Understanding Patterns and Trends in Income Mobility through Multiverse Analysis

Per Engzell* Carina Mood**

April 2023

Abstract

Rising inequalities in rich countries have led to concerns that the economic ladder is getting harder to climb. Yet, research on trends in intergenerational income mobility finds conflicting results. To better understand this variation, we adopt a multiverse approach that estimates trends over 82,944 different definitions of income mobility, varying how and for whom income is measured. Our analysis draws on comprehensive register data for Swedish cohorts born 1958–1977 and their parents. We find that income mobility has declined but for reasons neglected by previous research: improved gender equality in the labor market raises intergenerational persistence in women’s earnings and the household incomes of both men and women. Dominant theories that focus on childhood investments have blinded researchers to this development. Methodologically, we show how multiverse analysis can be used with abduction—inference to the best explanation—to improve theory building in social science.

Introduction

The late 20th century saw earnings and wealth inequality rise in most Western countries. This has sparked concerns about the consequences for younger generations. Do increased disparities mean that a child’s family of upbringing has become more important as a predictor of their attainment as an adult? Research to date provides no conclusive answer: studies both in the US and Scandinavia—the context of this study—report everything from no trend to a decrease in income mobility, or even a slight increase (Aaronson and Mazumder, 2008; Bloome, 2015; Bloome et al., 2018; Bratberg et al., 2007; Chetty et al., 2014b; Davis and Mazumder, 2020;

*UCL Social Research Institute, University College London; Nuffield College, University of Oxford; Swedish Institute for Social Research, Stockholm University. E-mail: p.engzell@ucl.ac.uk.

**Swedish Institute for Social Research, Stockholm University; Institute for Futures Studies, Stockholm. E-mail: carina.mood@sofi.su.se.

Fertig, 2003; Hansen, 2010; Hansen and Toft, 2021; Harding and Munk, 2020; Hertz, 2007; Jonsson et al., 2011; Lee and Solon, 2009; Mayer and Lopoo, 2005; Pekkala and Lucas, 2007; Pekkarinen et al., 2017; Sirniö et al., 2017).

How has a question so important kept eluding a clear answer? Some indeterminacy may be due to arbitrary differences in, e.g., sample or time span. If so, as more and better data become available, studies will eventually converge. Alternatively, these studies might have been asking not one but several questions, through subtle differences in target parameter or study design. The literature on intergenerational income mobility works with a wide range of models and definitions. While the question “has mobility decreased?” is generic, different models can speak to different estimands (Lundberg et al., 2021). If so, variation is an irreducible feature and no matter how much data we have, studies may not converge on a single answer.

As we will argue, the way forward lies in treating model variation not as a nuisance but as an indispensable source of information. In this study we focus on Sweden, where access to five decades of population data allows us to estimate a wide range of models. We ask how levels of and trends in intergenerational income mobility depend on the choice of income concept, differences between men and women, the age and period at which income is measured, how zero values are treated, and the parameter of association. Our use of a single high-quality dataset lets us abstract from variation due to context, sampling or measurement error. We examine 20 cohorts and 82,944 alternative specifications.

Our work extends current efforts to increase transparency in social science (Freese et al., 2022). Specifically, we use “multiverse analysis,” a procedure that exhausts all possible combinations that arise from set of reasonable analytical choices (Berk et al., 2010; Muñoz and Young, 2018; Western, 1996). Tools for increased transparency have yet to gain widespread adoption. One reason, we believe, is that the solutions they offer are often wedded to a deductive paradigm quite far removed from what many social scientists actually do. Existing uses of multiverse analysis treat model uncertainty as akin to sampling variance, indicating the “robustness” of results. On this view, model variance is a bad thing: the more results vary across specifications, the weaker the support for a given hypothesis. This risks imposing unreasonable standards, because variation is almost always rife.

In this article, we argue that increased transparency can help foster a different model of inquiry that, incidentally, better represents what many sociologists have always done. Instead of testing a given hypothesis derived from theory, we ask: what is the explanation that best accounts for the sum of results? This approach, known as abduction or inference to the best explanation (Lipton, 2003; Peirce, 1974), provides a powerful model for how transparency can accelerate knowledge production. On this alternative model, the goal is not to accept or refute a given hypothesis, but rather to generate a wide range of observations that help modify and improve upon existing theory (Brandt and Timmermans, 2021). We address quantitative researchers, but parallel arguments have been put forth in the qualitative literature (Tavory and Timmermans, 2014).

Substantively, we find that mobility has declined in recent cohorts, but for reasons neglected by previous literature. The most consistent contributor to trends is the advancement of women in the labor market, which leads to increased persistence in women's earnings. Importantly, this influence shows not only in women's own incomes but also in the household incomes of both men and women. For specifications that isolate men's earnings, mobility has mostly remained flat or increased. In other words, intergenerational mobility is declining as women are realizing their earnings potential to a greater degree.

We also contribute to several methodological strands of the income mobility literature. Recent research has abandoned measures based on log income in favor of rank-based approaches that are supposedly more robust (Bloome et al., 2018; Chetty et al., 2014a; Dahl and DeLeire, 2008). At the same time, it is often presumed that log-based measures are preferable when data limitations do not preclude their use (Mazumder, 2016; Mitnik et al., 2019; Mitnik and Grusky, 2020). We move this debate forward by showing that a) rank-based measures are far from insensitive to considerations such as life-cycle bias, and b) log-based measures behave erratically even with close to ideal data, due to an extreme dependence on the bottom of the distribution.

Ultimately, our study offers an opportunity for scholars to put past and future work on income mobility in context, and gauge how it may reflect the combinations of decisions reached by authors.¹ Because studies often differ in more than one dimension, it is hard to draw out

the implications of differences across them. Yet, for research in the field to be cumulative, we must know the consequences of different income definitions and model specifications. A multiverse analysis formalizes this process and provides a yardstick by which to contextualize studies that only explore a small part of the model space. Moreover, such knowledge can move the field from broad descriptions towards a deeper understanding of the mechanisms behind intergenerational persistence.

Previous research on income mobility

The extent to which poverty or riches are perpetuated across generations has long been a topic of social concern. A high degree of intergenerational mobility is generally viewed as desirable, being a proxy for a society that offers equal opportunities (Breen and Jonsson, 2005). Mobility is typically measured by the strength of the association in status between generations. In the case of income, this becomes a correlation or regression coefficient from an equation where parent income is used to predict the income of the child. In other words, the basic datum of mobility research is a measure of its inverse: intergenerational transmission or persistence.

Country differences

The maturation of income mobility as a field is largely a story of how researchers learned to address two sources of variation: measurement error and life-cycle bias. In one of the earliest reviews, Becker and Tomes (1986, p. 291) concluded that: “regression to the mean . . . appears to be rapid” and that relative earnings differences between families are mostly “wiped out in three generations”.

Today, we know that this conclusion was premature and stemmed from studies using snapshots of fathers’ and sons’ income that are weak proxies of lifetime income. Solon (1992) was early to point this out, and over the decades that followed, a string of studies led to a gradual revision upward of the estimated association. Current best estimates suggest that at least as much as half of earnings inequality is inherited in the US today (Cheng and Song, 2019; Gregg et al., 2017a; Mazumder, 2016; Mitnik et al., 2019).

Along with the accumulation of US evidence, estimates also surfaced for other countries. Björklund and Jäntti (1997) showed that persistence of incomes was less pronounced in Sweden, a Scandinavian-type welfare state. Their results contradicted the notion of the US as a “land of opportunity” where high inequality in the cross-section is offset by the absence of a rigid class structure. The idea that more equal countries provide a more level playing field soon gained traction, and was eventually epitomized in the “Great Gatsby Curve” (henceforth GGC; Corak, 2013), a graph showing that high income inequality tends to go together with less income mobility.

Time trends

Most wealthy countries have seen income inequality grow since the 1970s or 1980s. If we believe that the GGC reflects a causal relationship, we would expect intergenerational transmission to rise with inequality over time. Here the evidence is much less consistent (Torche, 2015). The best available data for the US suggest no trend in income mobility for cohorts born from the 1970s through the 1980s (Chetty et al., 2014b). Similar conclusions are reached by earlier US studies, which include Hertz (2007), Lee and Solon (2009), and Bloome (2015). However, this has been contradicted by studies claiming to detect a mobility decline (Aaronson and Mazumder, 2008; Davis and Mazumder, 2020), or even an increase in mobility (Fertig, 2003; Mayer and Lopoo, 2005).

There is some evidence for Scandinavia: Bratberg et al. (2007), Hansen (2010) and Pekkarinen et al. (2017) in Norway, and Pekkala and Lucas (2007) in Finland all find a tendency toward equalization in cohorts born before 1960 and stable or slightly increasing persistence thereafter, but the results are sometimes sensitive to alternative specifications. Jonsson et al. (2011) find an increasing elasticity but a decreasing correlation over Swedish cohorts born 1960 to 1970. Harding and Munk (2020) study the intergenerational rank correlation in family income with Danish data, and report that income persistence increased among both men and women from cohorts born in the late 1950s onward.

Related evidence comes from sibling correlations. Here, Björklund et al. (2009) find decreasing income correlations for Swedish brothers born until 1950 and a slight increase

thereafter. Wiborg and Hansen (2018) report a similar increase in earnings and wealth correlations among recent cohorts of Norwegian brothers and sisters. Also in Norway, Hansen and Toft (2021) find that class-origin income gaps increased for daughters but remained stable for sons whereas class-origin wealth gaps increased for both sexes.

Abductive multiverse analysis

That previous studies have reached mixed results is not surprising. Studies cover different contexts and populations, but also vary in other respects. Any statistical analysis faces a wide range of options in how to set up or clean the data, construct key variables, treat missing or extreme values, select functional form, estimation method, and so on. Some alternatives may be unavailable and beyond the researcher's control, while others are subject to choices that must be made more or less consciously. Without a systematic approach to heterogeneity, it is difficult to learn from these varied results. A multiverse analysis renders the variation transparent by considering the consequences of every alternative choice.

Existing uses of multiverse analysis presuppose that a researcher aims to test one hypothesis, and treat variation as indicating the “robustness” of results (Muñoz and Young, 2018; Simonsohn et al., 2020; Steegen et al., 2016; Young and Holsteen, 2017). The more specifications a given result survives, supposedly the stronger the evidence. On this approach, a researcher would use theory or hunch to develop a prediction of the form: “mobility is declining.” Testing the prediction under a range of specifications may then render it disconfirmed, robustly confirmed across multiple specifications, or “remarkably dependent on a knife-edge specification” (Young, 2018).

In our view, this multiverse-as-robustness approach fails to fully capitalize on the data. Different specifications can speak to different questions in ways that are not obvious before a researcher sets out on an analysis. If we find that mobility appears to be declining under some specifications but not others, the logical next step is to ask what characterizes these specifications. This is the essence of the approach we propose here, abductive multiverse analysis. Unlike deduction, abduction is not intended to test hypotheses, but to come up with

them (Brandt and Timmermans, 2021). Unlike induction, it goes beyond simple generalization to engage theory, in ways that we elaborate next.

The role of theory

Under a deductive model, the aim of theory is to provide predictions which can be tested against data. Call this the “map” view of theorizing. The theory provides the roadmap to an outcome; if at the end of the road we find the predicted outcome, we consider the theory at least provisionally valid. This deductive model is what we aspire to when we structure our writing around hypotheses, significance tests, and so on—although it is an open secret that these trappings of scientific rigor often enter at a late stage of the process.

In the world that sociologists inhabit, a more flexible interplay between theory and data would seem more fitting to many research problems. With abduction, or inference to the best explanation (Lipton, 2003; Merton, 1987; Peirce, 1974), theory is not used to derive sharp predictions. Rather, it serves as a scaffold to arrange a set of loosely held beliefs that may be revised as evidence continues to build. Call this the “scaffolding” view of theorizing. Here, theories meet the data not in a binary confirmation-or-refutation way, but one that uses heterogeneous results to get at scope conditions and eventually, underlying mechanisms.²

This model of knowledge accumulation has been likened to the way a crossword puzzle is solved, by carefully fitting pieces of evidence until only one plausible explanation remains (Haack, 2000), an approach found in many classical works. We can see it in Weber’s analysis of the economic effects of Protestantism, in Durkheim’s analysis of suicide, and in Darwin’s development of the theory of natural selection. John Snow’s pioneering work on cholera in the 1850s, often cited as a forerunner in causal inference, has more in common with the crossword model than with modern causal inference (Freedman, 1991).

Assumptions of previous research

Entering a field with too strong priors risks blinding us to plausible alternatives. Take the “Great Gatsby” argument. What ostensibly is a simple prediction—mobility will decrease with rising inequality—encompasses a host of assumptions about how and why. Focusing on parental investments, it assumes that the intergenerational association represents, at least partly,

a causal effect of income (Mayer, 1997). By centering the role of inequality during childhood, it reinforces what has been called the “economization of early life” (Griffen, 2022). This focus on the family in turn risks detracting from wider societal factors, such as market imperfections or power struggles in the arena of work.

Recent neglect of the labor market in intergenerational mobility has a parallel in the status attainment paradigm, once dominant in stratification research (Sewell et al., 1969; Sewell and Hauser, 1975). Like the Becker and Tomes (1979, 1986) framework that guides income mobility research today, status attainment emphasized processes linking individual orientations to education and subsequent jobs. On the flip side, it remained silent on structural sources of inequality in the labor market, and the fraught social and political choices that link jobs to rewards (Engzell and Wilmers, 2023; Tomaskovic-Devey and Avent-Holt, 2019).

Dominant paradigms tend to be durable and self-reinforcing. The types of questions asked depend on available data, and shape how data are collected, curated, and analyzed (Hirschman, 2021). If we see intergenerational persistence rising with inequality, it is easy to take this as confirmation of a causal chain from parental investments to mobility. In reality, mobility might shift for many reasons, only some of them driven by parenting. A more flexible interplay between theory and data can lead us out of such ignorance traps and point toward better and revised theories.

[FIGURE 1 ABOUT HERE.]

A model of intergenerational mobility

We sketch a model of intergenerational income mobility in Figure 1. This model, which we borrow from Breen and Jonsson (2007), incorporates key components of the status attainment and Becker–Tomes models.³ It is deliberately flexible: its purpose is not to serve as a map yielding sharp predictions, but as a scaffold to help make sense of heterogeneous results.

Mobility can be seen as a series of interlinked processes (cf. Breen and Jonsson, 2007; Grusky and Szelenyi, 2018). First, a system of socialization that endows children with unequal amounts of cultural and social capital (“assets”). Such traits are often constitutive of the individual, inalienable, and embedded in her identity. Second, a system of institutional differentiation that

enables personal traits to be converted into recognized, institutional markers of status such as educational qualifications or job titles (“class”). And third, a system of reward that endows different locations in the class structure with unequal compensation (“rewards”).

Income mobility captures the correlation of rewards across generations. It follows that a change in mobility can come about through a change in any one of the six paths in Figure 1.⁴ The common hypothesis that inequality will hamper mobility rests on extrapolating from one trend (inequality) through one pathway (parental investments). A deductive approach to testing it would have to make the heroic assumption that everything else in the system stays constant. The abductive approach that we take lets the data speak first, and only then seeks to identify the most plausible explanation for the patterns identified.

The Swedish context

The increase in inequality across rich countries is well documented, and started around the mid-1970s in the US case (Morris and Western, 1999; Neckerman and Torche, 2007). In Scandinavian countries, income inequality did not start to rise until the 1980s and took off significantly after the recession in the 1990s (Jonsson et al., 2016). While Sweden is known as a redistributive welfare state with extensive social safety nets, the rise in inequality has been more pronounced in disposable incomes than labor earnings (Jonsson et al., 2011). This is due both to a lowering of real taxes and benefits and a steep rise in capital incomes.

Our cohorts (1958–1977) grew up during a time of increasing equality but experienced the labor market during one of increasing inequality. It is hard to know whether the decreasing inequality during childhood or rising inequality later in life should guide the prediction of mobility across these cohorts. The typical argument emphasizes childhood, with inequality magnifying “the difference in the capacities of rich and poor families to invest in their children” (Ermisch et al., 2018, p. 501). At the same time, other authors have emphasized the role of inequality when children enter the labor market (e.g., Davis and Mazumder, 2020).

The formative years of these cohorts saw several other social transformations. Tertiary education which in Sweden is publicly financed expanded from about 30% enrolment in our first cohorts to nearly 50% only a decade later (Jonsson and Erikson, 2007). Occupational

mobility is higher among college graduates (Hout, 1988), but there may be offsetting effects for income (Torche, 2016; Zhou, 2019). In the generation of both parents and children, couples increasingly became dual breadwinners following a 1970 individualized tax reform (Hwang and Broberg, 2014), and women’s and men’s careers have become increasingly similar (Härkönen and Bihagen, 2011; Härkönen et al., 2016).

Women’s inroads into the labor market went together with delayed childbearing, a deinstitutionalization of the family, and a weakening of the link between children and marriage (Gähler and Palmtag, 2015). Partly in response, high quality state-subsidized daycare expanded from the 1960s onwards (Andersson et al., 2004). Women’s changing labor market behavior should matter not only because women will contribute a growing share of family income (Beller, 2009; Hansen, 2010), but also because realized income becomes a better proxy for their earnings capacity (cf. Herd et al., 2019).

Unemployment rates in Sweden have been rather stable around 6 to 7% since the end of the 1990s, which stands in dramatic contrast to the low rates of 2 to 3% for the period 1950 to 1990. The dividing line between these periods was the mid-1990s recession, when unemployment rose to rates of around 10% and several structural reforms of the economy took place (Forslund, 2008; SCB, 2021). Hence, while unemployment was uncommon in the parental generation, it is a more tangible risk in the child generation.

Analytical roadmap

To study how specifications influence mobility estimates, we first specify a set of choices that are commonly faced by researchers. Next, we use all possible combinations of those choices to define the model space. We then go on to estimate all specifications, and explore how the parameter of interest varies across them.

To start, we address the question of robustness that typical multiverse analyses focus on. This simply asks about the extent of variation, without seeking to understand its sources. For levels, we pay special attention to the upper bound of persistence estimates, given that Sweden is commonly seen as a high-mobility country. The previous literature contains far more estimates for the US, with preference typically given to those largest in size (Corak, 2006). Recent

scholarship questions the high Scandinavian mobility and suggests that it is isolated to certain measures (Landersø and Heckman, 2017). Given that US estimates reflect a wide search across data sources and specifications, it is relevant to conduct a similar search in a Scandinavian setting.

Our results for levels turn out remarkably consistent with the received view that mobility is high in Sweden. For trends, the story is more mixed. Depending on specification, it is possible to conclude that income mobility is increasing, decreasing, or remaining flat. In the next step, we identify the most influential contributors to levels and trends. We formalize this procedure by inspecting the variance explained (R^2) in the outcome space by model components individually and in combination. While some of the patterns we detect defy easy summary, others reveal insights that become apparent only against the relief of the full model space.

The main upshot of our analysis is that declining mobility appears restricted to specifications that include women's earnings, either directly or as part of family income. A deductive approach using a single specification might have attributed this decline to rising inequality. Instead, our results are suggestive of a different explanation in progress on gender equality. We go on to corroborate this explanation using our own data as well as auxiliary evidence. This step highlights how abductive analysis is driven neither exclusively by theory nor by data, but represents an interplay between the two.

While we base most of our analyses on the intergenerational rank correlation, we examine a broader range of parameters next. We use this opportunity to contribute to existing methodological debate around income mobility. A commonly held opinion is that the intergenerational elasticity is the theoretically preferred measure, but the rank correlation is useful when data have a limited observation span. We question both notions by showing that elasticities behave erratically even with close to ideal data, while rank correlations remain sensitive to life-cycle bias. No measure is therefore immune to considerations of specification, but mapping the full range of variation can help researchers make an informed choice.

Data

Our data consist of the full population of men and women born in Sweden 1958–1977, and are merged from various administrative registers: The *register of the total population* gives basic information about, e.g., birth year, country of birth, and sex, and *demographic event registers* contain information about migration and civil status changes. The *multigenerational register* contains links between (biological and adoptive) parents and children, covering all children in our cohorts where at least one parent has been registered as resident in Sweden at any point since 1947. In our cohorts, virtually all individuals can be linked to the mother, and 98 to 99% to the father. Around 200 to 1000 persons (0.1 to 1.5%) in a given cohort have a link to both a biological and an adoptive parent of the same sex, and in these cases the adoptive parent is given priority.

Information on earnings and incomes comes from the *annual income registers* 1968–2019. The primary source for the income registers is tax records, covering all taxable incomes and taxes, and to these are added any non-taxable benefits. All incomes are expressed in 2019 prices using Statistics Sweden’s official consumer price index. The zero earnings or incomes in our data are “real” zeros rather than missing values insofar as the target quantity is official Swedish income/earnings, but people with zero observed incomes can have undisclosed foreign income or income from unofficial sources. The only missing values on income are for individuals who are not registered as resident in Sweden a given year (which is due to either migration or death). We top code incomes higher than 4 standard deviations above the mean, which matters only for the linear correlation.⁵

Earnings are defined as the sum of individual pre-tax salary, self-employment income, and (from 1974) taxable earnings-related social insurance benefits (e.g., parenting or sickness payment). Inclusion of social insurance benefits makes only a slight difference to estimates (Mood, 2017). Disposable personal income is defined as earnings (as defined above) and all other registered taxable and tax-free income, subtracting taxes. In contrast to earnings, it includes redistributing components but also incomes from capital. The disposable family income is the sum of the personal disposable incomes of the adults in the household (excluding incomes of any adult children living with parents). For parents, this variable is the same in a

given year (but not at a given age if parents differ in age) if they live together, but if they are separated this variable captures the income of the new (single-adult or reconstituted) family.

Restriction to the specific cohorts we study is dictated by a number of data demands. The lower bound, 1958, is motivated by the fact that full-population income data are only available from the year 1968 onwards. Thus, while we are able to link offspring to their parents further back, we want to record parental incomes at a time when the children grew up (or, at least, when their parents were still active in the labor market). With the current selection, most of the parents in the oldest cohort are between 30 and 50 at the time when they first appear in our income data. The upper bound, 1977, is imposed to be able to observe offspring earnings at prime ages of labor market activity (up until age 42).

Sources of model variation

We address five sources of variation: 1) income concept, 2) differences between men and women, 3) the age and period at which income is measured, 4) how to treat zero values, and 5) the parameter of association. These are dimensions that often vary in the existing literature.

Our use of the term “specification” is deliberately broad. Whether to study women, men, or both is a different kind of choice than how to treat zero incomes, or at which age to observe income. Some alternatives clearly speak to different questions, while others seem more arbitrary from a theoretical standpoint. However, theoretical concerns are seldom explicit when authors present a given specification. Moreover, even choices that seem to carry less theoretical weight may, upon inspection, turn out to have a more substantive interpretation than thought. Therefore, we refrain from distinguishing *a priori* between dimensions that are more or less theoretically important.

Income concept

Income has been defined in various ways in the literature. We distinguish between labor earnings, disposable personal income, and disposable family income (see Data section above), and allow any combination of them on the left-hand and right-hand side.

One can easily conceive of different combinations of parent and child income measures as more or less suitable depending on the question motivating the study. If we are interested in how parents' economic investments translate into unequal attainments, we should study the disposable income of parents during the child's formative years. By contrast, if we believe that parents' transmit (genetically or culturally) traits that enhance the child's income, labor earnings is the appropriate proxy. Similarly, different outcome measures may be relevant depending on whether we are interested in the child's living standard or their capacity to generate earnings in the labor market.

The common focus on parental investments would suggest using disposable family income, possibly equivalized for household size. Until recently, the standard has instead been to focus on men's labor earnings. Lately it has become more common to use family income in both the parent and child generation (Bloome et al., 2018; Chetty et al., 2014a). This is a more encompassing measure of living standards, and more aligned with theories emphasizing investment. Family income also makes women and men look more similar and may therefore seem like a tempting way to abstract from sex. At the same time, it brings in mechanisms of partner selection and family formation that can make estimates hard to interpret (Chadwick and Solon, 2002; Choi et al., 2020; Holmlund, 2022).

Parent and child sex

For a long time, it was common to study the intergenerational mobility of men to the exclusion of women. This is an understandable choice if most women do not participate in the labor force, but that time has long passed, making the near-exclusive focus on men untenable (Beller, 2009; Charles, 2011; Hout, 2018). Results on women are still not as common as those on men, but tend to show that women's labor market attainment is less strongly predicted by parental origin than that of men, leading some to conclude that there is greater equality of opportunity among women than among men (Hederos et al., 2017). We study mothers, daughters, fathers, and sons separately.

Age and observation window

What is the appropriate age to observe income? We measure income of parents centered around ages 35, 40, 45, and 50, and for the offspring centered around age 25, 30, 35 and 40. For each of these ages, we study incomes for single years, or averaged over all non-missing observations over 3 and 5 years, respectively. In supplementary analyses, we expand the observation window to more than 30 years for both parents and children.

This dimension is subject to a large literature on its own, centering on the twin issues of transitory income shocks and life-cycle bias (Haider and Solon, 2006; Jenkins, 1987). The quest to mitigate these sources of bias has guided the literature, giving rise to shifting conventions over the years. There are three reasons why we address them despite extensive coverage in earlier work. First, given the heavy emphasis on these issues in the literature, it is worth knowing how important age and observation window are relative to other, less recognized sources of variation. Second, we make a new contribution by studying how these and other dimensions interact to produce variation. Third, work on life-cycle bias has mainly focused on mobility levels, and we know less about how it may affect trends.

Theoretical models of income transmission often refer to lifetime income, that is, income accumulated over the whole career (Solon, 2004). If this is the target concept, averaging incomes over several years gives more reliable estimates (Corak and Heisz, 1999; Solon, 1992), as does the choice of an age range more likely to be representative of lifetime income. Income differences are understated at young ages when many are still in education, and slightly overstated at the height of the career (Chen et al., 2017; Nybom and Stuhler, 2017). The effect of age of observation is likely to differ for men and women, because women on average take more extended periods of family leave and thereby peak later in the career. Chetty et al. (2014a) claim that life-cycle considerations become less important when using rank correlations, and that cohort ranks stabilize by age 30. Others have argued that rank-based estimates may still suffer from age biases (Gregg et al., 2017b; Mazumder, 2016; Mitnik et al., 2019).

Although it is often taken for granted that lifetime income is the target concept, this is not necessarily so. Income may be seen as a proxy for a broad set of social, economic and/or cultural advantages, which may or may not map onto lifetime income. And even when income

is the exclusive dimension of interest, there can be good reasons to focus on income at certain stages of life. Increased attention to how intergenerational persistence manifests itself across different life stages (Carneiro et al., 2021; Cheng and Song, 2019; Muller, 2010) is therefore an important complement to the common focus on averages presumed to capture an entire lifetime.

Zero values

How are zero incomes to be treated? We study how all association measures behave with zeros included and excluded. To preserve zeros with logarithmic transformation, we add 1 to all income measures before taking logs.⁶ The number of zeros in our population is small: mostly on the order of 0 to 3% in a given year, and even fewer when taking multi-year averages. Even among those registered as unemployed within a given year, it is rare to have zero earnings during the full year. Zero disposable incomes are even rarer.⁷

In previous work it has often been the practice to exclude zeros, especially when using logged incomes where zero is undefined. In many datasets, zero incomes may reflect underreporting or short-term spells of unemployment and if so, their inclusion might increase measurement error and lead to lower correlations. Lately, however, there has been growing awareness that exclusion of zero incomes can be problematic (Chetty et al., 2014a; Mitnik and Grusky, 2020). Exclusion of the poorest creates a selected sample that may miss mechanisms of severe economic vulnerability (Gregg and Macmillan, 2020; Jenkins and Siedler, 2007; Parolin et al., 2023). The focus has so far primarily been on zero incomes in the child generation, but leaving out the poorest in the parent generation can also be problematic.

Parameter of association

Previous studies have used various parameters of association. We focus on the rank correlation but contrast it with three other measures: the linear correlation, the log-linear correlation, and the elasticity. We define these in detail in Appendix A.

The rank correlation has rapidly become the new standard in this literature, following the work of Chetty et al. (2014a), thereby replacing the elasticity which was common in earlier work. The rank correlation is foremost motivated by the notion that it is less sensitive to issues

of measurement error and life-cycle bias, two major concerns that have guided practice in the field.

The linear correlation—the Pearson correlation in real incomes—is perhaps the simplest measure but has with few exceptions been shunned by researchers (Mood, 2017). In Appendix A, we show analytically that the linear and rank correlation are closely linked. Empirically, the choice between the two makes little difference in our data.

With income instead transformed to logarithms, one of two measures are produced: the log-linear correlation or the elasticity.⁸ The former is a correlation coefficient, the latter a regression coefficient. As such, the elasticity depends on the relative dispersion of parent and child income in a way that makes it respond mechanically to changes in inequality: if inequality is higher in the child generation, the elasticity will rise even if the correlation of (log) incomes does not (see Appendix A).

The choice between measures of association is a choice of functional form which should ideally be motivated by theory. The elasticity was given a theoretical rationale by Becker and Tomes (1986), resting on the idea of parental investments with diminishing returns. However, the resulting fit is often weak and may differ across countries in ways that complicate international comparison (Bratsberg et al., 2007). The rank correlation has been claimed to provide a good fit (Chetty et al., 2014a), but this has been questioned in the Swedish context (Nybom and Stuhler, 2017). Mood (2017) shows that the linear correlation fits well in the Swedish case.

Results

Given the above choices of income definition (9 combinations), parent and child sex (4 combinations), parent and child age (16 combinations), observation window (9 combinations), treatment of zeros (4 combinations), and choice of parameter (4 alternatives), we end up with $9 \times 4 \times 16 \times 9 \times 4 \times 4 = 82,944$ unique specifications, or 1,658,880 different associations estimated across the 20 cohorts.

In what follows, we define the *level* of association as the average across all cohorts for a given specification; the *trend* is defined as the absolute change in the parameter over the full 20

cohorts. We extract this information by first fitting a linear regression with a trend in year and then multiplying the slope coefficient by 20 to extrapolate to the whole period.

[FIGURE 2 ABOUT HERE.]

Distribution of levels and trends

Figure 2 shows the distribution of levels and trends across the four measures we study: the rank correlation, linear correlation, log-linear correlation, and elasticity. On average, linear and rank correlations are about twice as high as the log-linear correlation or elasticity (Figure 2, left panel). The elasticity has extremely long tails on either side: While 90% of the elasticities lie between 0 and 0.17, the overall range is from -0.19 to 0.41 . The other parameters have smaller ranges but the variation is still substantial, moving from weak negative correlations to positive ones around 0.2 to 0.3 (Appendix Table A2–A5).

What is the upper bound of intergenerational income associations in Sweden? The elasticity has a higher upper bound: 0.41 vs 0.26 and 0.28 for rank and linear correlations, respectively (Appendix Table A2–A5), but the very high elasticities are observed only in a few specifications. The log-linear correlation is both lowest on average and has the lowest upper bound: 0.20 (Appendix Table A4). In the vast majority of cases, we do not reach higher associations than in previous literature on Scandinavian countries. A substantial fraction of associations are negative, foremost accounted for by early measurement of child income (i.e., life-cycle bias).

In additional analyses, we expand the observation span to more than 30 years in each generation.⁹ The maximum associations we observe in these analyses all pertain to father/son associations, and are 0.30 (rank correlation), 0.33 (linear correlation), 0.31 (log-linear correlation), and 0.41 (elasticity), see Appendix Table A6. This rather low sensitivity to expansion of the observation window is likely to hold in other studies using high-quality tax register data, while studies using survey data may be more sensitive to measurement error.

For trends, most estimates point to an increased persistence over time. The shape of the distribution is similar to that of levels, although it is more concentrated around zero and somewhat less dispersed (Figure 2, right panel). The elasticity shows steeper trends than other measures of association (Appendix Table A5). This is explained by the rise of inequality, which

causes a mechanic increase in the elasticity, as we detail in Appendix A. Although most trend estimates show rising persistence, for all parameters of association and combinations of parent and child sex, there are trends in either direction (Appendix Table A2–A5).

[FIGURE 3 ABOUT HERE.]

What explains the variation?

To unpack which model components exert the most influence on results, we focus on the rank correlation; detailed results for other parameters are presented in the Online Appendix. We return to the choice of parameter later below.

Figure 3 displays how the level of the rank correlation varies across 20,736 different specifications defined by parent and child sex, income type, age and observation window, and the treatment of zero values. The top panel (a) displays a heatmap showing the estimated correlation for each specification. The bottom panel (b) focuses separately on each quadrant defined by parent and child sex and shows how remaining model components affect the level of correlation. The markers report coefficient estimates from a linear regression where the level is modeled as a function of income type, age, observation span, and zeros, and fit separately for father-son, father-daughter, mother-son, and mother-daughter pairs.

Which model components matter most for the level of rank correlations? Focusing on Figure 3, panel (a), two dimensions stand out: the child's age at measurement and the sex of both the parent and child. Intergenerational correlations measured when the child is 25 are close to zero and in some cases negative. This is the well-known life-cycle bias (Haider and Solon, 2006): children from advantaged origins spend longer time in schooling and experience steeper earnings growth, so they will have low earnings early in the career. Dropping incomes at age 25 eliminates negative associations in our data (Appendix Figure A3).

However, age at measurement exerts a clear influence also later in the career and correlations grow gradually stronger at 30, 35, and 40 years of age. This contradicts the notion, made popular by Chetty et al. (2014a), that the rank correlation reduces the need for mature incomes. In fact, child age is the single most important predictor of variation in levels (Appendix Table A8), but again less so when focusing solely on income at age 30 or above (Appendix Table A12).

After child age, the most influential components in Figure 3 are parent sex, parent income type, child sex, child income type, and parent age (Appendix Table A8). Notably, the number of income years observed in either generation and the exclusion of zero incomes are inconsequential for rank correlations (but not for log-based measures, which we discuss below). As for the sex of parent and offspring, father/son correlations are strongest, followed by father/daughter, mother/daughter, and finally mother/son correlations which are the weakest.

Correlations involving mothers' incomes become more similar to those of fathers when using family income, which is unsurprising as this includes fathers' incomes in most households. Notably, correlations increase sharply with mothers' age. This points to the later maturation of women's income careers and the risk of underestimating the role of mothers if applying an analytical template optimized for the typical career pattern of men.

[FIGURE 4 ABOUT HERE.]

Which choices affect the trend in estimated rank correlations? Figure 4 follows the same logic as Figure 3 but now showing how the trend over a 20-year period depends on various components. As we saw in Figure 2, most specifications show a trend toward increasing persistence. Figure 4 shows that the dimensions that predict trends are largely the same as those that predict levels: age, sex, and income type—although sex and income type matter more on the child side for trends than for levels where parents are instead more important (Appendix Table A8). The trend toward increased persistence is mostly absent at young child ages. This may be explained by the increasing average length of schooling over the period, such that earnings differences are realized increasingly late in the career.

A notable pattern in Figure 4 is that most of the specifications that show increased persistence contain either mothers or daughters. In fact, comparing Figures 3 and 4 reveals that correlations between fathers and sons, or mothers' family income and sons, both show the highest level of correlation and no trend or one towards weakening persistence. By contrast, focusing on the quadrants involving mothers and daughters, correlations are weaker at baseline but rising over time. We now go on to explore the role of women in these shifts over time.

The changing role of women

One upshot of our analysis is that women's earnings, either directly or indirectly (as a component of family income) are the predominant driver of increased persistence. Figure 5 shows trends in the rank correlation separately by income type and parent and child sex. The male earnings correlation remains flat or slightly decreasing, while the correlation between father family income and son earnings sees a weak increase in persistence. For all other curves, there is a clear trend of increasing persistence over time.

[FIGURE 5 ABOUT HERE.]

To gain a more thorough understanding of the role of women, we return to our theoretical model in Figure 1. That women's earnings drive increased persistence could mean several things. Women's rising earnings may contribute to rising inequality between households and thereby unequal investments in children. Such a pattern would depend on the degree of assortative mating. Another possibility is that we have seen a strengthening of the paths from women's assets to rewards in the vocabulary of Figure 1.

We first consider the unequal investments pathway. In general, female labor market participation tends to go together with decreasing, not increasing, inequality between families (Mastekaasa and Birkelund, 2011; Nieuwenhuis et al., 2017; Rosche, 2022), and assortative mating in practice contributes little to inequality between households (Boertien and Bouchet-Valat, 2022). In Sweden, assortative mating has decreased or been largely stable (Henz and Jonsson, 2003; Holmlund, 2022), and income inequality was at its lowest point during the 1980s, when the youngest cohorts in our study grew up. Hence, potential childhood investments grew more equal over these cohorts, so inequality is unlikely to be driving increased persistence. Moreover, such an explanation cannot account for the strikingly different trends we see for daughters and sons.

[FIGURE 6 ABOUT HERE.]

A more plausible explanation is increased gender equality in the labor market. In Figure 6, we show that over our studied cohorts, education has gone from explaining 7–8 percent of

the variance in women’s earnings ranks, to explaining 17–21 percent (the lower number is for level of education, the higher number for a combination of level and field). Among men, the corresponding change is from 17–18 to 14–17 percent. At the same time, fathers’ earnings percentile has had a stable, or slightly decreasing, power to predict whether the child gets a university education or not. In other words, the changing trends in mobility that we find for women and family income does not reflect changing investments in children, but rather the extent to which women’s earnings mirror their underlying human capital.

Rank correlation vs other parameters

So far, we have focused on the rank correlation; we now examine differences between all four parameters of association. The rank correlation was popularized in work using US tax data, where the elasticity has been difficult to estimate due to limited observation spans (Chetty et al., 2014a). Many scholars maintain that the elasticity remains theoretically preferred when data quality does not hinder its use (Mazumder, 2016; Mitnik et al., 2019; Mitnik and Grusky, 2020). There has been some work comparing how these measures are affected by measurement error and life-cycle biases (Nyblom and Stuhler, 2017). We know less about how sensitive trends are, and whether this might differ across parameters.

[FIGURE 7 ABOUT HERE.]

To condense information about levels and trends, we plot estimates for all four measures in Figure 7, where each dot represents a specification. Detailed results for the linear correlation, log-linear correlation, and elasticity are available in Appendix Figure A4–A9. The first thing that stands out is that the linear correlation shows a near-identical pattern to the rank correlation: estimates from these two measures correlate at $r = 0.99$ across specifications (Appendix Table A7). This follows from the linear correlation providing a good fit in our data: whenever standard normality assumptions are satisfied, linear and rank correlations are by definition closely linked (see Appendix A).

The log-linear correlation differs from rank and linear correlations in two respects. The level of the correlation is lower, and the estimates are clustered more tightly together, without evidencing the same clear patterning by parent and child sex. While this might suggest that

log-linear correlations are in one sense more “robust,” it is not clear that this invariance is a good thing if specifications speak to different questions. The elasticity equals the log-linear correlation multiplied by the ratio of standard deviations in parent and child income (see Appendix A). It shows a wider dispersion in both levels and trends. This could be driven in part by specifications with different income definitions on the parent and child side, which should differ in dispersion. However, the picture looks similar when we restrict ourselves to specifications that treat income symmetrically on each side (Appendix Figure A11).

What components account for variation in the log-based measures? The same components tend to matter for the level of estimated associations, and in similar ways, as for the rank or linear correlation. The main exception is that log-based measures are more sensitive to the number of income years and, particularly, the treatment of zeros, which in our data make up less than 3% in all groups but mothers (Appendix Table A13).¹⁰ This sensitivity to low values suggests that the functional form may provide a poor fit to data. We examine the model fit directly in Appendix Figure A12 and confirm that the log functional form overfits low values and performs poorly in the upper half of the distribution. In other words, using log-based measures amounts to a judgement that the upper half of the distribution is of less weight, and should be treated as a substantive choice.

Do different measures tell the same story about trends? The agreement is lower for trends than it is for levels (Appendix Table A7). In other words, whereas most model components have a similar influence on the level, this is not true for trends: the choices that matter for log-based measures differ from those that influence rank or linear correlations.¹¹ For some choices, the influence is the opposite across different parameters. For example, measuring income at high father ages increases the trend in the rank correlation but decreases that in the log-linear correlation or elasticity (Appendix Figure A8–A9). For all four measures of association, variation in trends is less systematic than that in levels. While the bulk of variation in levels is explained by the main effects of individual model ingredients, trends depend to a higher extent on two-way or higher-order interactions that are hard to predict or interpret (Appendix Table A8–A11).

Where does this leave us with respect to the debate on the relative merits of rank correlations and log-based measures? The rank correlation, as well as the linear one, fits the data closely and picks up systematic patterns of variation that are easier to miss with log-based measures that behave more erratically. Elasticities and log-linear correlations are sensitive to a number of additional dimensions and have a tendency to overfit the bottom of the distribution. This extreme dependence is evidenced in Figure 8, which shows a wide range of levels and trends depending on the treatment of a small number of zeros among men in our data. Even with the kind of high-quality data we have access to here—prime ages, high coverage, long timespans—it is difficult to recommend log-based measures as a reliable basis for inference about income mobility at all.

[FIGURE 8 ABOUT HERE.]

Conclusions

The social sciences are currently undergoing a credibility crisis, or credibility revolution, depending on whom you ask (Engzell and Rohrer, 2021). There is growing awareness of how the many and varied options faced by an analyst can lead to selective reporting that risks systematically biasing a literature. While each analytical choice may seem trivial or innocuous on its own, they accumulate into a proverbial “garden of forking paths,” allowing a researcher to pick almost any desired result (Gelman and Loken, 2014). The field of income mobility research is no exception: given the variety of specifications and lack of general guidelines, this area would seem like a paradigm case of forking paths. To shed light on this issue, we have applied multiverse analysis, which maps variation across specifications to bring model dependency out in the open.

We have demonstrated how this tool can be used not only to gauge robustness, but also—with an abductive logic of inference—to shift our theoretical understanding of the phenomenon studied. Selecting a given specification to test a prediction such as “mobility is declining,” we would have been likely to confirm it. By contrast, examining the full model space we can begin to address questions not only of if but why. In our case, the striking conclusion is that rising gender equality, not inequality, is the main driver of declining mobility in Sweden today.

Correlations rise over time because women's earnings become a better proxy for their underlying human capital, and this also influences family income, which subsumes the income of a female spouse for many men. Our results show that rising intergenerational persistence can be a result of something most would see as desirable: gender equalization in the labor market.

The implication for mobility research is that it must go from merely acknowledging gender to placing it center stage. Women's rising earnings will affect not only women themselves, but also the men they share families and labor markets with. This is a force powerful enough to be the main driver of trends and differences across countries, and cannot be ignored. More generally, our results draw attention to the broader role of labor market processes in intergenerational stratification. Work in this area has focused on early-life investments, and ignored the relative pay of different segments of the labor market. Arguably, this research would benefit from tighter integration with literature on the sources of wage inequality in the labor market. Work parallel to ours confirms the importance for mobility analyses of considering characteristics of labor markets (Deutscher and Mazumder, 2023; Engzell and Wilmers, 2023; Granström and Engzell, 2023) and women's earnings (Ahrens et al., 2023; Brandén et al., 2023).

Another important observation is that variation is very large even for a given measure of association, and for a given combination of parent and child sex: For example, the rank correlation, which is generally taken to be the most robust measure of association, spans from weakly negative to around 0.30 for the father/son-combination, using different reasonable specifications. This large variation means that researcher degrees of freedom can give rise to varying conclusions. For example, there have been reports about rising persistence in some Scandinavian studies (Hansen, 2010; Harding and Munk, 2020; Pekkala and Lucas, 2007; Wiborg and Hansen, 2018), while others find conflicting results (Bratberg et al., 2005; Jonsson et al., 2011; Pekkarinen et al., 2017). This variation is hardly surprising in light of our analysis, as it is easy to reach conflicting conclusions about trends even with the same dataset—sometimes due to seemingly arbitrary choices of specification.

How should applied researchers tackle this staggering variation? A multiverse analysis may not be the appropriate course to take for all research projects. But arguably it should be incorporated as a standard tool among others. The form that a given multiverse analysis takes

must depend on the specific purpose and theory underlying that analysis. If the question is precise and all specifications can reasonably be seen as approximating the same underlying concept, a researcher may proceed with methods such as model averaging to arrive at more robust estimates. In practice, however, this will seldom be the case, and a more reasonable approach will be to display a range of estimates. Ideally, theory can lead us to agree on specifications that are more or less reasonable but even so, the chase for a single “best” estimate may be misplaced.

It is worth distinguishing the idea of robustness from variation that is more substantively or theoretically grounded. However, as we have argued, a sharp line can be difficult to draw *a priori* and will often have to arise from the data at hand. In fact, even choices that are motivated by certain theoretical considerations might turn out to have quite different implications once confronted with data. Take elasticities, motivated by a model rooted in human capital theory (Becker and Tomes, 1986). The motivation may be sound, but is little worth if the data are clearly at odds with the resulting functional form. In this case, the log transform turns out to put disproportionate weight on cases in the bottom of the distribution. This itself amounts to a substantive judgement that movements in the bottom of the distribution are of greater interest than in the upper half.

We have placed particular focus on the rank correlation, given its increasing popularity and its apparent promise in terms of robustness. On the one hand, the rank correlation is less sensitive to some choices—the number of years that income is observed and the treatment of zeros—that can have a large influence on log-based measures such as the elasticity. On the other, it remains heavily influenced by child age and income type. Regarding age, we find that measuring income at age 25 gives rank correlations that are close to zero and for later cohorts even negative. Although age 25 is younger than best practices would recommend, the fact that inclusion of these early incomes affects both levels and trends is notable, as researchers have assumed that trends would be unaffected (Chetty et al., 2014b). Age remains an important predictor of levels and trends in rank correlations, with clear differences also between the more mature ages of 35 and 40. Although our results cannot be generalized beyond the Swedish

setting, they show that rank correlations do not allow researchers to drop their guard against life-cycle bias.

The literature on intergenerational income mobility often seems like a flurry of numbers, and in this article we contribute quite a few more. Our goal, however, has been to anchor all these numbers in a systematic framework so that differences between them can become a source of information rather than a source of confusion. While model dependency is a very real challenge to the field, we believe that it is a challenge that we can rise to in productive ways. Most importantly, variation in estimates along systematic lines should spur researchers to sharpen their questions: “How large is intergenerational economic persistence?” is an important question, yet a vague one. Much time and energy have been spent on the chase for the one best estimate (0.3, 0.6 or perhaps 0.42?), but this chase for a “best specification” is futile if there is no stable target: If different measures of economic resources to a large extent proxy for different underlying factors, they cannot be treated as interchangeable (Lundberg et al., 2021).

By embracing variation and using an abductive approach what now sometimes seems like a jumble of numbers can be transformed into informative patterns. Patterns, however, do not always form neat narratives. As we have shown, a lot of variation—particularly in trends—is seemingly unsystematic. Moreover, even with a clear target concept, many operationalizations will seem equally reasonable, and even good data put limits to what can be achieved. With steadily expanding high quality data and computational power, the field is ready for a more systematic incorporation of variability through multiverse estimation. Accumulation of multimodel evidence from various sources will increase transparency and credibility, and holds promise for theoretical progress not just in intergenerational mobility research, but across a wide range of fields.

Notes

¹We make our full set of estimates available in a repository at the Open Science Framework, which can be accessed at: <https://osf.io/sqem7/>.

²A related but distinct approach is *implication analysis* (Lieberson and Horwich, 2008), which strives to derive many different predictions from theory and assess these with different data. This approach also emphasizes the importance of a wide range of results in informing theory but is deductive in that it explicitly tests hypotheses derived from a specific theory. An excellent example of this approach is Mayer (1997).

³We differ in our definition of key terms: Breen and Jonsson (2007) see “class” predominantly in terms of occupational attainment, and hence, educational qualifications are for them an example of “assets”. They also use

the term “consequences” as a broader alternative to our “rewards” that encompasses non-market outcomes such as class consciousness.

⁴For example, a lowering of the school starting age may limit the time young children are socialized by their parents and hence weaken the “endowment” link between assets in one generation and the next. A policy that favors underprivileged candidates in admissions or hiring decisions will weaken the “selection” link between assets and class. Policies of redistribution or collective wage bargaining that improve the position of workers relative to managers will tend to weaken the “return” link between class and rewards. Reforms that limit the influence of economic markets in education or housing may weaken the “investment” link between rewards in one generation and assets in the next.

⁵Top coded incomes make up 0.1 to 0.5% of observations in a given year. Top coding is by definition irrelevant for the rank correlation, and in practice for the log-linear correlation and the elasticity. Log-based measures put overwhelming weight on the bottom of the distribution, where very low values can instead create a far left tail. For the linear correlation, extreme outliers occur in individual years that create large year-on-year fluctuations in the association unless dealt with. An alternative cut-off at the 99.9 percentile gives similar results, but makes linear correlations slightly more similar to rank correlations.

⁶As an alternative way to keep zeros on the child side we have also estimated elasticities with the Poisson Pseudo Maximum Likelihood estimator proposed by Mitnik and Grusky (2020). In our case, this estimator gave virtually identical results as when excluding zero child incomes from the sample, probably because the number of zeros among children is small.

⁷0.1 to 1.3% of a given cohort in a given income year have zero disposable family income, while 1 to 3% have zero earnings. Up to 10% of mothers in the earliest cohorts lack earnings, see Appendix Table A13.

⁸Following Mitnik and Grusky (2020), we take logs after multi-year averages rather than averaging log income. If we instead use averages of log annual incomes, associations tend to be lower.

⁹This can only be done for a limited number of cohorts and thus only for levels, and not trends.

¹⁰We include zeros by adding 1 before taking the logarithm. Inclusion of zeros suppresses the log-linear correlation (Appendix Figure A5), but can either decrease the elasticity—when occurring on the parent side—or increase it, when occurring on the child side (Appendix Figure A6). This asymmetric pattern is due to a sharp increase in the standard deviation when including zero incomes. Distances at the lowest end of the distribution are magnified when incomes are log transformed, resulting in a long left tail. The elasticity has a mechanical relationship with the ratio of standard deviations in the parental and child incomes. When including zeros on the child side but not the parent side, the ratio of child to parent standard deviation increases, and if including zeros only on the parent side the opposite happens.

¹¹Correlations in trends by specification range from $r = 0.86$ when rank and linear correlations are compared to $r = 0.64$ – 0.69 when the log-linear correlation is compared to all other measures, and a low of $r = 0.34$ when the elasticity is compared to either the rank correlation or linear correlation (Appendix Table A7).

References

- Aaronson, Daniel and Bhashkar Mazumder. 2008. “Intergenerational economic mobility in the United States, 1940 to 2000.” *Journal of Human Resources* 43:139–172.
- Ahrsjö, Ulrika, René Karadakic, and Joachim Kahr Rasmussen. 2023. “Intergenerational Mobility Trends and the Changing Role of Female Labor.” arXiv preprint arXiv:2302.14440.
- Andersson, Gunnar, Ann-Zofie Duvander, and Karsten Hank. 2004. “Do child-care characteristics influence continued child bearing in Sweden?: An investigation of the quantity, quality, and price dimension.” *Journal of European Social Policy* 14:407–418.

- Becker, Gary S and Nigel Tomes. 1979. "An equilibrium theory of the distribution of income and intergenerational mobility." *Journal of Political Economy* 87:1153–1189.
- Becker, Gary S and Nigel Tomes. 1986. "Human capital and the rise and fall of families." *Journal of Labor Economics* 4:S1–S39.
- Beller, Emily. 2009. "Bringing intergenerational social mobility research into the twenty-first century: Why mothers matter." *American Sociological Review* 74:507–528.
- Berk, Richard, Lawrence Brown, and Linda Zhao. 2010. "Statistical inference after model selection." *Journal of Quantitative Criminology* 26:217–236.
- Björklund, Anders and Markus Jäntti. 1997. "Intergenerational income mobility in Sweden compared to the United States." *American Economic Review* 87:1009–1018.
- Björklund, Anders, Markus Jäntti, and Matthew J Lindquist. 2009. "Family background and income during the rise of the welfare state: brother correlations in income for Swedish men born 1932–1968." *Journal of Public Economics* 93:671–680.
- Bloome, Deirdre. 2015. "Income inequality and intergenerational income mobility in the United States." *Social Forces* 93:1047–1080.
- Bloome, Deirdre, Shauna Dyer, and Xiang Zhou. 2018. "Educational inequality, educational expansion, and intergenerational income persistence in the United States." *American Sociological Review* 83:1215–1253.
- Boertien, Diederik and Milan Bouchet-Valat. 2022. "Are increasing earnings associations between partners of concern for inequality? A comparative study of 21 countries." *Social Forces* 101:639–664.
- Brandt, Philipp and Stefan Timmermans. 2021. "Abductive Logic of Inquiry for Quantitative Research in the Digital Age." *Sociological Science* 8:191–210.
- Brandén, Gunnar, Martin Nybom, and Kelly Vosters. 2023. "Like mother, like child? The rise of women's intergenerational income persistence in Sweden and the United States." Working Paper.

- Bratberg, Espen, Øivind Anti Nilsen, and Kjell Vaage. 2005. "Intergenerational earnings mobility in Norway: Levels and trends." *Scandinavian Journal of Economics* 107:419–435.
- Bratberg, Espen, Øivind Anti Nilsen, and Kjell Vaage. 2007. "Trends in intergenerational mobility across offspring's earnings distribution in Norway." *Industrial Relations* 46:112–129.
- Bratsberg, Bernt, Knut Røed, Oddbjørn Raaum, Robin Naylor, Markus Jäntti, Tor Eriksson, and Eva Österbacka. 2007. "Nonlinearities in intergenerational earnings mobility: consequences for cross-country comparisons." *Economic Journal* 117:C72–C92.
- Breen, Richard and Jan O Jonsson. 2005. "Inequality of opportunity in comparative perspective: Recent research on educational attainment and social mobility." *Annual Review of Sociology* 31:223–243.
- Breen, Richard and Jan O Jonsson. 2007. "Explaining change in social fluidity: educational equalization and educational expansion in twentieth-century Sweden." *American Journal of Sociology* 112:1775–1810.
- Carneiro, Pedro, Italo López García, Kjell G Salvanes, and Emma Tominey. 2021. "Intergenerational mobility and the timing of parental income." *Journal of Political Economy* 129:757–788.
- Chadwick, Laura and Gary Solon. 2002. "Intergenerational income mobility among daughters." *American Economic Review* 92:335–344.
- Charles, Maria. 2011. "A world of difference: international trends in women's economic status." *Annual Review of Sociology* 37:355–371.
- Chen, Wen-Hao, Yuri Ostrovsky, and Patrizio Piraino. 2017. "Lifecycle variation, errors-in-variables bias and nonlinearities in intergenerational income transmission: new evidence from Canada." *Labour Economics* 44:1–12.

- Cheng, Siwei and Xi Song. 2019. “Linked Lives, Linked Trajectories: Intergenerational Association of Intragenerational Income Mobility.” *American Sociological Review* 84:1037–1068.
- Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014a. “Where is the land of opportunity?: The geography of intergenerational mobility in the United States.” *Quarterly Journal of Economics* 129:1553–1623.
- Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner. 2014b. “Is the United States still a land of opportunity?: Recent trends in intergenerational mobility.” *American Economic Review* 104:141–147.
- Choi, Seongsoo, Inkwan Chung, and Richard Breen. 2020. “How Marriage Matters for the Intergenerational Mobility of Family Income: Heterogeneity by Gender, Life Course, and Birth Cohort.” *American Sociological Review* 85:353–380.
- Corak, Miles. 2006. “Do poor children become poor adults?: Lessons from a cross-country comparison of generational earnings mobility.” *Research on Economic Inequality* 13:143–188.
- Corak, Miles. 2013. “Income inequality, equality of opportunity, and intergenerational mobility.” *Journal of Economic Perspectives* 27:79–102.
- Corak, Miles and Andrew Heisz. 1999. “The intergenerational earnings and income mobility of Canadian men: Evidence from longitudinal income tax data.” *Journal of Human Resources* 34:504–533.
- Dahl, Molly W and Thomas DeLeire. 2008. “The association between children’s earnings and fathers’ lifetime earnings: estimates using administrative data.”
- Davis, Jonathan and Bhashkar Mazumder. 2020. “The Decline in Intergenerational Mobility After 1980.”
- Deutscher, Nathan and Bhashkar Mazumder. 2023. “Measuring intergenerational income mobility: A synthesis of approaches.” *Journal of Economic Literature* p. forthcoming.

- Engzell, Per and Julia M Rohrer. 2021. "Improving Social Science: Lessons from the Open Science Movement." *PS: Political Science & Politics* 54:297–300.
- Engzell, Per and Nathan Wilmers. 2023. "Firms and the Intergenerational Transmission of Labor Market Advantage." SocArXiv.
- Ermisch, John, Markus Jäntti, Timothy Smeeding, and James A Wilson. 2018. "Advantage in comparative perspective." In *Social Stratification, 4th edition*, edited by David B Grusky and Katherine R Weisshaar, pp. 501–505. New York: Routledge.
- Fertig, Angela R. 2003. "Trends in intergenerational earnings mobility in the United States." *Journal of Income Distribution* 12:108–130.
- Forslund, Anders. 2008. "Den svenska jämviktsarbetslösheten: En översikt. Rapport 2008:17."
- Fox, Liana, Florencia Torche, and Jane Waldfogel. 2016. "Intergenerational mobility." In *Oxford Handbook of the Social Science of Poverty*, edited by David Brady and Linda M Burton. Oxford University Press.
- Freedman, David A. 1991. "Statistical models and shoe leather." *Sociological methodology* pp. 291–313.
- Freese, Jeremy, Tamkinat Rauf, and Jan Gerrit Voelkel. 2022. "Advances in transparency and reproducibility in the social sciences." *Social Science Research* p. 102770.
- Gähler, Michael and Eva-Lisa Palmtag. 2015. "Parental divorce, psychological well-being and educational attainment: Changed experience, unchanged effect among Swedes born 1892–1991." *Social Indicators Research* 123:601–623.
- Gelman, Andrew and Eric Loken. 2014. "The statistical crisis in science: data-dependent analysis – a "garden of forking paths" – explains why many statistically significant comparisons don't hold up." *American Scientist* 102:460–466.
- Granström, Olivia and Per Engzell. 2023. "The Geography of Intergenerational Mobility in Europe." SocArXiv.

- Gregg, Paul, Jan O Jonsson, Lindsey Macmillan, and Carina Mood. 2017a. "The role of education for intergenerational income mobility: A comparison of the United States, Great Britain, and Sweden." *Social Forces* 96:121–152.
- Gregg, Paul and Lindsey Macmillan. 2020. "Intergenerational joblessness across Europe: the role of labour markets, education, and welfare generosity." UCL Centre for Education Policy and Equalising Opportunities.
- Gregg, Paul, Lindsey Macmillan, and Claudia Vittori. 2017b. "Moving towards estimating sons' lifetime intergenerational economic mobility in the UK." *Oxford Bulletin of Economics and Statistics* 79:79–100.
- Griffen, Zachary. 2022. "The Economization of Early Life: Human Capital Theory, Biology, and Social Policy." *Science, Technology, & Human Values*. forthcoming.
- Grusky, David B and Szonja Szelenyi. 2018. "The stories we tell about inequality." In *Social Stratification, 4th edition*, edited by David B Grusky and Katherine R Weisshaar, pp. 17–25. New York: Routledge.
- Haack, Susan. 2000. *Manifesto of a passionate moderate: Unfashionable essays*. University of Chicago Press.
- Haider, Steven and Gary Solon. 2006. "Life-cycle variation in the association between current and lifetime earnings." *American Economic Review* 96:1308–1320.
- Hansen, Marianne N. 2010. "Change in intergenerational economic mobility in Norway: conventional versus joint classifications of economic origin." *Journal of Economic Inequality* 8:133–151.
- Hansen, Marianne N and Maren Toft. 2021. "Wealth Accumulation and Opportunity Hoarding: Class-Origin Wealth Gaps over a Quarter of a Century in a Scandinavian Country." *American Sociological Review* 86:603–638.

- Harding, David J and Martin D Munk. 2020. "The Decline of Intergenerational Income Mobility in Denmark: Returns to Education, Demographic Change, and Labor Market Experience." *Social Forces* 98:1436–1464.
- Härkönen, Juho and Erik Bihagen. 2011. "Occupational attainment and career progression in Sweden." *European Societies* 13:451–479.
- Härkönen, Juho, Anna Manzoni, and Erik Bihagen. 2016. "Gender inequalities in occupational prestige across the working life: An analysis of the careers of West Germans and Swedes born from the 1920s to the 1970s." *Advances in Life Course Research* 29:41–51.
- Hederos, Karin, Markus Jäntti, and Lena Lindahl. 2017. "Gender and inequality of opportunity in Sweden." *Social Choice and Welfare* 49:605–635.
- Henz, Ursula and Jan O Jonsson. 2003. "Who marries whom in Sweden?" In *Who Marries Whom?*, edited by Hans-Peter Blossfeld and Andreas Timm, pp. 235–266. Springer, Dordrecht.
- Herd, Pamela, Jeremy Freese, Kamil Sicinski, Benjamin W Domingue, Kathleen Mullan Harris, Caiping Wei, and Robert M Hauser. 2019. "Genes, gender inequality, and educational attainment." *American Sociological Review* 84:1069–1098.
- Hertz, Tom. 2007. "Trends in the intergenerational elasticity of family income in the United States." *Industrial Relations* 46:22–50.
- Hirschman, Daniel. 2021. "Rediscovering the 1%: Knowledge Infrastructures and the Stylized Facts of Inequality." *American Journal of Sociology* 127:739–786.
- Holmlund, Helena. 2022. "How much does marital sorting contribute to intergenerational socioeconomic persistence?" *Journal of Human Resources* 57:372–399.
- Hout, Michael. 1988. "More universalism, less structural mobility: The American occupational structure in the 1980s." *American Journal of Sociology* 93:1358–1400.
- Hout, Michael. 2018. "Americans' occupational status reflects the status of both of their parents." *Proceedings of the National Academy of Sciences* 115:9527–9532.

- Hwang, Philip and Anders G Broberg. 2014. "The historical and social context of child care in Sweden." In *Child care in context: Cross-cultural perspectives*, edited by Michael E Lamb, Kathleen J Sternberg, Carl-Philip Hwang, and Anders G Broberg, pp. 45–72. Psychology Press.
- Jenkins, Stephen. 1987. "Snapshots versus movies: 'lifecycle biases' and the estimation of intergenerational earnings inheritance." *European Economic Review* 31:1149–1158.
- Jenkins, Stephen P and Thomas Siedler. 2007. "The intergenerational transmission of poverty in industrialized countries." Chronic Poverty Research Centre Working Paper No. 75.
- Jonsson, Jan O and Robert Erikson. 2007. "Sweden: Why educational expansion is not such a great strategy for equality: Theory and evidence." In *Stratification in Higher Education: A Comparative Study*, edited by Y Shavit, R Arum, and A Gamoran. Stanford University Press.
- Jonsson, Jan O, Carina Mood, and Erik Bihagen. 2011. "Poverty in Sweden 1991–2007." Swedish Institute For Social Research (SOFI) Working Paper 10/2011.
- Jonsson, Jan O, Carina Mood, and Erik Bihagen. 2016. "Poverty trends during two recessions and two recoveries: lessons from Sweden 1991–2013." *IZA Journal of European Labor Studies* 5:1–20.
- Landersø, Rasmus and James J Heckman. 2017. "The Scandinavian fantasy: The sources of intergenerational mobility in Denmark and the US." *Scandinavian Journal of Economics* 119:178–230.
- Lee, Chul-In and Gary Solon. 2009. "Trends in intergenerational income mobility." *Review of Economics and Statistics* 91:766–772.
- Lieberson, Stanley and Joel Horwich. 2008. "Implication analysis: a pragmatic proposal for linking theory and data in the social sciences." *Sociological Methodology* 38:1–50.
- Lipton, Peter. 2003. *Inference to the best explanation*. New York: Routledge.

- Lundberg, Ian, Rebecca Johnson, and Brandon M Stewart. 2021. "What is your estimand? Defining the target quantity connects statistical evidence to theory." *American Sociological Review* 86:532–565.
- Mastekaasa, Arne and Gunn Elisabeth Birkelund. 2011. "The equalizing effect of wives' earnings on inequalities in earnings among households: Norway 1974–2004." *European Societies* 13:219–237.
- Mayer, Susan E. 1997. *What money can't buy: Family income and children's life chances*. Harvard University Press.
- Mayer, Susan E and Leonard M Lopoo. 2005. "Has the intergenerational transmission of economic status changed?" *Journal of Human Resources* 40:169–185.
- Mazumder, Bhashkar. 2016. "Estimating the intergenerational elasticity and rank association in the United States: Overcoming the current limitations of tax data." *Research in Labor Economics* 43:83–129.
- Merton, Robert K. 1987. "Three fragments from a sociologist's notebooks: Establishing the phenomenon, specified ignorance, and strategic research materials." *Annual Review of Sociology* 13:1–29.
- Mitnik, Pablo A, Victoria Bryant, and Michael Weber. 2019. "The Intergenerational Transmission of Family-Income Advantages in the United States." *Sociological Science* 6:380–415.
- Mitnik, Pablo A and David B Grusky. 2020. "The intergenerational elasticity of what?: The case for redefining the workhorse measure of economic mobility." *Sociological Methodology* 50:47–95.
- Mood, Carina. 2017. "More than money: Social class, income, and the intergenerational persistence of advantage." *Sociological Science* 4:263–287.
- Morris, Martina and Bruce Western. 1999. "Inequality in Earnings at the Close of the Twentieth Century." *Annual Review of Sociology* 25:623–657.

- Muller, Seán M. 2010. "Another problem in the estimation of intergenerational income mobility." *Economics Letters* 108:291–295.
- Muñoz, John and Cristobal Young. 2018. "We ran 9 billion regressions: Eliminating false positives through computational model robustness." *Sociological Methodology* 48:1–33.
- Neckerman, Kathryn M and Florencia Torche. 2007. "Inequality: Causes and consequences." *Annual Review of Sociology* 33:335–357.
- Nieuwenhuis, Rense, Henk Van der Kolk, and Ariana Need. 2017. "Women's earnings and household inequality in OECD countries, 1973–2013." *Acta Sociologica* 60:3–20.
- Nybohm, Martin and Jan Stuhler. 2017. "Biases in standard measures of intergenerational income dependence." *Journal of Human Resources* 52:800–825.
- Parolin, Zachary, Rafael Pinto Schmitt, Gosta Esping-Andersen, and Peter Fallesen. 2023. "The intergenerational persistence of poverty in high-income countries." Mimeo.
- Pearson, Karl. 1907. "On further methods of determining correlation." *Journal of the Royal Statistical Society* 70:655–656.
- Peirce, Charles Sanders. 1974. *Collected papers of Charles Sanders Peirce*. Harvard University Press.
- Pekkala, Sari and Robert EB Lucas. 2007. "Differences across cohorts in Finnish intergenerational income mobility." *Industrial Relations* 46:81–111.
- Pekkarinen, Tuomas, Kjell G Salvanes, and Matti Sarvimäki. 2017. "The evolution of social mobility: Norway during the twentieth century." *Scandinavian Journal of Economics* 119:5–33.
- Rosche, F Benjamin. 2022. "Treatment effects on within-group and between-group inequality. A causal decomposition approach." SocArXiv.
- SCB. 2021. "Unemployment from 1970." Data series, Statistics Sweden.

- Sewell, William H, Archibald O Haller, and Alejandro Portes. 1969. "The educational and early occupational attainment process." *American Sociological Review* pp. 82–92.
- Sewell, William H and Robert M Hauser. 1975. *Education, Occupation, and Earnings: Achievement in the Early Career*. Academic Press.
- Simonsohn, Uri, Joseph P Simmons, and Leif D Nelson. 2020. "Specification curve analysis." *Nature Human Behaviour* 4:1208–1214.
- Sirniö, Outi, Timo M Kauppinen, and Pekka Martikainen. 2017. "Cohort differences in intergenerational income transmission in Finland." *Acta Sociologica* 60:21–39.
- Solon, Gary. 1992. "Intergenerational income mobility in the United States." *American Economic Review* 82:393–408.
- Solon, Gary. 2004. "A model of intergenerational mobility variation over time and place." In *Generational income mobility in North America and Europe*, edited by Miles Corak, pp. 38–47. Cambridge University Press.
- Steege, Sara, Francis Tuerlinckx, Andrew Gelman, and Wolf Vanpaemel. 2016. "Increasing transparency through a multiverse analysis." *Perspectives on Psychological Science* 11:702–712.
- Tavory, Iddo and Stefan Timmermans. 2014. *Abductive analysis: Theorizing qualitative research*. University of Chicago Press.
- Tomaskovic-Devey, Donald and Dustin Avent-Holt. 2019. *Relational Inequalities: an Organizational Approach*. Oxford University Press.
- Torche, Florencia. 2015. "Intergenerational mobility and equality of opportunity." *European Journal of Sociology/Archives Européennes de Sociologie/Europäisches Archiv für Soziologie* 56:343–371.
- Torche, Florencia. 2016. "Education and the intergenerational transmission of advantage in the US." In *Education, Occupation and Social Origin*, edited by Fabrizio Bernardi and Gabriele Ballarino. Edward Elgar Publishing.

- Western, Bruce. 1996. "Vague theory and model uncertainty in macrosociology." *Sociological Methodology* pp. 165–192.
- Wiborg, Øyvind N and Marianne N Hansen. 2018. "The Scandinavian model during increasing inequality: Recent trends in educational attainment, earnings and wealth among Norwegian siblings." *Research in Social Stratification and Mobility* 56:53–63.
- Young, Cristobal. 2018. "Model uncertainty and the crisis in science." *Socius* 4.
- Young, Cristobal and Katherine Holsteen. 2017. "Model uncertainty and robustness: A computational framework for multimodel analysis." *Sociological Methods & Research* 46:3–40.
- Zhou, Xiang. 2019. "Equalization or selection? Reassessing the "meritocratic power" of a college degree in intergenerational income mobility." *American Sociological Review* 84:459–485.

Appendix A Measures of intergenerational mobility

The literature on economic mobility has generated a variety of measures. Recent research has preferred the rank-order correlation, also known as Spearman's ρ and equivalent to Pearson's r if each variable is transformed to percentile ranks:

$$\rho = \text{Corr}(R[y_t], R[y_{t-1}]) = \frac{\text{Cov}(R[y_t], R[y_{t-1}])}{\text{Var}(R[y_{t-1}])}, \quad (1)$$

where y_{t-1} and y_t denote parent and child income and $R \in \{1, 2, \dots, 100\}$ represents the rank transform. The second measure we examine is the linear correlation, or Pearson's r , imposing no transformation on incomes other than top coding of extreme outliers (4 standard deviations above the mean). This measure can be written as:

$$r = \text{Corr}(y_t, y_{t-1}) = \frac{\text{Cov}(y_t, y_{t-1})}{\sqrt{\text{Var}(y_t)}\sqrt{\text{Var}(y_{t-1})}}. \quad (2)$$

In practice, we find that the rank correlation and linear correlation behave similarly. This follows from the fact that the linear correlation provides a good fit in the Swedish data. In fact, with a bivariate normal distribution, there is a precise mathematical relationship between ρ and r (Pearson, 1907):

$$\rho = \frac{6}{\pi} \arcsin\left(\frac{r}{2}\right), \quad r = 2 \sin\left(\frac{\pi}{6}\rho\right). \quad (3)$$

Plotting this function reveals a near-linear dependency (see Appendix Figure A1). This means that for the bivariate normal case, ρ and r are bound to be almost identical.

More commonly, researchers tend to log transform incomes whenever the rank transform is not used. This leads to one of two measures: the log-linear correlation or the intergenerational elasticity. We denote the log-linear correlation φ following Fox et al. (2016), and the intergenerational elasticity β as conventional. The definition of φ follows that of Pearson's r above, except that income is transformed to its natural logarithm:

$$\varphi = \text{Corr}(\ln y_t, \ln y_{t-1}) = \frac{\text{Cov}(\ln y_t, \ln y_{t-1})}{\sqrt{\text{Var}(\ln y_t)}\sqrt{\text{Var}(\ln y_{t-1})}}. \quad (4)$$

Finally, the elasticity β reflects the derivative of expected log child income with respect to log parent income. As a regression coefficient, it is identical to φ with the exception that it does

not normalize by the ratio of standard deviations in each generation, and hence depends on the marginal distributions of parent and child income:

$$\beta = \frac{Cov(\ln y_t, \ln y_{t-1})}{Var(\ln y_{t-1})} = Corr(\ln y_t, \ln y_{t-1}) \frac{\sqrt{Var(\ln y_t)}}{\sqrt{Var(\ln y_{t-1})}}. \quad (5)$$

In particular, if the dispersion of y increases from $t - 1$ to t , the ratio $\sqrt{Var(\ln y_t)} / \sqrt{Var(\ln y_{t-1})}$ will increase and so will the estimated coefficient. In other words, there is a mechanical dependence where if income inequality follows a rising trend over time, all else equal, the elasticity will be larger.

Figure 1. A model of intergenerational mobility.

Figure 2. Levels and trends in intergenerational associations.

Note: The figure shows the distribution of estimated levels and trends in intergenerational income associations for Swedish cohorts of men and women born 1958–1977 and their parents, by parameter of association. All combinations of parent and child sex. Descriptive statistics appear in Appendix Table A2–A5.

Figure 3. Intergenerational rank correlation: variation in levels.

Note: The figure shows levels of the intergenerational rank correlation by specification. Panel (a): heatmap of estimated correlations, with specification choices indicated for parents (bottom margin) and children (right margin). Panel (b): average level by each model component, dashed lines indicate the reference categories stated in bold on the left axis.

Figure 4. Intergenerational rank correlation: variation in trends.

Note: The figure shows trends in the intergenerational rank correlation, defined as the absolute change across 20 cohorts, by specification. Panel (a): heatmap of estimated trends, with specification choices indicated for parents (bottom margin) and children (right margin). Panel (b): average trend by each model component, dashed lines indicate the reference categories stated in bold on the left axis.

Figure 5. Intergenerational rank correlation by sex and income type.

Note: The figure shows trends in the intergenerational rank correlation for selected specifications. Income/earnings measured as 5-year averages over parent ages 48–52 and child ages 38–42. Zero values are excluded. Parent family income is defined as the family income of the father.

Figure 6. Trends in returns to and social selection into education.

Note: The figure shows trends in the explained variance (R-squared) from regressions of earnings ranks on education, and of higher education on father's earnings rank. Earnings measured as 5-year averages over parent ages 48–52 and child ages 38–42.

Figure 7. Correlation between level and trend in intergenerational associations.

Note: The figure shows the average level and trend in intergenerational associations for each parameter, with parent and child sex denoted by marker color. Each dot represents one specification. The trend is defined as the absolute change in a given parameter across 20 cohorts.

Figure 8. Intergenerational elasticity by treatment of zeros and income type, men.

Note: The figure shows trends in the father/son elasticity for selected specifications. Income/earnings measured as 5-year averages over father ages 48–52 and son ages 38–42. Zeros included by adding 1 to the reported income before taking logs. Corresponding estimates for women appear in Appendix Figure A10.

Appendix Figures and Tables (for online publication only)

List of Figures

A1	Relationship between linear and rank correlation under normality.	51
A2	Levels and trends in intergenerational associations, men's individual income/earnings.	52
A3	Levels and trends in intergenerational associations, child ages 30 and above. . .	53
A4	Linear correlation: variation in levels.	54
A5	Log-linear correlation: variation in levels.	55
A6	Elasticity: variation in levels.	56
A7	Linear correlation: variation in trends.	57
A8	Log-linear correlation: variation in trends.	58
A9	Elasticity: variation in trends.	59
A10	Elasticity by treatment of zeros and income type, women.	60
A11	Estimates with same definition of parent/child income type.	61
A12	Actual and predicted earnings with different parameters of association.	62

List of Tables

A1	Summary of results.	63
A2	Rank correlation: summary statistics.	64
A3	Linear correlation: summary statistics.	64
A4	Log-linear correlation: summary statistics.	65
A5	Elasticity: summary statistics.	65
A6	Expanding the observation window.	66
A7	Correlation of estimates by specification across different parameters.	67
A8	Rank correlation: predictors by order of importance.	68
A9	Linear correlation: predictors by order of importance.	69
A10	Log-linear correlation: predictors by order of importance.	70
A11	Elasticity: predictors by order of importance.	71

A12 Predictors by order of importance, age 25 excluded.	72
A13 Percent zero incomes by cohort.	73

Figure A1. Relationship between linear and rank correlation under normality.

Note: The solid line shows the relationship between the Pearson (i.e., linear) correlation and rank correlation for a bivariate joint normal distribution. The dashed line shows the identity function ($y = x$) superimposed for comparison. For further details, see Appendix A: Measures of intergenerational mobility.

Figure A2. Levels and trends in intergenerational associations, men's individual income/earnings.

Note: The figure shows the distribution of estimated levels and trends in intergenerational income associations for Swedish cohorts of men born 1958–1977 and their fathers, by parameter of association. Estimates include earnings and disposable personal income but not disposable family income. There is no evidence of a rising trend when women's incomes are excluded.

Figure A3. Levels and trends in intergenerational associations, child ages 30 and above.

Note: The figure shows the distribution of estimated levels and trends in intergenerational income associations for Swedish cohorts of men and women born 1958–1977 and their parents, by parameter of association. All combinations of parent and child sex. Definitions follow those in the main text, but only child income/earnings at age 30 or above are included. There are nearly no negative associations when income/earnings at age 25 are excluded.

Figure A7. Linear correlation: variation in trends.

Note: The figure shows trends in the intergenerational linear correlation, defined as the absolute change across 20 cohorts, by specification. Panel (a): heatmap of estimated trends, with specification choices indicated for parents (bottom margin) and children (right margin). Panel (b): average trend by each model component, dashed lines indicate the reference categories stated in bold on the left axis.

Figure A8. Log-linear correlation: variation in trends.

Note: The figure shows trends in the intergenerational log-linear correlation, defined as the absolute change across 20 cohorts, by specification. Panel (a): heatmap of estimated trends, with specification choices indicated for parents (bottom margin) and children (right margin). Panel (b): average trend by each model component, dashed lines indicate the reference categories stated in bold on the left axis.

Figure A9. Elasticity: variation in trends.

Note: The figure shows trends in the intergenerational elasticity, defined as the absolute change across 20 cohorts, by specification. Panel (a): heatmap of estimated trends, with specification choices indicated for parents (bottom margin) and children (right margin). Panel (b): average trend by each model component, dashed lines indicate the reference categories stated in bold on the left axis.

(a) Father–Daughter

(c) Mother–Daughter

(b) Mother–Son

Figure A10. Elasticity by treatment of zeros and income type, women.

Note: The figure shows trends in the rank correlation for father/daughter, mother/son, and mother/daughter, selected specifications. Income/earnings measured as 5-year averages over parent ages 48–52 and child ages 38–42. Zeros included by adding 1 to the reported income before taking logs.

Figure A11. Estimates with same definition of parent/child income type.

Note: The figure shows the average level and trend in intergenerational associations for each parameter, only specifications with the same income concept (disposable family income/disposable personal income/labor earnings) for parent and child. Each dot represents one specification. Parent and child sex denoted by marker color. The trend is defined as the absolute change in a given parameter across 20 cohorts.

Figure A12. Actual and predicted earnings with different parameters of association.

Note: The graph shows actual child earnings, and predicted earnings from regressions with linear, log-linear, and rank-rank functional form, within each percentile of father earnings. Cohort born 1965. Top coded earnings at child age 38-42 and father age 48-52. Scales on the vertical axis differ between men and women. Patterns are almost identical for (a) other income measures, and (b) other cohorts.

Table A1. Summary of results.

Dimension	Level	Trend
Parameter	Log-based measures (elasticity, log-linear correlation) fit the data poorly and are highly sensitive to model specification. This holds for levels, and even more so for trends. Rank and linear correlations are more robust and behave similarly.	
	<i>For rank and linear correlations:</i>	
Women vs men	Less persistence	More persistence
Mothers vs fathers	Less persistence	More persistence
Higher age (c)	More persistence	More persistence
Higher age (p)	More persistence	More persistence
More years (c)	No effect	More persistence for daughters
More years (p)	No effect	No effect
Zero incomes excluded (c)	No effect	No effect
Zero incomes excluded (p)	No effect	No effect
Income type (c)	Effect varies with parent and child sex and age, and with parent income type. See Figures 3 and 4.	
Income type (p)	Effect varies with parent and child sex and age, and with child income type. See Figures 3 and 4.	

Table A2. Rank correlation: summary statistics.

Level									
	mean	sd	min	p10	p25	p50	p75	p90	max
Father-Son	0.153	0.089	-0.036	0.001	0.081	0.188	0.222	0.237	0.263
Father-Daughter	0.107	0.066	-0.056	0.012	0.057	0.132	0.159	0.174	0.197
Mother-Son	0.090	0.073	-0.038	-0.001	0.032	0.081	0.140	0.205	0.238
Mother-Daughter	0.088	0.054	-0.026	0.008	0.046	0.098	0.131	0.157	0.196
Total	0.110	0.076	-0.056	0.003	0.041	0.117	0.170	0.212	0.263

Trend									
	mean	sd	min	p10	p25	p50	p75	p90	max
Father-Son	0.012	0.028	-0.050	-0.027	-0.011	0.011	0.031	0.051	0.104
Father-Daughter	0.051	0.038	-0.072	0.002	0.036	0.061	0.076	0.086	0.121
Mother-Son	0.033	0.043	-0.083	-0.025	0.005	0.032	0.071	0.089	0.124
Mother-Daughter	0.048	0.045	-0.048	-0.021	0.013	0.061	0.083	0.099	0.137
Total	0.036	0.042	-0.083	-0.024	0.005	0.038	0.071	0.087	0.137

Table A3. Linear correlation: summary statistics.

Level									
	mean	sd	min	p10	p25	p50	p75	p90	max
Father-Son	0.154	0.099	-0.086	-0.017	0.088	0.192	0.228	0.247	0.280
Father-Daughter	0.116	0.075	-0.065	-0.008	0.067	0.145	0.171	0.190	0.224
Mother-Son	0.096	0.076	-0.041	-0.003	0.037	0.089	0.146	0.213	0.251
Mother-Daughter	0.093	0.059	-0.027	0.003	0.048	0.102	0.138	0.167	0.214
Total	0.114	0.082	-0.086	-0.004	0.044	0.126	0.178	0.220	0.280

Trend									
	mean	sd	min	p10	p25	p50	p75	p90	max
Father-Son	0.008	0.043	-0.094	-0.048	-0.026	0.003	0.037	0.071	0.135
Father-Daughter	0.043	0.039	-0.052	-0.006	0.018	0.040	0.075	0.095	0.136
Mother-Son	0.032	0.038	-0.068	-0.023	0.004	0.037	0.062	0.076	0.120
Mother-Daughter	0.046	0.039	-0.043	-0.013	0.017	0.053	0.079	0.092	0.125
Total	0.032	0.043	-0.094	-0.029	0.002	0.034	0.066	0.087	0.136

Table A4. Log-linear correlation: summary statistics.

Level									
	mean	sd	min	p10	p25	p50	p75	p90	max
Father-Son	0.077	0.047	-0.074	0.020	0.050	0.075	0.104	0.144	0.201
Father-Daughter	0.048	0.036	-0.053	0.004	0.024	0.044	0.069	0.099	0.162
Mother-Son	0.049	0.042	-0.043	0.009	0.022	0.037	0.069	0.111	0.195
Mother-Daughter	0.043	0.031	-0.012	0.011	0.022	0.035	0.057	0.085	0.170
Total	0.054	0.042	-0.074	0.010	0.025	0.046	0.077	0.112	0.201

Trend									
	mean	sd	min	p10	p25	p50	p75	p90	max
Father-Son	0.010	0.025	-0.073	-0.022	-0.006	0.010	0.026	0.041	0.110
Father-Daughter	0.033	0.021	-0.038	0.008	0.022	0.033	0.045	0.057	0.115
Mother-Son	0.022	0.022	-0.055	-0.005	0.009	0.022	0.035	0.050	0.086
Mother-Daughter	0.030	0.026	-0.041	-0.003	0.012	0.030	0.047	0.064	0.108
Total	0.024	0.025	-0.073	-0.009	0.008	0.024	0.040	0.055	0.115

Table A5. Elasticity: summary statistics.

Level									
	mean	sd	min	p10	p25	p50	p75	p90	max
Father-Son	0.104	0.083	-0.189	0.019	0.040	0.089	0.161	0.221	0.404
Father-Daughter	0.059	0.053	-0.107	0.004	0.022	0.048	0.093	0.136	0.247
Mother-Son	0.064	0.076	-0.096	0.007	0.014	0.032	0.087	0.188	0.405
Mother-Daughter	0.050	0.050	-0.023	0.007	0.015	0.030	0.070	0.129	0.267
Total	0.070	0.070	-0.189	0.007	0.019	0.047	0.106	0.174	0.405

Trend									
	mean	sd	min	p10	p25	p50	p75	p90	max
Father-Son	0.040	0.056	-0.115	-0.024	0.003	0.033	0.071	0.114	0.346
Father-Daughter	0.056	0.045	-0.090	0.007	0.024	0.051	0.082	0.114	0.259
Mother-Son	0.063	0.061	-0.122	0.009	0.024	0.049	0.088	0.140	0.420
Mother-Daughter	0.066	0.055	-0.091	0.011	0.027	0.053	0.095	0.138	0.369
Total	0.056	0.055	-0.122	0.000	0.020	0.047	0.084	0.126	0.420

Table A6. Expanding the observation window.

Child age 30-50						
Father age	40-50	40-55	50-60	40-60	30-60	
Rank						
Min	0.233	0.239	0.235	0.244	0.246	
Mean	0.261	0.268	0.264	0.274	0.277	
Max	0.292	0.296	0.291	0.299	0.297	
Linear correlation						
Min	0.265	0.272	0.267	0.279	0.280	
Mean	0.287	0.294	0.287	0.301	0.302	
Max	0.315	0.319	0.310	0.322	0.320	
Log-linear correlation						
Min	0.184	0.198	0.181	0.205	0.209	
Mean	0.230	0.242	0.230	0.250	0.255	
Max	0.291	0.296	0.283	0.300	0.300	
Elasticity						
Min	0.196	0.221	0.154	0.234	0.269	
Mean	0.277	0.299	0.240	0.309	0.353	
Max	0.363	0.372	0.303	0.373	0.414	
Cohorts	58-69	58-69	58-69	58-69	64-69	

Child age 30-60						
Father age	40-50	40-55	50-60	40-60	30-60	
Rank						
Min	0.234	0.234	0.230	0.239	n/a	
Mean	0.261	0.265	0.264	0.272	n/a	
Max	0.289	0.295	0.298	0.301	n/a	
Linear correlation						
Min	0.269	0.270	0.266	0.276	n/a	
Mean	0.291	0.294	0.291	0.302	n/a	
Max	0.320	0.325	0.323	0.332	n/a	
Log-linear correlation						
Min	0.198	0.211	0.194	0.215	n/a	
Mean	0.239	0.249	0.241	0.256	n/a	
Max	0.296	0.300	0.301	0.305	n/a	
Elasticity						
Min	0.202	0.236	0.192	0.252	n/a	
Mean	0.287	0.313	0.266	0.329	n/a	
Max	0.380	0.396	0.333	0.406	n/a	
Cohorts	58-59	58-59	58-59	58-59		

Child age 23-50						
Father age	40-50	40-55	50-60	40-60	30-60	
Rank						
Min	0.222	0.229	0.227	0.234	0.237	
Mean	0.252	0.260	0.257	0.266	0.270	
Max	0.285	0.289	0.280	0.292	0.293	
Linear correlation						
Min	0.251	0.259	0.257	0.266	0.268	
Mean	0.276	0.284	0.279	0.291	0.293	
Max	0.305	0.308	0.300	0.311	0.317	
Log-linear correlation						
Min	0.191	0.206	0.184	0.214	0.225	
Mean	0.231	0.243	0.232	0.251	0.257	
Max	0.285	0.290	0.278	0.294	0.297	
Elasticity						
Min	0.172	0.194	0.137	0.205	0.234	
Mean	0.241	0.261	0.210	0.269	0.309	
Max	0.310	0.319	0.263	0.320	0.367	
Cohorts	58-69	58-69	58-69	58-69	64-69	

Child age 23-60						
Father age	40-50	40-55	50-60	40-60	30-60	
Rank						
Min	0.229	0.230	0.227	0.235	n/a	
Mean	0.257	0.262	0.262	0.270	n/a	
Max	0.287	0.293	0.297	0.299	n/a	
Linear correlation						
Min	0.261	0.263	0.261	0.269	n/a	
Mean	0.286	0.290	0.288	0.298	n/a	
Max	0.310	0.317	0.320	0.325	n/a	
Log-linear correlation						
Min	0.201	0.215	0.197	0.220	n/a	
Mean	0.241	0.251	0.244	0.260	n/a	
Max	0.293	0.298	0.300	0.303	n/a	
Elasticity						
Min	0.184	0.216	0.176	0.230	n/a	
Mean	0.261	0.286	0.244	0.301	n/a	
Max	0.343	0.359	0.305	0.370	n/a	
Cohorts	58-59	58-59	58-59	58-59		

Note: Measures of father/son-association with incomes averaged over longer spans. Correlations are estimated within cohorts with at least 10,000 observations per sex, and averaged within each combination of income types, and including/excluding zero incomes.

Table A7. Correlation of estimates by specification across different parameters.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Rank correlation	1.000							
(2) Linear correlation	0.991	1.000						
(3) Log correlation	0.818	0.819	1.000					
(4) Elasticity	0.738	0.730	0.771	1.000				
(5) Trend, Rank correlation	0.148	0.204	0.073	-0.006	1.000			
(6) Trend, Linear correlation	-0.224	-0.165	-0.206	-0.260	0.860	1.000		
(7) Trend, Log correlation	-0.081	-0.039	-0.071	-0.105	0.691	0.682	1.000	
(8) Trend, Elasticity	0.106	0.129	-0.005	0.259	0.342	0.342	0.644	1.000

Table A8. Rank correlation: predictors by order of importance.

(a)		(b)	
Level: Main effects		Trend: Main effects	
Predictor	ΔR^2	Predictor	ΔR^2
Child age	0.634	Child age	0.247
Parent sex	0.072	Child sex	0.103
Parent income type	0.052	Child income type	0.099
Child sex	0.025	Parent age	0.029
Child income type	0.015	Parent sex	0.013
Parent age	0.014	Parent income type	0.006
Child number of years	0.002	Child number of years	0.005
Parent number of years	0.001	Parent number of years	0.000
Child zeros included	0.000	Parent zeros included	0.000
Parent zeros included	0.000	Child zeros included	0.000
Total	0.818	Total	0.506

Level: Two-way interactions		Trend: Two-way interactions	
Predictor	ΔR^2	Predictor	ΔR^2
Parent sex * Parent income type	0.035	Parent sex * Child age	0.092
Parent sex * Child age	0.032	Child sex * Child age	0.044
Parent sex * Child sex	0.020	Child income type * Child age	0.038
Child sex * Child age	0.012	Parent age * Child age	0.029
Child income type * Child age	0.008	Parent sex * Parent income type	0.024
Parent income type * Child age	0.005	Parent income type * Parent age	0.020
Child sex * Parent income type	0.004	Parent sex * Child sex	0.020
Parent sex * Parent age	0.003	Parent sex * Child income type	0.018
Parent income type * Child income type	0.002	Parent sex * Parent age	0.010
Parent age * Child age	0.001	Child sex * Parent income type	0.008
Child sex * Child income type	0.001	Parent income type * Child age	0.006
Parent income type * Parent age	0.001	Child sex * Child income type	0.001
Child sex * Parent age	0.000	Child age * Child number of years	0.001
Parent sex * Child income type	0.000	Child income type * Parent age	0.001
Child age * Parent number of years	0.000	Parent income type * Child income type	0.001
Child age * Child number of years	0.000	Child sex * Child number of years	0.000
Child income type * Child number of years	0.000	Parent sex * Parent zeros included	0.000
Parent income type * Child number of years	0.000	Child age * Parent zeros included	0.000
Parent sex * Child number of years	0.000	Child income type * Parent zeros included	0.000
Parent income type * Parent number of years	0.000	Child income type * Child number of years	0.000
Parent sex * Parent number of years	0.000	Child age * Child zeros included	0.000
Child age * Parent zeros included	0.000	Child sex * Parent zeros included	0.000
Parent sex * Parent zeros included	0.000	Parent income type * Parent zeros included	0.000
Child income type * Child zeros included	0.000	Child sex * Parent age	0.000
Child income type * Parent age	0.000	Child sex * Parent number of years	0.000
Child age * Child zeros included	0.000	Child age * Parent number of years	0.000
Child sex * Parent number of years	0.000	Child sex * Child zeros included	0.000
Parent income type * Parent zeros included	0.000	Parent age * Child number of years	0.000
Child sex * Parent zeros included	0.000	Parent age * Parent number of years	0.000
Child income type * Parent zeros included	0.000	Child income type * Parent number of years	0.000
Parent age * Parent number of years	0.000	Parent sex * Child zeros included	0.000
Parent age * Child number of years	0.000	Parent income type * Child zeros included	0.000
Parent age * Parent zeros included	0.000	Parent income type * Parent number of years	0.000
Parent number of years * Parent zeros included	0.000	Child number of years * Child zeros included	0.000
Parent sex * Child zeros included	0.000	Parent number of years * Parent zeros included	0.000
Parent income type * Child zeros included	0.000	Parent sex * Parent number of years	0.000
Child income type * Parent number of years	0.000	Parent income type * Child number of years	0.000
Parent number of years * Child number of years	0.000	Parent sex * Child number of years	0.000
Child sex * Child number of years	0.000	Parent age * Parent zeros included	0.000
Parent zeros included * Child zeros included	0.000	Child income type * Child zeros included	0.000
Child number of years * Child zeros included	0.000	Parent number of years * Child number of years	0.000
Parent age * Child zeros included	0.000	Parent age * Child zeros included	0.000
Child sex * Child zeros included	0.000	Parent zeros included * Child zeros included	0.000
Child number of years * Parent zeros included	0.000	Parent number of years * Child zeros included	0.000
Parent number of years * Child zeros included	0.000	Child number of years * Parent zeros included	0.000
Total	0.132	Total	0.324

Note: The table shows results from a set of linear regressions predicting variation in levels and trends for the intergenerational rank correlation. Values are the incremental increase in variance explained (ΔR^2) by including main effects and two-way interactions for each model component.

Table A9. Linear correlation: predictors by order of importance.

(a) Level		(b) Trend	
Main effects			
Predictor	ΔR^2	Predictor	ΔR^2
Child age	0.675	Child income type	0.164
Parent sex	0.061	Child sex	0.085
Parent income type	0.049	Child age	0.049
Child sex	0.015	Parent sex	0.026
Child income type	0.010	Parent age	0.019
Parent age	0.009	Parent number of years	0.006
Child number of years	0.005	Parent income type	0.005
Parent number of years	0.002	Child number of years	0.005
Child zeros included	0.000	Parent zeros included	0.000
Parent zeros included	0.000	Child zeros included	0.000
Total	0.829	Total	0.363
Two-way interactions			
Predictor	ΔR^2	Predictor	ΔR^2
Parent sex * Child age	0.039	Parent sex * Child age	0.159
Parent sex * Parent income type	0.029	Child sex * Child age	0.057
Child income type * Child age	0.013	Parent age * Child age	0.039
Child sex * Child age	0.011	Child income type * Child age	0.036
Parent sex * Child sex	0.011	Parent sex * Parent income type	0.020
Parent income type * Child age	0.007	Parent sex * Child income type	0.020
Child sex * Child income type	0.003	Parent income type * Parent age	0.016
Parent sex * Parent age	0.003	Parent sex * Parent age	0.015
Child sex * Parent income type	0.003	Parent sex * Child sex	0.014
Parent income type * Child income type	0.001	Parent income type * Child income type	0.010
Parent income type * Parent age	0.001	Parent income type * Child age	0.009
Child age * Parent number of years	0.000	Child sex * Child income type	0.008
Parent age * Child age	0.000	Child sex * Parent income type	0.007
Child income type * Child number of years	0.000	Child income type * Child number of years	0.002
Child age * Child number of years	0.000	Child income type * Parent age	0.001
Child sex * Parent age	0.000	Child age * Parent zeros included	0.001
Parent income type * Parent number of years	0.000	Parent income type * Parent number of years	0.000
Child age * Parent zeros included	0.000	Child sex * Child number of years	0.000
Parent income type * Child number of years	0.000	Child age * Parent number of years	0.000
Parent sex * Child number of years	0.000	Child sex * Parent age	0.000
Child income type * Parent age	0.000	Child age * Child number of years	0.000
Child income type * Child zeros included	0.000	Parent age * Parent number of years	0.000
Child age * Child zeros included	0.000	Child income type * Parent zeros included	0.000
Parent sex * Parent number of years	0.000	Parent sex * Parent zeros included	0.000
Parent sex * Child income type	0.000	Child age * Child zeros included	0.000
Parent age * Child number of years	0.000	Child sex * Parent zeros included	0.000
Parent age * Parent number of years	0.000	Parent income type * Parent zeros included	0.000
Parent sex * Parent zeros included	0.000	Child income type * Parent number of years	0.000
Child sex * Parent number of years	0.000	Child income type * Child zeros included	0.000
Parent sex * Child zeros included	0.000	Parent age * Child number of years	0.000
Child income type * Parent zeros included	0.000	Parent age * Child zeros included	0.000
Child sex * Parent zeros included	0.000	Child sex * Parent number of years	0.000
Child sex * Child number of years	0.000	Parent age * Parent zeros included	0.000
Parent income type * Parent zeros included	0.000	Parent sex * Parent number of years	0.000
Parent number of years * Child number of years	0.000	Parent number of years * Child number of years	0.000
Child income type * Parent number of years	0.000	Parent sex * Child zeros included	0.000
Parent age * Parent zeros included	0.000	Child sex * Child zeros included	0.000
Parent zeros included * Child zeros included	0.000	Parent income type * Child zeros included	0.000
Child sex * Child zeros included	0.000	Parent sex * Child number of years	0.000
Parent income type * Child zeros included	0.000	Parent income type * Child number of years	0.000
Child number of years * Child zeros included	0.000	Child number of years * Child zeros included	0.000
Parent number of years * Parent zeros included	0.000	Parent number of years * Parent zeros included	0.000
Child number of years * Parent zeros included	0.000	Parent zeros included * Child zeros included	0.000
Parent number of years * Child zeros included	0.000	Parent number of years * Child zeros included	0.000
Parent age * Child zeros included	0.000	Child number of years * Parent zeros included	0.000
Total	0.129	Total	0.429

Note: The table shows results from a set of linear regressions predicting variation in levels and trends for the intergenerational linear correlation. Values are the incremental increase in variance explained (ΔR^2) by including main effects and two-way interactions for each model component.

Table A10. Log-linear correlation: predictors by order of importance.

(a) Level		(b) Trend	
Main effects			
Predictor	ΔR^2	Predictor	ΔR^2
Child age	0.324	Child sex	0.090
Parent income type	0.105	Child income type	0.061
Child zeros included	0.076	Child age	0.031
Child sex	0.047	Parent age	0.017
Parent sex	0.039	Parent income type	0.012
Child number of years	0.017	Parent number of years	0.011
Parent age	0.014	Parent sex	0.008
Parent zeros included	0.009	Child number of years	0.003
Parent number of years	0.007	Child zeros included	0.003
Child income type	0.003	Parent zeros included	0.001
Total	0.646	Total	0.243
Two-way interactions			
Predictor	ΔR^2	Predictor	ΔR^2
Child age * Child zeros included	0.052	Parent sex * Child age	0.101
Parent sex * Parent income type	0.043	Child age * Child zeros included	0.062
Child age * Parent zeros included	0.038	Child sex * Child age	0.046
Parent sex * Child age	0.027	Child income type * Child age	0.045
Child income type * Child age	0.020	Parent sex * Child sex	0.021
Parent sex * Child sex	0.019	Parent income type * Parent zeros included	0.016
Parent income type * Child age	0.015	Parent sex * Parent age	0.012
Parent zeros included * Child zeros included	0.011	Child sex * Child zeros included	0.011
Child sex * Parent income type	0.005	Parent sex * Parent income type	0.010
Parent sex * Parent zeros included	0.004	Parent age * Parent zeros included	0.010
Child sex * Child income type	0.004	Child sex * Parent income type	0.009
Child sex * Child age	0.003	Child income type * Parent zeros included	0.009
Child age * Parent number of years	0.003	Parent age * Child age	0.008
Parent income type * Child zeros included	0.002	Parent income type * Parent age	0.008
Parent income type * Child income type	0.002	Child sex * Parent zeros included	0.006
Parent sex * Child zeros included	0.002	Parent sex * Child income type	0.006
Child income type * Child zeros included	0.001	Child age * Child number of years	0.005
Parent sex * Parent age	0.001	Child age * Parent zeros included	0.004
Parent income type * Parent zeros included	0.001	Parent income type * Child income type	0.004
Parent age * Child age	0.001	Child sex * Child number of years	0.003
Child sex * Parent age	0.000	Child income type * Child zeros included	0.003
Parent income type * Child number of years	0.000	Parent sex * Child zeros included	0.002
Parent sex * Parent number of years	0.000	Parent income type * Child age	0.002
Child sex * Child number of years	0.000	Child sex * Parent age	0.001
Parent income type * Parent number of years	0.000	Parent age * Parent number of years	0.001
Parent income type * Parent age	0.000	Child income type * Parent age	0.001
Child sex * Child zeros included	0.000	Parent sex * Parent zeros included	0.001
Child income type * Parent zeros included	0.000	Parent zeros included * Child zeros included	0.001
Parent number of years * Child zeros included	0.000	Parent number of years * Parent zeros included	0.000
Child income type * Child number of years	0.000	Parent sex * Child number of years	0.000
Parent sex * Child number of years	0.000	Parent income type * Child zeros included	0.000
Parent age * Child zeros included	0.000	Parent age * Child zeros included	0.000
Child age * Child number of years	0.000	Child sex * Child income type	0.000
Child sex * Parent zeros included	0.000	Parent age * Child number of years	0.000
Parent sex * Child income type	0.000	Child number of years * Parent zeros included	0.000
Parent number of years * Parent zeros included	0.000	Child income type * Child number of years	0.000
Child number of years * Parent zeros included	0.000	Child income type * Parent number of years	0.000
Parent number of years * Child number of years	0.000	Parent income type * Parent number of years	0.000
Child sex * Parent number of years	0.000	Child number of years * Child zeros included	0.000
Child income type * Parent number of years	0.000	Parent sex * Parent number of years	0.000
Parent age * Parent zeros included	0.000	Parent income type * Child number of years	0.000
Parent age * Child number of years	0.000	Parent number of years * Child number of years	0.000
Child income type * Parent age	0.000	Child age * Parent number of years	0.000
Child number of years * Child zeros included	0.000	Parent number of years * Child zeros included	0.000
Parent age * Parent number of years	0.000	Child sex * Parent number of years	0.000
Total	0.275	Total	0.427

Note: The table shows results from a set of linear regressions predicting variation in levels and trends for the intergenerational log-linear correlation. Values are the incremental increase in variance explained (ΔR^2) by including main effects and two-way interactions for each model component.

Table A11. Elasticity: predictors by order of importance.

(a) Level		(b) Trend	
Main effects			
Predictor	ΔR^2	Predictor	ΔR^2
Child age	0.244	Child zeros included	0.154
Parent income type	0.167	Parent income type	0.096
Parent zeros included	0.092	Parent age	0.073
Child sex	0.044	Child age	0.045
Parent sex	0.029	Parent number of years	0.032
Parent number of years	0.021	Parent sex	0.022
Child zeros included	0.015	Child income type	0.019
Child income type	0.006	Child sex	0.007
Parent age	0.002	Parent zeros included	0.001
Child number of years	0.000	Child number of years	0.000
Total	0.625	Total	0.452
Two-way interactions			
Predictor	ΔR^2	Predictor	ΔR^2
Child age * Parent zeros included	0.067	Parent income type * Parent age	0.050
Parent sex * Parent income type	0.056	Parent sex * Child age	0.043
Parent income type * Child age	0.025	Parent income type * Parent zeros included	0.023
Parent sex * Child age	0.021	Parent sex * Parent age	0.019
Child income type * Child age	0.020	Child income type * Child age	0.016
Parent sex * Parent zeros included	0.013	Parent income type * Child zeros included	0.016
Parent sex * Child sex	0.011	Child income type * Child zeros included	0.012
Child sex * Child age	0.010	Parent age * Parent zeros included	0.011
Child sex * Parent income type	0.007	Parent sex * Parent income type	0.011
Child age * Parent number of years	0.005	Child sex * Parent zeros included	0.010
Child sex * Parent zeros included	0.005	Child income type * Parent zeros included	0.009
Parent income type * Child zeros included	0.005	Child sex * Child age	0.009
Parent income type * Child income type	0.003	Parent age * Parent number of years	0.008
Child income type * Child zeros included	0.003	Parent income type * Child age	0.006
Parent income type * Parent number of years	0.003	Parent age * Child zeros included	0.004
Parent income type * Parent zeros included	0.003	Child sex * Child zeros included	0.004
Parent sex * Parent age	0.002	Parent number of years * Child zeros included	0.003
Child age * Child number of years	0.001	Child age * Child zeros included	0.003
Child sex * Child zeros included	0.001	Parent sex * Child sex	0.003
Parent sex * Parent number of years	0.001	Parent sex * Child income type	0.003
Child sex * Child income type	0.001	Child sex * Parent age	0.003
Child sex * Parent number of years	0.000	Parent income type * Child income type	0.003
Child number of years * Child zeros included	0.000	Child age * Child number of years	0.003
Parent sex * Child income type	0.000	Child number of years * Child zeros included	0.002
Parent zeros included * Child zeros included	0.000	Parent age * Child age	0.002
Parent number of years * Child zeros included	0.000	Parent income type * Parent number of years	0.001
Parent age * Parent zeros included	0.000	Child age * Parent number of years	0.001
Parent number of years * Parent zeros included	0.000	Parent number of years * Parent zeros included	0.001
Child sex * Parent age	0.000	Parent zeros included * Child zeros included	0.001
Child sex * Child number of years	0.000	Child age * Parent zeros included	0.001
Parent income type * Parent age	0.000	Parent sex * Child zeros included	0.001
Parent age * Child age	0.000	Child sex * Child number of years	0.000
Child income type * Parent zeros included	0.000	Child income type * Parent age	0.000
Parent age * Parent number of years	0.000	Child income type * Parent number of years	0.000
Child number of years * Parent zeros included	0.000	Parent sex * Child number of years	0.000
Parent age * Child zeros included	0.000	Child income type * Child number of years	0.000
Child income type * Parent number of years	0.000	Child sex * Parent income type	0.000
Parent sex * Child zeros included	0.000	Parent income type * Child number of years	0.000
Child age * Child zeros included	0.000	Parent sex * Parent number of years	0.000
Parent income type * Child number of years	0.000	Parent sex * Parent zeros included	0.000
Parent age * Child number of years	0.000	Parent age * Child number of years	0.000
Child income type * Parent age	0.000	Child sex * Child income type	0.000
Parent number of years * Child number of years	0.000	Child number of years * Parent zeros included	0.000
Child income type * Child number of years	0.000	Child sex * Parent number of years	0.000
Parent sex * Child number of years	0.000	Parent number of years * Child number of years	0.000
Total	0.277	Total	0.299

Note: The table shows results from a set of linear regressions predicting variation in levels and trends for the intergenerational elasticity. Values are the incremental increase in variance explained (ΔR^2) by including main effects and two-way interactions for each model component.

Table A12. Predictors by order of importance, age 25 excluded.

(a) Level		(b) Trend		(c) Level		(d) Trend	
Rank correlation, Main effects		Log-linear correlation, Main effects		Log-linear correlation, Two-way interactions		Elasticity, Main effects	
Predictor	ΔR^2	Predictor	ΔR^2	Predictor	ΔR^2	Predictor	ΔR^2
Parent sex	0.255	Child sex	0.249	Child zeros included	0.186	Child zeros included	0.134
Child age	0.151	Parent age	0.091	Parent income type	0.175	Parent income type	0.126
Parent income type	0.135	Parent sex	0.081	Parent sex	0.096	Parent age * Parent zeros included	0.078
Child sex	0.091	Child income type	0.057	Child age	0.082	Parent sex	0.055
Parent age	0.039	Parent income type	0.014	Child sex	0.071	Parent number of years	0.040
:	:	:	:	:	:	:	:
Total	0.713	Total	0.511	Total	0.715	Total	0.474
Rank correlation, Two-way interactions		Log-linear correlation, Two-way interactions		Elasticity, Two-way interactions		Linear correlation, Main effects	
Predictor	ΔR^2	Predictor	ΔR^2	Predictor	ΔR^2	Predictor	ΔR^2
Parent sex * Parent income type	0.107	Parent sex * Child age	0.066	Parent sex * Parent income type	0.080	Child zeros included	0.134
Parent sex * Child sex	0.055	Parent sex * Parent income type	0.064	Parent sex * Child sex	0.031	Parent income type	0.126
Parent sex * Parent age	0.013	Parent sex * Child sex	0.060	Parent zeros included * Child zeros included	0.018	Parent age	0.078
Child sex * Parent income type	0.011	Parent income type * Parent age	0.054	Parent sex * Parent zeros included	0.013	Parent age * Parent zeros included	0.038
Parent sex * Child age	0.007	Parent sex * Child income type	0.016	Child age * Parent zeros included	0.010	Parent income type * Parent zeros included	0.030
:	:	:	:	:	:	Parent sex * Parent income type	0.023
Total	0.219	Total	0.334	Total	0.228	Total	0.368
Linear correlation, Main effects		Log-linear correlation, Two-way interactions		Elasticity, Two-way interactions		Linear correlation, Two-way interactions	
Predictor	ΔR^2	Predictor	ΔR^2	Predictor	ΔR^2	Predictor	ΔR^2
Parent sex	0.274	Child sex	0.181	Parent income type	0.244	Parent income type * Parent age	0.061
Child age	0.162	Parent sex	0.123	Parent zeros included	0.193	Parent income type * Parent zeros included	0.037
Parent income type	0.151	Child income type	0.100	Child sex	0.069	Parent sex * Child age	0.027
Child sex	0.072	Parent age	0.056	Parent sex	0.063	Parent sex * Parent age	0.027
Parent age	0.026	Child age	0.034	Child age	0.052	Parent age * Parent zeros included	0.024
:	:	:	:	:	:	:	:
Total	0.734	Total	0.521	Total	0.703	Total	0.314
Linear correlation, Two-way interactions		Log-linear correlation, Two-way interactions		Elasticity, Two-way interactions		Linear correlation, Two-way interactions	
Predictor	ΔR^2	Predictor	ΔR^2	Predictor	ΔR^2	Predictor	ΔR^2
Parent sex * Parent income type	0.117	Parent sex * Child age	0.074	Parent sex * Parent income type	0.087	Parent income type * Parent age	0.061
Parent sex * Child sex	0.037	Parent sex * Parent income type	0.057	Parent sex * Parent zeros included	0.029	Parent income type * Parent zeros included	0.037
Parent sex * Parent age	0.016	Parent income type * Parent age	0.036	Parent sex * Child sex	0.017	Parent sex * Child age	0.027
Child sex * Parent income type	0.009	Parent sex * Child sex	0.035	Child age * Parent zeros included	0.016	Parent sex * Parent age	0.027
Parent sex * Child age	0.009	Child sex * Child income type	0.021	Child sex * Parent income type	0.012	Parent age * Parent zeros included	0.024
:	:	:	:	:	:	:	:
Total	0.215	Total	0.336	Total	0.236	Total	0.314

Note: The table shows the 5 most important main effects and two-way interactions from a set of linear regressions predicting variation in levels and trends for various parameters of association, and excluding child income/earnings at age 25. Values are the incremental increase in variance explained (ΔR^2) for each model component.

Table A13. Percent zero incomes by cohort.

Child cohort	Disposable family inc		Disposable income		Labor earnings	
	Son	Daughter	Son	Daughter	Son	Daughter
1958	0.56%	0.25%	0.88%	0.33%	1.95%	1.63%
1959	0.68%	0.30%	0.99%	0.38%	2.03%	1.79%
1960	0.59%	0.24%	0.88%	0.34%	2.03%	1.66%
1961	0.69%	0.28%	0.96%	0.34%	2.04%	1.55%
1962	0.73%	0.28%	1.12%	0.36%	2.22%	1.68%
1963	0.69%	0.27%	0.99%	0.32%	2.06%	1.63%
1964	0.73%	0.30%	0.83%	0.41%	2.25%	1.54%
1965	0.79%	0.40%	1.03%	0.65%	2.18%	1.61%
1966	0.80%	0.36%	1.06%	0.60%	2.15%	1.56%
1967	0.83%	0.33%	1.05%	0.53%	2.24%	1.53%
1968	0.88%	0.38%	1.16%	0.62%	2.25%	1.58%
1969	1.04%	0.40%	1.35%	0.65%	2.54%	1.77%
1970	0.89%	0.41%	1.18%	0.67%	2.55%	1.84%
1971	0.99%	0.42%	1.28%	0.65%	2.39%	1.80%
1972	0.89%	0.44%	1.14%	0.67%	2.40%	1.77%
1973	1.01%	0.44%	1.33%	0.67%	2.52%	1.63%
1974	0.96%	0.41%	1.20%	0.64%	2.55%	1.78%
1975	1.04%	0.52%	1.32%	0.73%	2.71%	1.94%
1976	1.01%	0.46%	1.21%	0.62%	2.53%	1.67%
1977	1.05%	0.49%	1.27%	0.64%	2.69%	1.79%
1978	1.05%	0.53%	1.23%	0.71%	2.69%	1.93%
1979	1.25%	0.66%	1.46%	0.83%	3.00%	2.08%
Child cohort	Father	Mother	Father	Mother	Father	Mother
1958	0.77%	0.60%	1.15%	8.70%	1.45%	10.45%
1959	0.65%	0.49%	1.02%	7.62%	1.37%	9.30%
1960	0.63%	0.42%	0.97%	6.79%	1.28%	8.40%
1961	0.58%	0.37%	0.90%	5.77%	1.21%	7.33%
1962	0.52%	0.34%	0.83%	4.79%	1.14%	6.34%
1963	0.47%	0.23%	0.80%	3.88%	1.11%	5.44%
1964	0.44%	0.25%	0.74%	3.15%	1.14%	4.68%
1965	0.46%	0.21%	0.82%	2.50%	1.15%	4.06%
1966	0.38%	0.18%	0.74%	2.12%	1.10%	3.60%
1967	0.38%	0.15%	0.77%	1.75%	1.16%	3.21%
1968	0.38%	0.13%	0.74%	1.33%	1.18%	2.90%
1969	0.36%	0.13%	0.74%	1.11%	1.20%	2.69%
1970	0.43%	0.15%	0.81%	0.97%	1.29%	2.46%
1971	0.40%	0.14%	0.77%	0.76%	1.36%	2.14%
1972	0.36%	0.11%	0.78%	0.69%	1.35%	1.97%
1973	0.43%	0.12%	0.80%	0.64%	1.44%	1.93%
1974	0.45%	0.15%	0.86%	0.63%	1.49%	1.84%
1975	0.42%	0.17%	0.86%	0.64%	1.58%	1.78%
1976	0.44%	0.15%	0.86%	0.65%	1.64%	1.81%
1977	0.51%	0.17%	0.96%	0.62%	1.68%	1.81%
1978	0.53%	0.18%	0.97%	0.64%	1.78%	1.81%
1979	0.47%	0.19%	0.91%	0.65%	1.74%	1.86%

Note: The table shows the percent zero incomes in a single year by child cohort, observed at age 40 for children and 50 for parents.