and patterns of zero income data is included in Figure D1 in the online supplement, and the percentage of zero incomes by education and occupation for fathers and sons is presented in Figure D2. If a person has no earnings at a certain age due to nonemployment or school enrollment, we treat this observation as missing in the data setup.[6] The missing data are estimated as parameters and are assumed to follow the same distribution as the observed earnings.

Age. For specific models, we measure the temporal dimension of the life course as the father's and son's age minus 25. The rescaled age variable ranges from 0 to 30. We set age 25 as the starting point of the earnings trajectory, assuming a person has reached adulthood and entered the labor force around this age. For family income models, we measure childhood family income as a function of the child's age and adulthood family income as a function of the adult child's age minus 25. We also create the square of the age to measure possible nonlinear changes in income over the life course.

Additional variables. In the fully-specified models, we include education, race, birth cohorts, and occupations of fathers and sons, as well as their interactions with age and age squared as additional predictors. Education is measured as years of schooling completed. Race is measured as a binary variable, either black or non-black (reference category). Birth cohorts include 11 decennial birth groups for both generations. Occupation refers to respondents' primary occupation over the years observed in the PSID.[7] Because of a high percentage of missing data and inconsistent occupational coding schemes over time, we measure respondents' primary occupation that was reported most often, rather than treat occupation as a time-varying variable. Descriptive statistics for all measures are displayed in Table A in the online supplement.

METHODS

Linked Trajectory Mobility Model (LTMM)

We propose a linked trajectory mobility model (LTMM), also known as a bivariate growth curve location-scale model, to describe the repeated measures of parent and offspring earnings profiles and their associations. The model builds on previous hierarchical linear models (i.e., mixed-effects or multilevel models) that have been adapted to dyadic data analyses for paired outcome variables (Kenny, Kashy, and Cook 2006; Pugach et al. 2014; Raudenbush, Brennan, and Barnett 1995) and variance function regressions that jointly model the mean and variance of a dependent variable (Hedeker et al. 2012; Western and Bloome 2009).

Contrary to conventional IGE estimation that relies on a single-year or multiple-year averaged measure of lifetime earnings in each generation, we include longitudinal measures of earnings at different ages and explicitly model the pattern of earnings change over time. This model enables us to examine intergenerational associations in not only the overall level of earnings, as suggested by previous IGE estimates, but also the shape of earnings growth curves and the volatility of earnings. Specifically, our model accounts for four parameters of earnings growth trajectories—initial position, growth rate, growth deceleration, and volatility—within each generation and the associations of these parameters between generations.

The model is specified as follows. Consider a father-son dyad from family *i*. Y_{it}^{f} and Y_{it}^{s} denote the logged earnings for the father and the son at time *t*, respectively. Time *t* is specified as the number of years elapsed since age 25. For example, Y_{i0}^{f} and Y_{i0}^{s} refer to the earnings, respectively, of the father and the son at time 0, measured when each is age 25. We follow individuals in each generation from age 25 to 55. The intragenerational earnings trajectory of Y_{it} is modeled in a quadratic form—growing gradually but with the growth rate decelerating over time—as suggested by the age patterns of earnings in Table 1:

$$Y_{it}^{f} = \beta_{0i}^{f} + \beta_{1i}^{f} \cdot t + \beta_{2i}^{f} \cdot t^2 + \varepsilon_{it}^{f} \quad (3)$$

$$Y_{it}^{s} = \beta_{0i}^{s} + \beta_{1i}^{s} \cdot t + \beta_{2i}^{s} \cdot t^2 + \varepsilon_{it}^{s} \quad (4)$$

The intercept β_{0i}^{f} represents a father's earnings at age 25. The coefficient β_{1i}^{f} represents the earnings growth rate for the father from family i at age 25. This coefficient can also be viewed as the earnings growth rate at age 25 (i.e., $t = 0$). The coefficient β_{2i}^{f} captures the deceleration rate of earnings growth for the father from family i. Combining estimated β_{1i}^{f} and β_{2i}^{f}, we can derive from the growth function the initial growth rate at age 25, namely when $t = 0$, as well as at any age during the father's work history. Similar interpretations also apply to coefficients estimated from the son's growth curve.

We allow the intercept and growth coefficients in each generation to vary across families in our baseline models:

$$\beta_{0i}^{f} = \gamma_{00}^{f} + u_{0i}^{f} \text{ (Father's intercept)} \quad (5)$$

$$\beta_{1i}^{f} = \gamma_{10}^{f} + u_{1i}^{f} \text{ (Father's growth rate)} \quad (6)$$

$$\beta_{2i}^{f} = \gamma_{20}^{f} + u_{2i}^{f} \text{ (Father's growth deceleration)} \quad (7)$$

$$\beta_{0i}^{s} = \gamma_{00}^{s} + u_{0i}^{s} \text{ (Son's intercept)} \quad (8)$$

$$\beta_{1i}^{s} = \gamma_{10}^{s} + u_{1i}^{s} \text{ (Son's growth rate)} \quad (9)$$

$$\beta_{2i}^{s} = \gamma_{20}^{s} + u_{2i}^{s} \text{ (Son's growth deceleration)} \quad (10)$$

The β coefficients consist of fixed terms (γ) that represent the mean intercepts, growth rates, and growth decelerations among all fathers and sons, along with random terms (u) that represent variation among individuals within each generation. The controlled models also include the additive effects of a set of covariates $\sum_{k=1}^{K} \gamma_{0k}^{f} \cdot X_{ki}^{f}$ for fathers in Equation 5 and $\sum_{k=1}^{K} \gamma_{0k}^{s} \cdot X_{ki}^{s}$ for sons in Equation 8. These covariates include education, race, birth cohort, and occupation. The controlled models allow us to test whether the intergenerational correlations in trajectory parameters can be explained by the parent-offspring association in these covariates.

The random terms (u) are assumed to follow a multivariate normal distribution as formulated below:

$$\begin{pmatrix} u_{0i}^{f} \\ u_{1i}^{f} \\ u_{2i}^{f} \\ u_{0i}^{s} \\ u_{1i}^{s} \\ u_{2i}^{s} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \Sigma = \begin{pmatrix} \sigma_{u_0^f}^2 & & & & & \\ \sigma_{u_1^f u_0^f} & \sigma_{u_1^f}^2 & & & & \\ \sigma_{u_2^f u_0^f} & \sigma_{u_2^f u_1^f} & \sigma_{u_2^f}^2 & & & \\ \sigma_{u_0^s u_0^f} & \sigma_{u_0^s u_1^f} & \sigma_{u_0^s u_2^f} & \sigma_{u_0^s}^2 & & \\ \sigma_{u_1^s u_0^f} & \sigma_{u_1^s u_1^f} & \sigma_{u_1^s u_2^f} & \sigma_{u_1^s u_0^s} & \sigma_{u_1^s}^2 & \\ \sigma_{u_2^s u_0^f} & \sigma_{u_2^s u_1^f} & \sigma_{u_2^s u_2^f} & \sigma_{u_2^s u_0^s} & \sigma_{u_2^s u_1^s} & \sigma_{u_2^s}^2 \end{pmatrix}\right] \quad (11)$$

Given that the variance-covariance matrix of Σ is symmetric, we present only lower triangular elements in the matrix. The diagonal elements refer to variances in earnings at age 25, earnings growth rate at age 25, and growth deceleration in each generation. The off-diagonal elements indicate associations in these trajectory parameters within and between generations. We formulate and explain the intergenerational association estimators using the variance-covariance matrix of Σ in the Results section.

The residual terms ε_{it}^{f} and ε_{it}^{s} from each earnings trajectory are also assumed to follow a multivariate normal distribution. The variance-covariance matrix of the residual distributions can be expressed as

$$\begin{pmatrix} \varepsilon_{it}^{f} \\ \varepsilon_{it}^{s} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{\varepsilon_{it}^{f}}^2 & 0 \\ 0 & \sigma_{\varepsilon_{it}^{s}}^2 \end{pmatrix}\right] \quad (12)$$

The dimension of the within-generation residual distribution varies by i, because we may not have complete observations from age 25 to 55 for every father and son in the data. Specifically, we assume that within each generation, the residual terms are identically and independently distributed (i.e., $\sigma_{\epsilon_{it}^f \epsilon_{it'}^f} = 0$). For example, fathers' earnings residuals at ages 25 and 45 are assumed to be uncorrelated. To simplify our model, any two residual terms from fathers and sons are specified as independent, namely, $\sigma_{\epsilon_{it}^f \epsilon_{it'}^s} = 0$ for $\forall t, t' \in [0,30]$. For example, earnings residuals of fathers at age 25 and sons at age 25 are assumed to be independent.[8]

A key feature of the model is the specification of individual heterogeneity in earnings volatility, which is measured by the residual variances over all the observed earnings years for a specific person, namely, $\sigma^2_{\varepsilon_i^f}$ (and $\sigma^2_{\varepsilon_i^s}$). This is equivalent to including a random effect for the heteroscedastic residual variance (also known as the random scale effect). We model the variances with a log link function:

$$\log\left(\sigma^2_{\varepsilon_{it}^f}\right) = \delta_0^f + \omega_i^f \quad \text{(Father's volatility)} \tag{13}$$

$$\log\left(\sigma^2_{\varepsilon_{it}^s}\right) = \delta_0^s + \omega_i^s \quad \text{(Son's volatility)} \tag{14}$$

Similar to the specification of *u*, the random terms, ω, are assumed to follow a multivariate normal distribution:[9]

$$\begin{pmatrix} \omega_i^f \\ \omega_i^s \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Omega = \begin{pmatrix} \sigma^2_{\omega^f} & \\ \sigma_{\omega^f \omega^s} & \sigma^2_{\omega^s} \end{pmatrix}\right] \tag{15}$$

where $\sigma^2_{\omega^f}$ $\left(\sigma^2_{\omega^s}\right)$ captures the between-person variation in earnings volatility among fathers (sons), and $\sigma_{\omega^f \omega^s}$ captures the intergenerational association in earnings volatility.

As described above, the variance-covariance matrices of the random effects in our LTMM approach characterize both intra- and intergenerational patterns of earnings dynamics. Together, they provide sufficient information to derive the intergenerational associations in trajectory parameters and single- or multiple-year intergenerational earnings elasticity. We discuss the technical details in Part A of the Appendix.

Estimation

We propose a Bayesian hierarchical modeling approach to estimate the model using Stan, a programming package based on Hamiltonian Monte Carlo sampling (Gelman et al. 2014). The Bayesian approach is more flexible than the common maximum likelihood estimation approach in fitting hierarchical models with complex variance-covariance structures of random effects and residual terms. The Bayesian inference also provides a general framework for missing data resulting from incomplete observations of fathers' and sons' earnings trajectories. The missing data are implicit in the model and represented as parameters in the posterior distribution. We specify 24 Markov chains drawn from the marginal distribution $p(\theta \mid y, x)$ with 8,000 to 15,000 iterations and 500 to 1,000 post-warmup iterations for each chain. All parameters are converged with $\hat{R} \leq 1.1$.[10] We describe the details of the Bayesian Markov Chain Monte Carlo (MCMC) estimation of the linked trajectory mobility model in Part B of the Appendix.

RESULTS

Intergenerational Elasticity Based on the Traditional Regression Approach

We begin by estimating IGE using the traditional regression models described in Equations 1 and 2. Table 2 includes two panels. The upper panel shows variations in IGE by the age at which fathers' and sons' earnings are measured. If either the father's or the son's earnings are unobserved at that age, we drop the father-son dyad from the analysis. We vary the ages of both generations from 30 to 50. The results show much variation by age, with an average IGE around .3. The results are largely consistent with findings in previous studies using PSID (e.g., Mazumder and Acosta 2015), which suggest a range of IGE between .141 and .553 when fathers' and sons' ages vary from 30 to 55.

Yet we also observe a lot of year-to-year variations because of the small sample size at certain ages. The lower panel shows variations

Table 2. IGE Estimates Using Various Snapshots of Earnings in Fathers' and Sons' Lives

		Sons' Earnings: Age				
		30	35	40	45	50
Fathers' Earnings: Age	30	.474 (.083)	.247 (.105)	.219 (.171)	.095 (.148)	.174 (.290)
	35	.265 (.060)	.230 (.097)	.263 (.093)	.333 (.185)	.441 (.206)
	40	.264 (.053)	.294 (.067)	.442 (.079)	.241 (.131)	.263 (.131)
	45	.254 (.046)	.389 (.051)	.341 (.056)	.234 (.105)	.220 (.109)
	50	.330 (.054)	.375 (.050)	.397 (.065)	.579 (.099)	.270 (.096)
		Time Avg. Sons' Earnings				
		5	10	15		
Time Average of Fathers' Earnings: Years	5	.361 (.048)	.345 (.039)	.351 (.036)		
	10	.398 (.048)	.388 (.039)	.394 (.036)		
	15	.436 (.046)	.419 (.038)	.417 (.035)		

Data source: Panel Study of Income Dynamics (SRC Sample), 1968 to 2017.
Note: N = 2,323. Each entry represents the β from a regression of sons' log earnings on fathers' log earnings. In the upper panel, earnings are measured at each of five ages in both generations. In the lower panel, the rows include a 5-year, 10-year, and 15-year average of fathers' and sons' log earnings. We estimate combinations of lengths of time averages that are all centered around age 40. For example, the five-year average includes earnings from ages 38, 39, 40, 41, and 42. Standard errors are presented in parentheses.

in IGE by the number of years averaged of earnings at each generation. The estimates are more stable across columns and rows compared to those in the upper panel, and they fall within the range of previous estimates (reviewed in Mazumder 2018:Table 2; Solon 1999:Table 3), suggesting that the long-run IGE of individual earnings is at least .4. However, these estimates do not disentangle the permanent and transitory components of earnings or capture life-cycle earnings growth patterns within each generation. We discuss new findings provided by the linked trajectory mobility perspective in the next section.

Intergenerational Associations in Intragenerational Trajectory Parameters

Next, we estimate population-average earnings growth patterns using the LTMM approach. Table 3 shows similar age-graded earnings trajectories for fathers and sons. The intercepts, which represent logged earnings for fathers and sons at age 25, are 10.34 and 10.25. Combining the age and age-squared variables, we find that earnings grow by age, but the growth rate declines. Specifically, earnings grow by 3 percent at age 25 for fathers and by 4.3 percent for sons, and the annual earnings growth rate decreases by .2 (= −.001 × 2) percentage points for every additional year. Peak earnings are reached at age 40 $(=25+\frac{.030}{.001\times 2})$ and 46.5 $(=25+\frac{.043}{.001\times 2})$ for fathers and sons, respectively.[11] The patterns of change are largely consistent across generations in our analysis.

As discussed earlier, the main advantage of the LTMM approach is that the model simultaneously estimates intragenerational earnings growth parameters and the associations in

Table 3. Within-Generation Predictors of Earnings Growth Trajectories

	Father		Son	
	Coeff.	95% interval	Coeff.	95% interval
Intercept, β_0	10.341	[10.316, 10.368]	10.250	[10.224, 10.276]
Age minus 25, β_1	.030	[.027, .033]	.043	[.039, .047]
Age minus 25, squared, β_2	–.001	[–.001, –.001]	–.001	[–.001, –.001]
Volatility (logged) δ_0	–2.777	[–2.851, –2.706]	–2.424	[–2.503, –2.344]
Number of person-year observations	30,427		16,921	
Number of persons	2,323		2,323	

Data source: Panel Study of Income Dynamics (SRC Sample), 1968 to 2017.
Note: These fixed-effects parameters are estimated from bivariate growth curve location-scale models described in Part A of the Appendix. The variance-covariance matrices of the random effects are reported in Table B2 in the online supplement. Full results from the models are available upon request. The 95 percent credible intervals are calculated as the interval between the 2.5 and 97.5 percent quantiles of the posterior distributions of model parameters.

these parameters across generations. We derive the association in trajectory parameters from the variance-covariance matrices of the parameters (shown in Tables B1 and B2 in the online supplement).[12] By standardizing these random-effect parameters using the method described in Appendix A, we calculate the intergenerational correlations in earnings trajectory parameters; we report the point estimates in the "uncontrolled model" column in Table 4. Several results are worth noting.

First, the correlation in initial earnings is consistent with Hypothesis 1: positive earnings associations between parents and offspring begin to emerge when children are in their 20s. The correlation in the uncontrolled model is .220 at age 25, a level similar to previous estimates based on single-year earnings observations of fathers and sons (Becker and Tomes 1994; Behrman and Taubman 1985; Sewell and Hauser 1975) but lower than the multi-year average estimates of around .4 (Mazumder 2005).

Second, the results support Hypothesis 2: earnings growth rates between the parent and offspring generations are positively associated. Because of the presence of the quadratic term, the correlation in growth rate varies by age (see Figure A in the online supplement). The correlation in fathers' and sons' earnings growth rates is highest at age 30, reaching .084. This positive correlation implies that children of fathers with faster earnings growth are likely to experience faster earnings growth themselves. As we will see in the next section, the associations in growth rates, albeit smaller than the association in initial earnings, can contribute to substantial life-cycle variations in IGE.

Finally, the results are consistent with Hypothesis 3: parents and offspring are correlated in the level of earnings volatility throughout their working lives; however, the association in earnings volatility is smaller than the associations in other growth parameters.

Can demographic and socioeconomic variables account for the observed intergenerational associations of earnings trajectories? We estimate a model for earnings growth after individuals' demographic and employment characteristics are adjusted for. We report the correlations between trajectory parameters under the "controlled model" columns in Table 4 (full results are shown in Tables C, D1, and D2 in the online supplement). The model includes fathers' and sons' demographic factors, such as birth cohort, race, and their interaction terms, and socioeconomic factors, such as years of education and occupation. The controlled model shows smaller but still significant correlations in growth parameters. Some proportion of father-son resemblance in earnings levels, although not all, can be

Table 4. Estimated Intergenerational Trajectory Parameter Correlations

Intergenerational Association	Model Parameters	Uncontrolled Model	Controlled Model
Initial earnings	Corr$(\hat{Y}_0^f, \hat{Y}_0^s)$	.220	.114
Growth rate at age 25	Corr$(\beta_1^f, \beta_1^s \mid \text{age} = 25)$	.074	.032
Growth rate at age 30	Corr$(\beta_1^f, \beta_1^s \mid \text{age} = 30)$	.084	.040
Growth rate at age 35	Corr$(\beta_1^f, \beta_1^s \mid \text{age} = 35)$	.076	.020
Earnings volatility	Corr$(\sigma^2_{\omega^f}, \sigma^2_{\omega^s})$	.026	.027
Model Controls			
Demographic characteristics		No	Yes
Years of schooling		No	Yes
Occupation dummies		No	Yes

Data source: Panel Study of Income Dynamics (SRC Sample), 1968 to 2017.
Note: The total number of father-son pairs is 2,323, and the number of father-son person-year pairs is 40,951. The correlations are estimated from variance-covariance matrices of models shown in the appendices. The uncontrolled model only includes fathers' and sons' ages and age squared. The controlled model includes fathers' and sons' demographic factors, such as birth cohort, race, and their interaction terms, and socioeconomic factors, such as years of education and occupation. See Table A in the online supplement for a full list of the control variables. Full results from the controlled models are available upon request.

attributed to their common socioeconomic and demographic characteristics. Hence, there still exists a *direct* effect of the father's earnings trajectory on that of the son. The intergenerational associations in earnings volatility remain unchanged when these covariates are included.

Intergenerational Earnings Elasticity: Model-Based Estimates

To compare our trajectory approach with the person-averaged approach, we derive standard IGE measures based on the variance-covariance matrix estimated from the LTMM (see Part A of the Appendix for technical details on the computation). Figure 1 presents a full range of IGE estimates by varying ages of fathers, sons, and both.[13] Note that the model-based IGE estimates rely on the predicted age-specific earnings rather than those observed in the data. We assume all earnings fluctuations characterized by the residual term in the earnings growth trajectories result from measurement errors in survey data. A robustness check in which we relax this assumption will be discussed later.

Figure 1 consists of three plots: (A) the distribution of IGE by ages of fathers and sons; (B) the marginal distribution of IGE as a function of son's age, fixing father's age at 45; and (C) the marginal distribution of IGE as a function of father's age, fixing son's age at 45. Overall, the plots suggest substantial variation by father's and son's age, but the age pattern differs for the two generations. IGE is strongest when fathers' earnings are observed at the early 30s and sons' earnings at the mid-40s. Specifically, holding father's age at 45, the IGE increases from roughly .25 when a son is 25 to about .45 when the son is in his mid-40s and declines thereafter. This result is consistent with that of previous literature and supports Hypothesis 4a in the case of sons: mid-career earnings provide the best approximation of lifetime earnings. However, the variation in IGE by father's age contradicts the common belief that IGE is highest when fathers' earnings are measured around age 30. In fact, the IGE increases with the father's age but reaches its peak around age 31. Hence, the results reveal a particularly strong effect of fathers' *early-career* earnings on sons'

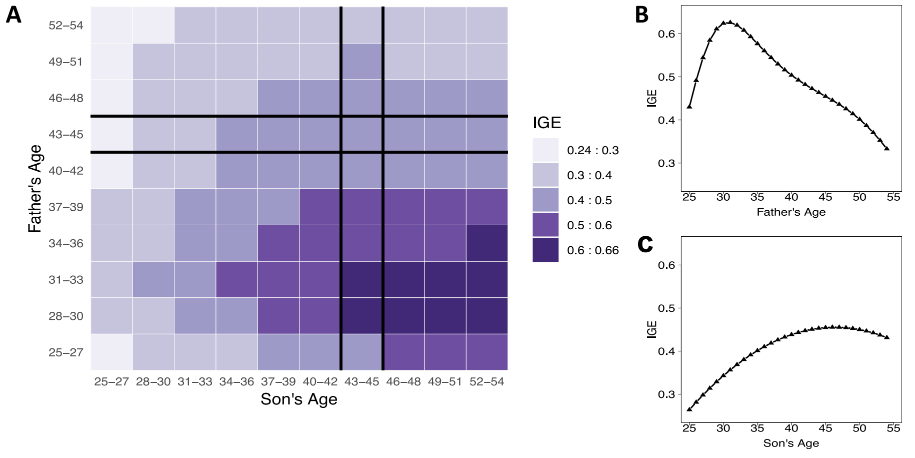

Figure 1. Intergenerational Elasticity by Ages of Fathers and Sons
Data source: Panel Study of Income Dynamics (SRC Sample), 1968 to 2017.
Note: Panel A plots changes in IGE by the joint distribution of fathers' and sons' ages. Larger values are represented by dark squares and smaller values by lighter squares. We highlight IGEs at ages 43 to 45 for both fathers and sons, which are typically the focus in previous studies. Panel B plots changes in IGE by the marginal distribution of father's age. The IGE first increases and then declines, with a peak age of around 31 years for fathers. Panel C plots changes in IGE by the marginal distribution of son's age. The IGE increases with the son's age, peaking around age 46, with a gradual decline thereafter throughout working life.

socioeconomic attainment.[14] This finding favors Hypothesis 4c over Hypothesis 4b, suggesting fathers' earnings during their early careers, not mid-careers, matter most for adult sons' socioeconomic outcomes. The next subsection investigates potential explanations for this finding.

Why Is IGE Highest at Father's Early Career? A Closer Inspection of Variation by Childhood Age

A key result so far is that IGE is highest when fathers' earnings are measured around early career rather than mid-career. This finding suggests previous mobility studies that measure earnings in both generations in their 40s may have underestimated the intergenerational association in economic status.[15] As we discussed, this early peaking of IGE by fathers' age may be explained by the fact that a father's early career overlaps with the child's early childhood. To assess this explanation, we test two more hypotheses.

First, if the IGE peak at the father's early career is due to the influence of parental economic resources during the son's childhood, then we would expect to observe heterogeneity in the IGE peaking age by parents' childbearing age. In particular, early-career earnings may be more important for fathers who had children at a younger age, rather than at a later age, because their early career is more likely to overlap with their offspring's early childhood. Therefore, we test the following hypothesis:

> *Hypothesis 5a (heterogeneity by father's age at son's birth):* IGE peaks at a younger age of father among fathers who had children at an earlier age.

To test this hypothesis, we divide all fathers into early and late childbearing groups, using age 28 as the threshold, which is the median age of fatherhood in our sample. Results in Figure 2 confirm our conjecture. For men who had a son before age 28, the IGE first increases and then declines, with a peak around age 31. By contrast, for men who had a son after age 28, the IGE increases with the father's age, peaking around age 38, with a gradual decline thereafter. The IGE measured at fathers' early career around age 25 to

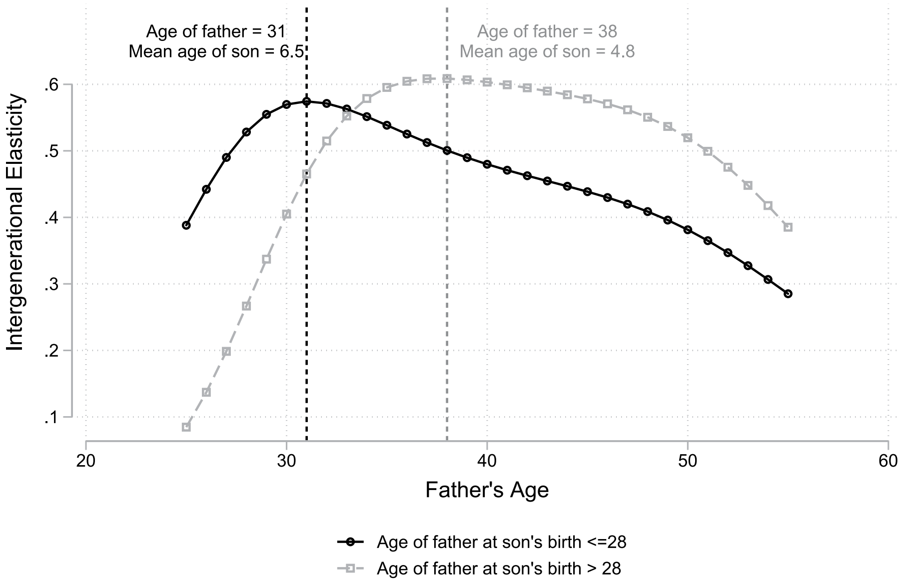

Figure 2. IGE by Father's Age and Father's Age-Group at Son's Birth
Data source: Panel Study of Income Dynamics (SRC Sample), 1968 to 2017.
Note: The IGEs are estimated from uncontrolled models by father's age at son's birth. We divide respondents into two groups: those who were born before their father reached age 28 and those born after their father turned 28 (the mean age of childbearing in the father's generation). Age 28 is the median age of fathers when they gave birth to their sons in our sample. For fathers who had sons before age 28, the IGE peaks around age 31 of fathers when the sons were around age 6. For fathers who had sons after age 28, the IGE peaks around age 38 of fathers when the sons were around age 5.

30 varies between .4 and .57 for the early-childbearing group, but it is significantly lower for the late-childbearing group, many of whom have not had children yet. From the perspective of sons, the influence of fathers' earnings is strongest when earnings are measured around age 6.5 for sons of early-childbearing fathers and age 4.8 for sons of late-childbearing fathers.

Second, because the IGE peak during fathers' early career reflects the fact that family economic resources during early childhood may be particularly important in determining children's own economic success during adulthood, we expect the IGE in family income to exhibit a similar pattern as the IGE in individual earnings—that is, family income during early childhood should have the strongest effect on adulthood attainment:

> *Hypothesis 5b (IGE in family income):* IGE between one's childhood and adulthood family income is higher when family income is measured at the early stage of childhood and mid-career stage of adulthood.

To test this hypothesis, we fit a similar LTMM for family income, replacing the father's income with the son's childhood family income from birth to age 17, and the son's individual income with his adulthood family income. Figure 3 presents the results. The left panel shows the estimated IGE by the son's childhood age, with adulthood family income fixed at age 25, 35, and 45, respectively; the right panel shows the estimated IGE by the son's adult age, with childhood family income fixed at age 5, 10, and 15, respectively. Overall, the IGE based on family income is higher than that based on individual earnings at similar ages, which likely reflects the impact of various demographic and social processes that contribute to inequality at the family level, such as differential marriage rates, assortative mating, and women's growing contribution to family income (McLanahan

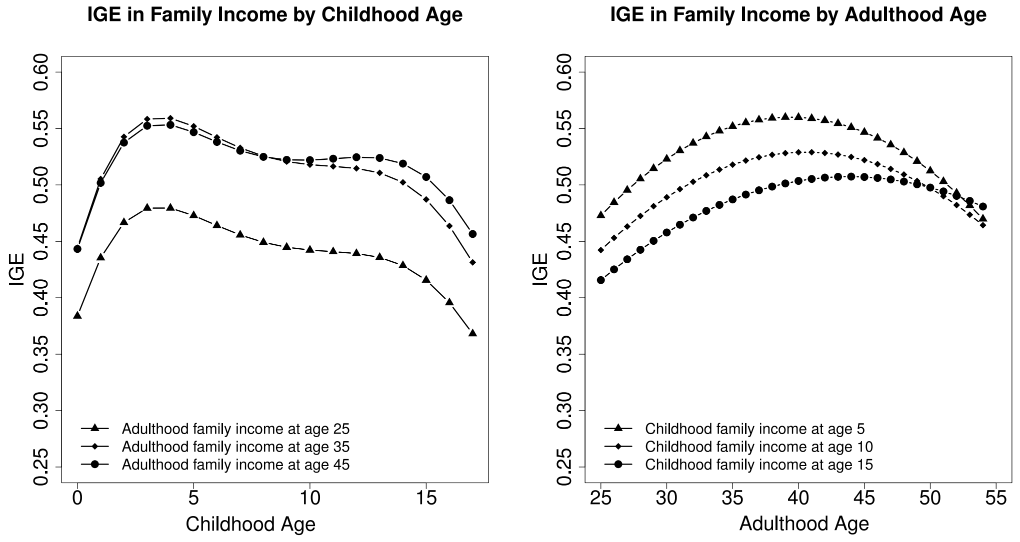

Figure 3. IGE in Family Income by Childhood Age and Adulthood Age
Data source: Panel Study of Income Dynamics (SRC Sample), 1968 to 2017.
Note: The IGEs are estimated from a total of 64,910 person-year observations for 3,166 individuals, with 48,237 person-year observations for childhood and 16,673 for adulthood.

2004; Schwartz 2010; Sweeney and Cancian 2004). Most importantly, the age-specific IGE patterns seen in the two panels are consistent with Hypothesis 5b: childhood family income, when measured around ages 3 to 6, has the strongest association with adulthood income; adulthood family income, when measured around ages 38 to 42, has the strongest association with childhood income.

These findings provide new insights into the life-cycle process of social mobility. Although sociologists of the life course and human development have long realized the importance of early childhood family environment on individuals' later social achievement, few studies directly examine the intergenerational implications of these processes. One exception is Duncan and colleagues (2010), which, by measuring childhood family income at ages 0 to 5, 6 to 10, and 11 to 15, shows a strong association between family income during early childhood and individuals' earnings during middle adulthood. Our analysis, with a wider range of age-specific IGE estimates for both generations, supports this finding and further reveals that, regardless of when a child's earnings are measured, intergenerational association tends to be strongest when the parent's economic position is measured during the offspring's early childhood.[16] A possible explanation is that parental income from a child's birth through age 5 is an important indicator of early-life family resources, assets, consumption behaviors, and borrowing constraints (Caucutt and Lochner 2012). From a human capital accumulation perspective, investment during early childhood, compared to later ages, leads to greater returns in education, career, and life by fostering children's brain development, abilities, and aspirations that are the foundation for future success (Cunha and Heckman 2009; Hanson et al. 2013; Hsin and Xie 2017; Jencks, Crouse, and Mueser 1983; Sewell, Haller, and Portes 1969). Therefore, instead of exclusively focusing on the mid-career or averaged economic circumstances in the parent generation, our results suggest the need for future work evaluating the enduring effect of parents' long-term earnings trajectories, especially the period during early childhood development, on offspring's socioeconomic attainment in adulthood.

ROBUSTNESS CHECKS

We examined the sensitivity of our findings with regard to assumptions about the magnitude of measurement error in earnings. Our main empirical analysis attributes all residual variance to measurement error and calculates IGE in Figure 2 without the volatility parameters. We now relax this assumption, partitioning residual variance in reported earnings into two distinct sources. The first is the "true" year-to-year fluctuations, which capture volatility in earnings across the life cycle. This may result from instability in employer profitability, temporary unemployment, job changes, or shifts between full-time and part-time work. The second is the "noise" in reported earnings due to measurement error in the PSID instrument, such as memory recall errors and coding mistakes.[17] When the entirety of residual variance is due to measurement error rather than "true" earnings fluctuations, the true IGE should reach its upper bound and, when measurement error in the data is zero, the residual variance should reflect the real earnings volatility, and therefore true IGE should reach its lower bound.

Figure B in the online supplement reports the upper and lower bounds of IGE as well as the predicted IGE under the assumption that measurement error in earnings takes up half of the residual variance. The three subplots correspond to the multi-year-average IGE calculation starting at 25, 35, and 45, respectively. The variation in IGE by the number of years averaged, now illustrated with its upper and lower bounds, exhibits a similar pattern to that reported in Figure 2. Overall, when we take into account the uncertainty in the magnitude of measurement error in earnings measures, our results still provide strong evidence against the presumption that IGE always increases with the number of years used in calculating average earnings.

We also examined alternative model specifications with regard to the shape of the earnings growth curve over age. Our main analysis follows the standard Mincer equation that relies on a quadratic function of age to model intragenerational trajectories (Lemieux 2006; Mincer 1974). But we also experimented with three alternative model specifications: a linear function of age, a cubic function of age, and a natural log transformation of age. To assess which specification best fits the observed data, we calculate two model fit statistics—the adjusted R-squared and Bayesian Information Criterion (BIC) statistics—under these model specifications. In the online supplement, Table F reports the estimated coefficients and model fit statistics, and Figure C plots the predicted mean earnings trajectories. For both generations, the quadratic functional form, which we use in our main analysis, has the highest adjusted R-squared and the lowest BIC. Hence, it is preferred in the set of all candidate models.

Finally, based on our model estimates, we simulate a variety of multi-year IGE estimates. Our results, presented in Figure E in the online supplement, highlight the nonlinearity in IGE change with the number of years of data included in the analysis. The results caution against previous researchers' suggestion that more data, especially longitudinal data that follow individuals over a prolonged period of time, will lead to higher estimates in IGE. Instead, we show that when late-career earnings are taken into account, estimated IGE may level off, or even decline, because of the slow-down of earnings growth.

DISCUSSION

Summary of the Results

Table 5 summarizes our major findings. We refer to a hypothesis as supported if the model coefficients are statistically significant and in the expected direction (Hypotheses 1, 2, and 3) or if the model-based predicted IGE pattern accords with our expectation (Hypotheses 4 and 5). The first three hypotheses consider the intergenerational association of intragenerational trajectories and are supported by our empirical results. Specifically, by simultaneously modeling earnings trajectories for the parent and offspring generations, we find a positive association between

Table 5. Summary of Hypotheses and Results

Hypothesis	Description	Results
Intergenerational Association of Trajectories		
Hypothesis 1	The baseline level of earnings of parents and offspring are positively associated.	Supported
Hypothesis 2	The steepness or growth rate of earnings trajectory for parents and offspring are positively associated.	Supported
Hypothesis 3	The amount of earnings volatility of parents and offspring are positively associated.	Supported
Intergenerational Earnings Elasticity		
Hypothesis 4a	IGE is higher when offspring's earnings are measured at mid-career rather than at early or late career.	Supported
Hypothesis 4b	IGE is higher when parents' earnings are measured at mid-career rather than at early or late career.	Not supported
Hypothesis 4c	IGE is higher when parents' earnings are measured at the early career stage rather than at mid or late career.	Supported
Explaining Early Peaking of IGE by Parent's Age		
Hypothesis 5a	IGE peaks at a younger age of father among fathers who had children at an earlier age.	Supported
Hypothesis 5b	IGE between one's childhood and adulthood family income is higher when family income is measured at the early stage of childhood and mid-career stage of adulthood.	Supported

the two generations in initial earnings, rates of earnings growth, and earnings volatility.

Hypotheses 4a, 4b, and 4c relate to various forms of the life-cycle pattern of IGE. Contrary to the perception that IGE will be highest when fathers and sons are at their mid-career ages, our results suggest the strongest IGE appears between the son's mid-career (around age 43 to 48) and the father's early-career years (around age 28 to 33). A possible explanation is that fathers' early-career earnings serve as a proxy for sons' childhood family socioeconomic environment and as a predictor for sons' socioeconomic status in adulthood. We assessed the empirical implications of this account in Hypotheses 5a and 5b, which show that the age of fathers at which IGE tops out varies by father's age at childbirth. The maximum IGE in earnings between fathers and sons emerges at an earlier age for fathers who had children earlier in life. The IGE between a person's childhood family income and adulthood family income around age 40 is also largest when childhood income is measured around age 3 to 6 years, approximately the father's early career years.

Limitations and Suggestions for Future Research

We acknowledge several limitations of this study and point to directions for future work. First, following prior work on social mobility, we focus on annual labor income as the outcome variable. Our analysis includes only years with positive income, excluding years when individuals were unemployed, out of the labor force, or enrolled in school. If labor market transitions over an individual's lifetime are nonrandom, or the risk of job displacement is transmitted across generations (Oreopoulos, Page, and Stevens 2008), our results may be subject to sample selection bias leading to distorted statistical estimates and undermining the generalizability of these intergenerational mechanisms (Western and Pettit 2005; Winship and Mare 1992).

Second, our earnings variable includes only the labor part of farm and business income, wages, bonuses, overtime, commissions, and professional practice (PSID 2017). Capital or business income, which is excluded from our analysis, may represent another important aspect of income inequality and is thus a potential locus of future research (Piketty and Saez 2003). Third, following the tradition in the mobility literature, we focus on father-son dyads. However, with the rise in female labor force participation and the narrowing gender wage gap in recent decades (Goldin and Katz 2016), it is equally important to study intergenerational mobility for men and women. Given the prevalence of single-parent households, especially among African American families, future work should also consider the roles of mothers and grandparents in the reproduction of social status, race, and gender inequalities (McLanahan and Percheski 2008).

Fourth, the PSID sample size limits our ability to fully explore the trends in IGE across cohorts, therefore, our analysis treats cohort as a control variable instead of a primary dimension of temporal variation. Additional data sources, such as linked census data, may provide new opportunities to explore trends in mobility across cohorts. Finally, our analyses may suffer from two common problems of earnings data based on longitudinal social surveys: non-response and sample attrition over time, and measurement errors in self-reported earnings (Kopczuk, Saez, and Song 2010; Mazumder 2005; Mitnik et al. 2015). Although these problems may be less salient in the PSID than in many other surveys (Rodgers, Brown, and Duncan 1993), future research with more refined earnings data (e.g., linked, two-generation administrative data based on income tax records) should allow better identification of income distributions and dynamics across individuals and generations.[18]

Implications for the Study of Social Mobility

This study provides new evidence of intergenerational earnings mobility in the United States using a "linked trajectory" approach that attends to the evolution of economic statuses within parent and offspring generations—including initial earnings, changes in earnings growth rates, and earnings volatility. Findings from our linked trajectory mobility models not only improve point-in-time IGE estimates based on the conventional snapshot approach, but they also shed light on several broader aspects of social stratification and mobility.

Our results highlight the theoretical and empirical relevance of the life course approach in mobility research. For both parents and offspring, economic status unfolds as a dynamic, long-term social process. Having a high-earnings father creates an initial advantage for a son's earnings and, over time, leads to successive increments of advantage. Therefore, the reproduction of economic inequality operates along the family line partly through the *intergenerational transmission* process and partly through the long-lasting *intragenerational accumulation* process (Cheng 2014; DiPrete and Eirich 2006; Riley 1987; Warren et al. 2002).

Our findings suggest that research exclusively focusing on attainment during offspring's early careers may overestimate the fluidity and underestimate the rigidity in the stratification system. This finding is germane to recent policy discussions regarding early childhood interventions, as it suggests policies and programs targeted at promoting economically disadvantaged children's upward mobility opportunities should consider not just equalizing opportunities during schooling (e.g., Gamoran and Mare 1989; Lucas 2001) or in the transition from school to work (DiPrete et al. 2017; Mare et al. 1984), but also helping children from low-income families maintain and develop better long-term trajectories (Bernhardt et al. 2001).

Our results also reveal that research on intergenerational mobility should focus not only on the level of earnings in each generation, but also on earnings trajectories throughout the life course for both generations. The conventional approach that characterizes family socioeconomic status by a single-year measure may be increasingly unreliable (Becker and Tomes 1994; Blau and Duncan 1967), especially given rising intragenerational mobility in recent decades (Jarvis and Song 2017), as this measure is sensitive to random errors and the specific life stage at which earnings data are acquired. The multi-year average measure of parental earnings, which has become a new standard in recent mobility studies, often improves upon single-year measures, particularly when measurement error or transitory fluctuations in earnings data are considerable (Mitnik et al. 2016; Torche 2015b). However, because the initial earnings and earnings growth rate have distinct effects on offsprings' socioeconomic attainment, a simple multi-year average measure may still mask age-specific pathways through which parental earnings influence children's socioeconomic attainment. By analyzing the entire shape of earnings trajectories for both generations simultaneously, our study presents a more comprehensive account of the process through which intergenerational transmission of socioeconomic (dis)advantages unfolds over parents' and offspring's lives.

Policy Implications

Regarding the potential pathways of intergenerational transmission of advantages (and disadvantages), our findings suggest intergenerational influences may depend on the mutual exposure of offspring and parents. Offspring's prime-age earnings are more strongly associated with parents' earnings at early rather than late career stages, that is, children's early years when they live and frequently interact with their parents, and the years when parental investment and influence matter the most.[19] As a result, early childhood programs designed to help disadvantaged families may not only have short-term effects on children's skill formation and educational performance, as suggested by empirical evidence from the Perry Preschool Program (Heckman et al. 2010), the Carolina Approach to Responsive Education (Ramey et al. 2000), and the Infant Health and Development Program (Duncan and Sojourner 2013; Gross, Spiker, and Haynes 1997), but they might also exert long-term effects on earnings trajectories decades later (Schweinhart et al. 2005).

We join this line of research in stressing the family as the primary locale where policy interventions can take place, and we further suggest that changes in economic conditions during early, rather than later, childhood are more likely to be transmitted across generations. Therefore, compared to policies designed to reduce inequality uniformly among all families, policies prioritizing working families with young children are likely to have greater intergenerational benefits.

Implications for Future Research

Finally, our findings point to two promising directions for future stratification research, especially given the increasing availability of longitudinal, multi-generational, and linked administrative data that provide information about families for two or more generations. First, we have shown that the intergenerational association in status attainment varies as a function of the timing and duration of intergenerational lifetime exposure. The demographic trends that influence intergenerational exposure through changing fertility, mortality, marriage patterns, and structure of family life are well-documented (Goldscheider and Lawton 1998; Mare 1997; Ruggles 2007; Silverstein and Giarrusso 2010; Song and Mare 2019), but little is known about their consequences for intergenerational social mobility.

For example, the prolonged life expectancy for the older generation, and the delayed transition into adulthood for the younger generation, may increase both the shared lifetimes and the years of coresidence of parents and their offspring, leading to a stronger intergenerational resemblance in life course trajectories. Second, an emerging concern in career mobility research is that low-skilled workers' earnings trajectories are becoming flat, unstable, or even downwardly sloping (Bernhardt et al. 2001; Cappelli 1998; Kalleberg 2011). Such decline of intragenerational upward career mobility is particularly pronounced with recent macroeconomic trends in skill-biased technological change (Levy and Murnane 1992), labor market polarization (Autor, Katz, and Kearney 2008; Morris and Western 1999), and the rise of precarious work (Kalleberg 2003, 2009). Consequences of changing career mobility are rarely incorporated into the study of trends in intergenerational mobility over historical periods and birth cohorts, but they warrant future consideration given the linked trajectory perspective demonstrated in the present study.

APPENDIX

Part A. Model-Based Intergenerational Earnings Elasticity Estimates

In contrast to the conventional IGE method that relies on intergenerational elasticity of lifetime earnings approximated by a single-year observation or multiple-year averaged earnings, the LTMM approach includes longitudinal measures of earnings at different ages and time-varying measures of IGE. Based on the variance-covariance matrices of model parameters, we first derive intergenerational associations in growth trajectories. The correlation of earnings intercept is defined as

$$\mathrm{Corr}\left(\beta_{0i}^{f},\beta_{0i}^{s}\right)=\frac{Cov\left(\beta_{0i}^{f},\beta_{0i}^{s}\right)}{\sqrt{Var\left(\beta_{0i}^{f}\right)\cdot Var\left(\beta_{0i}^{s}\right)}}=\frac{\sigma_{u_0^f u_0^s}}{\sqrt{\sigma_{u_0^f}^2\cdot\sigma_{u_0^s}^2}} \tag{16}$$

The correlation of earnings growth rates is

$$\mathrm{Corr}\left(\beta_{1i}^{f},\beta_{1i}^{s}\right)=\frac{Cov\left(\beta_{1i}^{f},\beta_{1i}^{s}\right)}{\sqrt{Var\left(\beta_{1i}^{f}\right)\cdot Var\left(\beta_{1i}^{s}\right)}}=\frac{\sigma_{u_1^f u_1^s}}{\sqrt{\sigma_{u_1^f}^2\cdot\sigma_{u_1^s}^2}} \tag{17}$$

Given the log-normal distributions of $\sigma_{\varepsilon_{it}^f}^2$ and $\sigma_{\varepsilon_{it}^s}^2$ and their transformed variance-covariance matrix specified in Equation 15, the intergenerational association of earnings volatility is estimated as[20]

$$\mathrm{Corr}\left(\sigma_{\epsilon_{it}^f}^2,\sigma_{\epsilon_{it}^s}^2\right)=\frac{Cov\left(e^{\delta_0^f+\omega_i^f},e^{\delta_0^s+\omega_i^s}\right)}{\sqrt{Var\left(e^{\delta_0^f+\omega_i^f}\right)\cdot Var\left(e^{\delta_0^s+\omega_i^s}\right)}}=\frac{e^{\frac{\sigma_{\omega_i^f}^2+\sigma_{\omega_i^s}^2+2\cdot\sigma_{\omega_i^f\cdot\omega_i^s}}{2}}-e^{\frac{\sigma_{\omega_i^f}^2+\sigma_{\omega_i^s}^2}{2}}}{\sqrt{\left(e^{\sigma_{\omega_i^f}^2}-1\right)\cdot e^{\sigma_{\omega_i^f}^2}}\cdot\sqrt{\left(e^{\sigma_{\omega_i^s}^2}-1\right)\cdot e^{\sigma_{\omega_i^s}^2}}} \tag{18}$$

The traditional IGE estimate based on single-year observations of fathers at age t and sons at age t' can also be retrieved from the LTMM model,

$$\mathrm{IGE}\left(Y_{it}^{f},Y_{it'}^{s}\right)=\frac{Cov\left(\hat{Y}_{it}^{f},\hat{Y}_{it'}^{s}\right)}{Var\left(\hat{Y}_{it}^{f}\right)}, \tag{19}$$

where $\hat{Y}_{it}^{f}$ and $\hat{Y}_{it}^{s}$ are predicted logged earnings from Equations 3 and 4.

Analogously, intergenerational elasticity based on multiple years of earnings observations of fathers and sons can be calculated as follows. For example, the IGE based on earnings of fathers and sons from age 35 to 40 is expressed as

$$\mathrm{IGE}\left(\overline{Y}_{it}^{f},\overline{Y}_{it'}^{s}\right)=\frac{Cov\left(\log\left(\sum_{t=10}^{15}e^{\hat{Y}_{it}^{f}}\right),\log\left(\sum_{t'=10}^{15}e^{\hat{Y}_{it'}^{s}}\right)\right)}{Var\left(\log\left(\sum_{t=10}^{15}e^{\hat{Y}_{it}^{f}}\right)\right)}. \tag{20}$$

In general, the multiple-year average IGE based on earnings of fathers from age t_0^f to t_n^f and sons from age t_0^s to t_n^s follows

$$\mathrm{IGE}\left(\overline{Y}_{it}^{f},\overline{Y}_{it'}^{s}\right)=\frac{Cov\left(\log\left(\sum_{t=t_0^f}^{t_n^f}e^{\hat{Y}_{it}^{f}}\right),\log\left(\sum_{t'=t_0^s}^{t_n^s}e^{\hat{Y}_{it'}^{s}}\right)\right)}{Var\left(\log\left(\sum_{t=t_0^f}^{t_n^f}e^{\hat{Y}_{it}^{f}}\right)\right)}. \tag{21}$$

Note that the beginning and ending ages used to calculate the average earnings of fathers and sons may vary by generations.

Following Haider and Solon (2006), we estimate the intergenerational elasticity of lifetime earnings by first calculating the present discounted value of lifetime earnings at age 25. The adjusted earnings at year t is defined as $V_{it}=e^{Y_{it}}\cdot\left(1+r\right)^{-t}$, where r is a constant real interest rate and often assumed to be 2 percent. Accordingly, the IGE of fathers' and sons' lifetime earnings over their whole careers from age 25 to 55 is estimated by

$$\mathrm{IGE}\left(V_{life}^{f},V_{life}^{s}\right)=\frac{Cov\left(\sum_{t=0}^{30}e^{\hat{Y}_{it}^{f}}\cdot\left(1+r\right)^{-t},\sum_{t=0}^{30}e^{\hat{Y}_{it}^{s}}\cdot\left(1+r\right)^{-t}\right)}{Var\left(\sum_{t=0}^{30}e^{\hat{Y}_{it}^{f}}\cdot\left(1+r\right)^{-t}\right)}. \tag{22}$$

We compute the predicted outcome variables, $\hat{Y}_{it}^{f}$ and $\hat{Y}_{it}^{s}$, based on the posterior distribution of growth trajectory parameters (discussed in

Appendix B). We generate life course earnings histories for a simulated population of father-son dyads by drawing from their posterior distributions in the Bayesian LTMM model. The following steps describe the procedure:

1. Draw 1,000,000 samples of random-effects u and ω from the posterior distributions.
2. Generate β^f and β^s in Equations 5 to 10 based on the fixed-effects estimates from the LTMM model and the random effects drawn in step 1.
3. Generate logged earnings for fathers and sons based on Equations 3 and 4 and the coefficients generated in step 2. This gives us a simulated population of 1,000,000 father-son dyads.
4. Regress sons' logged earnings on fathers' logged earnings to obtain the age-specific IGE measures.

As discussed earlier, the volatility ω estimated from survey data may include real earnings transitory fluctuations over a period of time as well as measurement errors caused by misreporting or coding errors. Administrative data such as individuals' annual taxable earnings based on IRS tax records or SERs (Chetty et al. 2014; Mazumder 2005) often yield higher IGE than do traditional estimates based on survey data. The LTMM approach allows us to gauge the effects of measurement errors by providing the upper bounds of model-based IGE estimates. Specifically, we assume all year-to-year earnings changes only result from earnings growth over the life course characterized by the β coefficients, and all fluctuations caused by the volatility measures ω are attributed to measurement errors. We then repeat the above steps 1 to 4 to estimate IGE using the predicted y with $\omega = 0$.

Part B. Bayesian MCMC Estimation of the Linked Trajectoy Mobility Model

According to the model specification described in the Methods section, the conditional distribution of earnings $\boldsymbol{Y}_i = \left(Y_{i1}^f \ldots Y_{iT}^f, Y_{i1}^s \ldots Y_{iT}^s\right)^T$ follows the multivariate normal distribution

$$\mathbf{Y}_i \mid \boldsymbol{u}_i, \boldsymbol{\omega}_i \sim N(\boldsymbol{X}_i\boldsymbol{\beta}_i, \boldsymbol{\Lambda}_i(\boldsymbol{\omega}_i)), \tag{23}$$

where $\mathbf{X}_i = \left(1^f, \boldsymbol{t}1^f, \boldsymbol{t}2^f, 1^s, \boldsymbol{t}1^s, \boldsymbol{t}2^s\right)$, namely the growth predictors, where the column vectors are specified as: $1^f = (1,1,\ldots 1,0,0,\ldots 0)$, $1^s = (0,0,\ldots 0,1,1,\ldots 1)$, $\boldsymbol{t}1^f = (1,2,\ldots \mathrm{T},0,0,\ldots 0)$, $\boldsymbol{t}1^s = (0,0,\ldots 0,1,2,\ldots \mathrm{T})$, $\boldsymbol{t}2^f = (1,4,\ldots \mathrm{T}^2,0,0,\ldots 0)$, and $\boldsymbol{t}2^s = (0,0,\ldots 0,1,4,\ldots \mathrm{T}^2)$. $\boldsymbol{\beta}_i = \gamma + \boldsymbol{u}_i$ is a six-dimensional vector that represents the sum of fixed and random parameters as defined in Equations 5 through 10. $\boldsymbol{\Lambda}_i(\boldsymbol{\omega}_i)$ is the variance-covariance matrix of the residual vector $\boldsymbol{\varepsilon}_i$ expressed as

$$\boldsymbol{\Lambda}_i(\boldsymbol{\omega}_i) = \begin{pmatrix} \boldsymbol{\Lambda}_{\varepsilon_i^f} & \boldsymbol{\Lambda}_{\varepsilon_i^f\varepsilon_i^s} \\ \boldsymbol{\Lambda}_{\varepsilon_i^f\varepsilon_i^s} & \boldsymbol{\Lambda}_{\varepsilon_i^s} \end{pmatrix} \tag{24}$$

Where $\boldsymbol{\Lambda}_{\varepsilon_i^f} = \begin{pmatrix} \sigma^2_{\varepsilon_{i1}^f} & \cdots & \sigma_{\varepsilon_{i1}^f\varepsilon_{iT}^f} \\ \vdots & \ddots & \vdots \\ \sigma_{\varepsilon_{iT}^f\varepsilon_{i1}^f} & \cdots & \sigma^2_{\varepsilon_{iT}^f} \end{pmatrix}$ and $\boldsymbol{\Lambda}_{\varepsilon_i^s} = \begin{pmatrix} \sigma^2_{\varepsilon_{i1}^s} & \cdots & \sigma_{\varepsilon_{i1}^s\varepsilon_{iT}^s} \\ \vdots & \ddots & \vdots \\ \sigma_{\varepsilon_{iT}^s\varepsilon_{i1}^s} & \cdots & \sigma^2_{\varepsilon_{iT}^s} \end{pmatrix}$ represent within-generation variance-covariance matrices of residuals; and $\boldsymbol{\Lambda}_{\varepsilon_i^f\varepsilon_i^s} = \begin{pmatrix} \sigma_{\varepsilon_{i1}^f\varepsilon_{i1}^s} & \cdots & \sigma_{\varepsilon_{i1}^f\varepsilon_{iT}^s} \\ \vdots & \ddots & \vdots \\ \sigma_{\varepsilon_{iT}^f\varepsilon_{i1}^s} & \cdots & \sigma_{\varepsilon_{iT}^f\varepsilon_{iT}^s} \end{pmatrix}$ represents between-generation variance-covariance matrix of residuals. To simplify the model, we further assume $\sigma^2_{\varepsilon_{it}^f} = \exp\left(\delta_0^f + \omega_i^f\right)$ and $\sigma^2_{\varepsilon_{it}^s} = \exp\left(\delta_0^s + \omega_i^s\right)$ for all t; and $\sigma_{\varepsilon_{it}^f\varepsilon_{it'}^s} = \sigma_{\varepsilon_{it}^f\varepsilon_{it'}^f} = \sigma_{\varepsilon_{it}^s\varepsilon_{it'}^s} = 0$ for $t \neq t'$.

The parameters ($\boldsymbol{u}_i$, $\boldsymbol{\omega}_i$) refer to random location and scale effects that describe earnings growth shape and earnings volatility, respectively. The vector ($\boldsymbol{u}_i$, $\boldsymbol{\omega}_i$) is assumed to follow a multivariate normal distribution $N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \boldsymbol{\Gamma} = \begin{pmatrix} \Sigma & 0 \\ 0 & \Omega \end{pmatrix}\right]$, where the variance-covariance matrices of Σ and Ω are defined in Equations 11 and 15.

The marginal likelihood function can be written as

$$\log\mathrm{L} = \sum_{i=1}^{N} \log\left(\int_{\boldsymbol{u}_i,\boldsymbol{\omega}_i} f\left(\boldsymbol{Y}_i \mid \boldsymbol{u}_i,\boldsymbol{\omega}_i\right) g\left(\boldsymbol{u}_i,\boldsymbol{\omega}_i\right) d\boldsymbol{u}_i d\boldsymbol{\omega}_i \right)$$

(25)

where

$$f\left(\boldsymbol{Y}_i \mid \boldsymbol{u}_i,\boldsymbol{\omega}_i\right) \propto \left|\Lambda_i\left(\boldsymbol{\omega}_i\right)\right|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}\left(\boldsymbol{Y}_i - \boldsymbol{X}_i\boldsymbol{\beta}_i\right)^T \Lambda_i^{-1}\left(\boldsymbol{\omega}_i\right)\left(\boldsymbol{Y}_i - \boldsymbol{X}_i\boldsymbol{\beta}_i\right)\right\}$$

$$g\left(\boldsymbol{u}_i,\boldsymbol{\omega}_i\right) \propto \left|\boldsymbol{\Gamma}\right|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}\left(\boldsymbol{u}_i^T,\boldsymbol{\omega}_i^T\right)^T \boldsymbol{\Gamma}^{-1}\left(\boldsymbol{u}_i^T,\boldsymbol{\omega}_i^T\right)\right\}.$$

The likelihood function has no closed-form expression, but the model parameters can be obtained via numerical integration methods, such as Gauss-Hermite quadrature approximation and iterative optimization methods (Pugach et al. 2014). To our knowledge, current hierarchical linear and nonlinear modeling programs based on maximum likelihood estimation, such as HLM (Raudenbush et al. 2011), the GLLAMM program in Stata (Rabe-Hesketh and Skrondal 2012), MIXREGLS (Hedeker and Nordgren 2013), and Supermix (Hedeker et al. 2008), are not designed to estimate bivariate growth curve location-scale models.

We propose a Bayesian hierarchical modeling approach to estimate the model with Stan, a programming package based on Hamiltonian Monte Carlo sampling (Stan Development Team 2017). The Bayesian approach is especially useful for estimating multilevel generalized linear models structured with hierarchical predictors, covariance, nonconjugate coefficient priors, and varying output link functions and distributions (Gelman and Hill 2007). Access to the data, coding syntax, statistical commands, and documentation are available upon request and will be provided with the online supplementary materials.

The Bayesian approach is more flexible than the common maximum likelihood estimation approach in fitting hierarchical models with complex variance-covariance structures of random effects and residual terms. The Bayesian inference also provides a general framework for missing data caused by incomplete observations of fathers' and sons' earnings trajectories. The missing data are implicitly represented as parameters that are estimated in the posterior distribution (Gelman et al. 2014). Specifically, we assume the following likelihood and noninformative priors:

Likelihood:

$$\boldsymbol{Y}_i^{obs} \sim \mathrm{Normal}\left(\boldsymbol{X}_i\boldsymbol{\beta}_i, \Lambda_i(\boldsymbol{\omega}_i)\right)$$

Priors:

$$\boldsymbol{u} \sim \mathrm{Normal}\left(0,\Sigma\right), \omega \sim \mathrm{Normal}\left(0,\Omega\right)$$

$$\sigma_u^2, \sigma_\omega^2 \sim \mathrm{Uniform}\left(0,\infty\right)$$

$$\sigma_{u^f u^s}, \sigma_{\omega^f \omega^s} \sim \mathrm{Uniform}\left(-\infty,\infty\right)$$

$$\gamma, \delta_0 \sim \mathrm{Uniform}\left(-\infty,\infty\right)$$

Note that we added missing data to the likelihood function. All subscripts related to family id, year, and generation (except the covariance parameters) are omitted in the prior distributions. The distributions of variance parameters are truncated at zero because they are constrained to be positive. To facilitate model estimation, we place LKJ priors on the random-effects correlation matrices through Cholesky factorization (Stan Development Team 2017). The missing data are estimated as parameters and are assumed to follow the same distribution as the observed $\mathbf{Y}^{obs}$.

We specify four Markov chains drawn from the marginal distribution $p(\theta \mid y, x)$ with 15,000 iterations and 7,500 post-warmup iterations for each chain (namely, 30,000 posterior samples). Trace plots and the statistic $\hat{R}$ are used to evaluate model convergence. The $\hat{R}$ is a potential scale reduction statistic that represents the ratio of between-chain variance to within-chain variance (Gelman and Rubin 1992). A value close to 1 $\pm$ .1 suggests the chains have converged to the posterior distribution. A full list of the posterior distributions of the parameters is available upon request.

Authors' Note

The authors contributed equally to this work. Authorship is alphabetical.

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Notes

1. For simplicity, we consider intergenerational associations among father-son pairs, but the arguments and models can be applied to mothers and daughters as well (e.g., Chadwick and Solon 2002).
2. As we will show in Figure 2, our calculation based on the PSID sample suggests the median age of fathers at a son's birth is 28.
3. The maximum number of earnings records in our analytic sample is 28 for fathers and 24 for sons.
4. Transfer income includes items such as aid to dependent children and aid to dependent children with unemployed fathers for the entire family.
5. The maximum number of family income observations in our analytic sample is 18 for childhood and 15 for adulthood.
6. Missing income data may result from several sources: (1) structural missing for nonsurvey years given that the PSID switched from annual samples to biennial samples since 1997; (2) sample attrition from wave to wave that accumulates over time; or (3) missingness due to zero income in a given year (i.e., due to unemployment or dropping out of the labor force). The missing patterns are discussed in the online supplement.
7. These occupational categories include professional; management; self-employed; clerical and sales workers; craftsmen; operatives and kindred; laborers and service workers; farm laborers; farmers and farm managers; and miscellaneous (armed services, protective workers, unemployed for the last year but looking for work).
8. We also experimented with models that relax this assumption, and we found similar results to those reported here.
9. It is possible to model the distributions of u and ω jointly in a multivariate normal distribution, assuming that earnings growth parameters in u and volatility parameters in ω are correlated. For the sake of simplicity, we assume they are independent. We also experimented with models that allow correlations among all random parameters, but the estimated correlations between u and ω are low and inconsequential to our conclusions.
10. The number of iterations varies by models. The models that include covariates as control variables require more iterations than do the models without any controls. The models are estimated on Amazon Web Services (AWS). Access to the data, coding syntax, statistical commands, documentations, and trace plots are available upon request and will be provided with the online supplementary materials.
11. Peak ages can be solved as functions of β_1 and β_2 in Table 3: $t_{peak} = -\frac{\beta_1}{2\beta_2}$.
12. The highlighted panel in Table B2 in the online supplement refers to between-generation covariances in earnings trajectories, and the remaining refers to within-generation parameters. For the sake of simplicity, the covariance of earnings growth residual, namely, ε_{it} in Equations 3 and 4, and any other growth trajectory parameters, are fixed at zero, suggesting that earnings residuals change over time but are not a function of age. We relaxed this assumption in our sensitivity analysis and the estimates are very close to 0.
13. Table E in the online supplement reports the full matrix of the IGE estimates by one-year age groups of fathers and sons.
14. The highest IGE reaches a level of around .6, suggesting the United States is less mobile than indicated by previous estimates from the PSID.
15. Some notable exceptions in prior work highlight the importance of parents' early career earnings. For example, in their study using the PSID, Mazumder and Acosta (2015) analyze IGE of fathers and sons at age 30, 42, and 55. Among a range of IGE estimates, their results show the highest IGE between father's age at 30 and son's age at 42 to be .553, compared to .502 when earnings are measured at age 42 for both generations.
16. Duncan and colleagues (2010) show no variation in intergenerational association by age at which the adult child's earnings are measured; yet the present study shows such variation. A possible reason for this difference is that we follow individuals from age 25 to 55, whereas they only focus on ages 25 to 37.
17. For simplicity, we assume "classical" measurement errors in earnings; that is, the errors are independent of the true levels of earnings.
18. For example, administrative earnings data with complete earnings histories for both generations

may facilitate a further decomposition of transitory shocks into permanent and idiosyncratic components. Mazumder (2001) shows that the persistent component of transitory shocks can affect estimates of earnings profiles when the research question concerns between-group comparisons (e.g., college versus non-college, black versus white).

19. Our analysis does not distinguish between coresiding and non-coresiding fathers. Some fathers in our analyses may not live in the same household with their sons during early childhood.

20. In general, if two random variables $X_1 = e^{Y_1}$ and $X_2 = e^{Y_2}$ are log-normally distributed, and the joint distribution of $\begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} \sim N\left[\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix}\right]$, then

$$\mathrm{Corr}(X_1, X_2) = \frac{E(X_1X_2) - E(X_1)E(X_2)}{\sqrt{Var(X_1)Var(X_2)}}, \text{ where}$$

$$E(X_1) = e^{\mu_1+\sigma_1^2/2}, E(X_2) = e^{\mu_2+\sigma_2^2/2}, Var(X_1) = \left(e^{\sigma_1^2} - 1\right)\cdot e^{2\mu_1+\sigma_1^2}, Var(X_2) = \left(e^{\sigma_2^2} - 1\right)\cdot e^{2\mu_2+\sigma_2^2},$$

and $E(X_1X_2) = e^{\mu_1+\mu_2+(\sigma_1^2+\sigma_2^2+2\sigma_{12})/2}$.

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