Like mother, like child? The rise of women's intergenerational income persistence in Sweden and the United States*

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June 2023

Abstract

We examine intergenerational mobility in Sweden and the US since 1985, focusing on labor incomes of men, women, and households. Increased persistence among women, alongside stable father-son persistence, contributes to an overall mobility decline. Decomposition analysis highlights the role of maternal employment, emphasizing differences in the timing of women's rising labor force participation across countries. Surprisingly, mother-son and mother-daughter persistence show similar rising trends and levels across countries, despite the higher conventionally measured US persistence. Parental assortative mating is crucial, with negative income-based sorting in the US, but not in Sweden, offsetting the mobility-depressing effects of positive human capital sorting.

*This paper is an academic extension of a prior report for the Swedish Ministry of Finance (Brandén and Nybom, 2019). We thank seminar participants at the ZEW (Mannheim), University of Cologne, and the University of Nevada, Las Vegas, as well as participants at the SOLE 2023 meetings, the Opportunity and Mobility Workshop at LSE, and the Carolina Region Empirical Economics Day workshop for helpful suggestions. The paper has benefited from comments by Gary Solon, Jan Stuhler, Lucie Schmidt, and Melinda Morrill. We are also grateful to Anders Björklund, Robert Erikson, Martin Hällsten, Lena Lindahl, Susan Niknami, Mårten Palme, Per-Olof Robling and Johanna Åström for valuable comments on the Swedish report.

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1 Introduction

Questions on intergenerational mobility have garnered significant attention due to the growing inequality in society. Researchers have undertaken numerous studies to examine mobility trends, and a prevailing body of evidence suggests declining (or stable) intergenerational mobility in Western countries (e.g., Davis and Mazumder, 2022; Chetty, Hendren, Kline, Saez and Turner, 2014; Markussen and Røed, 2020; Connolly, Haeck and Lapierre, 2019). Interestingly, this period has also witnessed a remarkable increase in women's labor-force attachment. Yet the role of women's work in shaping mobility trends has received much less attention.[1] Consequently, there is a need to disentangle and investigate the role of women and their labor-force attachment during this crucial period, both for aggregate income mobility trends and for gender-specific rates of income mobility.

Our study makes significant contributions to the literature on intergenerational mobility in three regards. First, we provide a thorough depiction of how intergenerational mobility in labor income evolved since the 1980s in Sweden and the US, considering individual income measures separately for mothers, fathers, sons and daughters, as well as (parental) household income. Studying *all* dimensions of parent-child earnings transmission—including for mothers—fills out the existing but incomplete picture of how mobility has evolved during this period that was both transformative for women's labor market involvement and characterized by a marked rise in income inequality. Second, we offer a new potential explanation for the observed trend of downward pressure on intergenerational mobility in several Western countries. Previous studies have primarily attributed this trend to increasing skill premia and inequality (e.g., Davis and Mazumder, 2022). This explanation holds merit as intergenerational skill transmission becomes more crucial when skill premia rise, and higher skill premia incentivize affluent parents to invest more in their children's skills. Our paper instead emphasizes the growing significance of women's labor force participation as a key driver of recent mobility trends. Third, we document and explain an anomaly to the well-established Sweden-US gap in income mobility rates, as the levels (and trends) in mother-child associations are very similar across countries. Importantly, we show that this arises from country differences in parental assortative matching on income.

Our work sheds light on the intricate relationship between women's participation, assortative mating, and intergenerational mobility, with a primary focus on mothers. Studies typically focus on mechanisms in the child generation, yet there are a couple of reasons why increased participation of

[1] Previous trends studies either omit women or circumvent the issue by using aggregate family income measures, the income of a male relative, or a different measure of socioeconomic status (e.g., education).

mothers might influence mobility. With positive assortative matching among parents, the increasing involvement of women in the labor market and the rising value of women's skills amplify economic disparities between families. In addition, mothers' incomes might be more central than fathers' incomes for child investment (e.g., Phipps and Burton, 1998), and an increase in mothers' relative incomes might therefore influence intergenerational skill transmission. On the other hand, the time-cost of maternal labor supply may be detrimental to children's human capital formation (e.g., Ruhm, 2004; Morrill, 2011), in particular for children in high-income families (e.g., Cornelissen et al., 2018; Nicoletti, Salvanes and Tominey, 2023).[2] Consistent with these potential influences, our findings demonstrate that estimates of intergenerational income persistence for mothers—a topic that has received limited attention in the existing literature—have increased significantly in recent decades. This rise in maternal persistence contributes to a more general decline in mobility measured at the household level.

In the first part of the paper, we document how intergenerational mobility in labor income evolved in recent decades in Sweden and the US. We first estimate trends in intergenerational rank persistence (IRP) using parental *household* income. We then consider individual incomes separately for mothers, fathers, sons, and daughters, to both better understand the aggregate trends and provide a more complete portrayal of gender-specific mobility trends. Importantly, our primary focus on income ranks allows us to include zero incomes, which is crucial to avoid sampling divergences across time and place pertaining to mothers and daughters.

We find that persistence in household income has risen in both Sweden and the US, implying a decline in mobility. However, these trends are not necessarily a reflection of eroding social dynamism. First, rising persistence with respect to women (mothers/daughters) appear to be the driving force, while father-son persistence remained roughly stable. In fact, mother-son and mother-daughter persistence rose in a similar fashion in Sweden and the US through the time period. Second, mother-child persistence is very similar across countries, unlike the well established pattern of higher persistence in the US relative to Sweden among men. These findings are important given the scarcity of evidence on mother-child income mobility, but ultimately we want to understand the key factors driving these trends.

In the second part, we therefore seek to (descriptively) quantify the drivers of both parent-specific persistence and that in household income. We focus primarily on determinants of *parental*

[2] In contrast, Agostinelli and Sorrenti (2021) find that the negative time cost effect is more pronounced for low income households.

income, for a few reasons. First, mothers' persistence is the least studied and yet is a prominent feature of our gender-specific trends. Second, our maternal income measures are observed during the rise and subsequent plateauing of female labor force participation in both Sweden and the US, with the US lagging behind Sweden by about a decade. The staggered timing of these extensive margin changes also lends advantage to using these two countries for contrasting the drivers of income persistence. Third, while several prior studies address marital sorting among children (e.g., Ermisch, Francesconi and Siedler, 2006; Holmlund, 2020; Davis and Mazumder, 2022), the role of parental assortative mating has received less attention.

We use a descriptive model to quantify the relative contributions of maternal (paternal) human capital, employment, and other (residual) income determinants to mother-child (father-child) persistence. For Sweden, maternal human capital and employment are initially important and roughly balanced contributors, with a smaller role for residual income. Over time, residual income grows in importance and the relative roles of maternal characteristics evolve to be more similar to that for Swedish fathers. For the US, on the other hand, maternal human capital is initially the dominant channel, but over time the role of employment grows and the composition becomes similar to the initial one observed for Swedish mothers. These results align with the distinctive timing of the rise in women's labor force participation in Sweden and the US.

Extending our model to incorporate both parents' characteristics along with assortative mating provides a more complete account of both parent-specific and household-level transmission. In both countries, mother-child income persistence operates primarily through the mother's own characteristics, as opposed to correlated spousal characteristics. However, while such assortative mating factors account for roughly 25% of mother-child persistence in Sweden, they contribute only a negligible amount in the US. Though parental sorting on human capital is strongly positive in both countries, matching on income differs markedly and induces this divergent result. In the US, but not in Sweden, parental matching on income is actually negative (and nonlinear), arising from a negative income effect of a father's income on mother's labor supply. This fully offsets the influence of positive human-capital sorting, leading to the negligible net contribution of assortative mating to maternal persistence in the US. Absent this offsetting effect, maternal persistence would have been clearly higher in the US than in Sweden (all else equal).

Finally, we use our model to describe the relative contributions of mothers, fathers, and assortative mating to *household* income persistence. The contribution of mothers is small relative to fathers, but grows over time in both relative and absolute terms, to accounting for about 30% of overall persistence. Assortative mating here contributes positively in both countries, despite the aforementioned offsetting downward pressure from (negative) income-sorting in the US. Human capital sorting accounts for smaller shares, while the role of other mother-father associations are growing. If the labor supply of US mothers would rise—especially for those married to high income fathers (as in Sweden)—further increases in persistence with respect to both maternal income and household income can be expected.

Our results consistently point to a crucial role for maternal labor-supply changes in the rising persistence estimates. However, it remains unclear whether there is a changing intergenerational *effect* of mother's income or merely a growing link between her income and underlying status. In a final exercise, we use instrumental variables approaches to adjust for the measurement errors that arise from the fact that mothers' income can be a poor proxy both for their lifetime income and underlying social status. We find suggestive evidence that at least some of the increase in persistence may be attributable to an increasing causal impact of mothers.

Our paper adds to three different strands of the mobility literature: studies focusing on gender differences, time trends, and country differences in intergenerational income mobility. The limited evidence on persistence with respect to US mothers' labor income is from a couple of early studies of gender differences. Altonji and Dunn (1991) and Altonji and Dunn (2000) document intergenerational links in family income, earnings, wages and labor supply, and find that the latter linkage runs strongly along gender lines.[3] Focusing on gender in the child generation, Chadwick and Solon (2002) document that the association between own (i.e., individual) and father's income is considerably lower for daughters than for sons. Associations are higher, however, and gender differences smaller, when measured in terms of own family income and father's income, which highlights the potentially important role for marital sorting (see also Ermisch, Francesconi and Siedler, 2006). Raaum et al. (2008) document similar results for a set of Nordic countries and the UK. A number of subsequent papers have documented differences between men and women but address gender only in the child generation and/or use family incomes and do not explicitly study mothers (e.g., Holmlund, 2020; Davis and Mazumder, 2022). Of these studies, very few document gender-specific time trends.[4]

[3] Altonji and Dunn (1991) finds intergenerational elasticities (IGEs) in earnings that are stronger along gender lines, while Altonji and Dunn (2000) do not, presumably due to methodological differences, as both papers use the same data (National Longitudinal Surveys). Like most early mobility studies though, they exclude low (zero) incomes and estimate intergenerational elasticities (IGEs).

[4] See also Ahrsjö, Karadakic and Rasmussen (2022) which is ongoing work on the Scandinavian countries parallel to ours. US studies have shown trends separately for daughters—but not for mothers—using family income measures (Lee and Solon, 2009; Davis and Mazumder, 2022) or indirect two-sample instrumental variables approaches to gain

Existing work on mobility time trends concentrates on the US, with somewhat mixed findings. Earlier work failed to reject stable mobility trends for US cohorts born 1952-75 (e.g., Hertz, 2007; Lee and Solon, 2009) or later (Chetty, Hendren, Kline and Saez, 2014), a finding that is surprising given the concurrent increase in income inequality. However, Davis and Mazumder (2022) find that mobility declined sharply for cohorts born 1961-64, in comparison with those born 1948-53, and Justman and Stiassnie (2021) find declining mobility when extending the time frame considered by Hertz (2007) and Lee and Solon (2009) to more recent years. Our analysis introduces women (especially mothers) into the interpretation of income mobility trends. For example, Davis and Mazumder (2022) find no role for daughters' labor force participation in driving the decline in mobility. Our results are consistent with a limited role of the extensive margin labor supply of daughters, but instead point to the rise in *mother's* labor force participation as more crucial.[5]

Finally, we add to the extensive literature on country differences in intergenerational mobility by highlighting some new US-Sweden differences and similarities across various gender configurations. Studying Sweden and the US jointly has a couple of advantages. First, the two countries are polar opposites on the inequality spectrum.[6] By now it is well-established that US mobility is lower based on traditional father-son measures, and our study complements this view with country comparisons of female mobility. The second advantage is thus the differential timing of the evolution of women's labor market attachment in Sweden and US, with the former often seen as a trailblazer along this dimension. Moreover, the fact that we find largely similar trends across two quite different countries lends credence to the idea that the rise in women's intergenerational persistence is a more widespread feature and not specific to a particular country. Third, by leveraging Swedish administrative data jointly with the Panel Study of Income Dynamics (PSID), we can use the former to validate the robustness of some of the methodological choices necessitated when using the PSID. The fact that many of the gender-specific trends align across countries makes the smaller sample size of the PSID less of a concern.

a historical perspective (Olivetti and Paserman, 2015).

[5]Although Davis and Mazumder (2022) use different data (NLSY), the daughter cohorts (and thus mothers) overlap with ours.

[6]Björklund and Jäntti (1997) first showed that intergenerational income mobility in the US is likely lower than in Sweden, which many at the time saw as a surprise given the widespread view of the US as the "land of opportunity."

2 Data and specifications

The guiding principles of our choices of data and econometric specifications are comparability and efficiency. First, we want our samples to be as comparable as possible, both over time and across countries. Fortunately, the PSID and Swedish registers cover the same long time period, both starting in the late 1960s. Second, we choose samples, variable definitions, and econometric specifications not only to maximize comparability but also to make the most efficient use of our data. We thus seek to estimate mobility trends over as long of a time period as possible, while still taking measurement issues into account. But we also specifically prioritize an efficient usage of the relatively small samples in the PSID, while adapting our Swedish data accordingly. For this reason, we follow Lee and Solon (2009) and analyze mobility over calendar years rather than cohorts, since the latter approach throws out much of the earnings information in the PSID. We begin by describing the data and then provide details on the specification.

2.1 Data

We use data from the Panel Study of Income Dynamics (PSID) and Swedish administrative registers for the US and Sweden, respectively.

United States: The PSID began in 1968 with a sample of over 18,000 individuals in about 5,000 US families, which has been reinterviewed annually through 1997 and biennially since then. It is the most popular data source for analyses of intergenerational mobility in the US, due to a number of key features. First, it is intergenerational, following family members as they form new households. Second, it is longitudinal and follows the same individuals over long stretches of the life cycle. Third, the data are rich, including detailed information on, for example, incomes, employment, occupation, education, and family structure. The two main disadvantages of the PSID are the relatively small samples and survey attrition. We describe further below how we address these concerns.

Apart from a few modifications, we follow the sampling and variable definitions used by Lee and Solon (2009). As such, we use only the core sample, also known as the Survey Research Center component, which was the nationally representative portion of the sample at the start of the survey. We use data from all PSID survey waves conducted between 1968 and 2019, with labor-market information pertaining to the previous year. Our analysis covers children born 1952-1993. We exclude children born before 1952 to avoid oversampling those who left the family home at late ages. We consider annual earnings observations of adult children from ages 25-48 in the years 1985-2018, which ensures that those observations are informative about long-run labor income.[7]

We use the PSID parent identification file to link children to parents, which in the vast majority of cases corresponds to the child's parents at birth. Our main analysis uses individual pre-tax labor income of children and parents. Included in this income measure are all sources of labor income, such as that from wages, bonuses, overtime, commissions, farming, business, professional practice, and renters.[8] We exclude income observations imputed by "major assignments."

Sweden: We construct our Swedish data set in a way that maximizes the comparability both over time and with our PSID sample. The data are based on administrative registers held by Statistics Sweden and contain the universe of the Swedish population. Using personal identifiers, we merge individual-level data on annual labor income, education levels, and family relationships, among other things. The income data stem from tax records and consist of employer-reported information on annual gross salary, small business income, taxable fringe benefits, and some taxable labor-related social benefits for the period 1968-2019. The Multigenerational register provides family links between all children born in Sweden, and all residents starting from 1961, and their biological parents.[9] We focus on children born 1952-1994 and their annual incomes from ages 25-48 observed in the years 1985-2019.[10]

Definitions common for both countries: For both countries and generations, we adjust all annual incomes for inflation using the national CPI. Because we are using ranks, we retain all non-missing income observations, including zeros, for both parents and children.[11]

We then create individual-level labor income measures for mothers and fathers, defined as averages over the first five (potentially) observed and non-missing income observations starting from child age 12. We use only income observations from when the parent was age 65 or younger

[7]Given our age range and year-on-year specification (see below), we observe the 1952-1960 cohorts at ages 25-33 in 1985. Over time, later cohorts enter the sample successively and the age range expands. While we could have observed age-25 income already from 1977, as in Lee and Solon (2009), we discard those years here since the yearly estimates prior to 1985 are very noisy.

[8]Starting in the 1994 survey, the total labor income measure in the PSID excluded sources from farm and business income. We add the labor part of business income as well as farm income from separate variables to improve comparability over time. Nonetheless, our results are not sensitive to this conclusions (results available upon request).

[9]While we do not formally exclude immigrants, they will be somewhat underrepresented due to a lack of parental information; for example, from immigrants arriving to the country without parents or arriving with parents in retirement age. However, this feature of the samples should be roughly similar for both men and women and for both Sweden and the US.

[10]We observe labor income for the years 1968, 1970, 1971, 1973, 1975, 1976, 1979, 1980, 1982 and annually for 1985-2019.

[11]For the PSID, we drop incomes that are top-coded, which diverges slightly from Lee and Solon's (2009) choice to drop incomes that are higher than USD150000 (in 1967 USD as measured by the CPI-U).

and exclude parents with fewer than two valid annual income observations. This procedure ensures that the parental income averages are based on a similar number of annual observations across child cohorts, which is crucial since longer averages mechanically diminish attenuation bias due to transitory noise.[12] While our estimates may thus suffer from some attenuation bias, the key assumption is that this bias is constant over time.

We rank the income measures by child gender and year of birth separately for mothers and fathers as well as for sons and daughters. We also use a measure of joint household income, for which we average both parents' long-run labor income, and then take ranks of the average.

2.2 Empirical specification

In our analyses, we focus on intergenerational rank persistence (IRP) as our primary (inverse) measure of mobility. The IRP, or the "rank-rank slope", is the slope coefficient (β) from a linear regression of (adult) child income rank on the income rank of his or her parent(s). Using log incomes instead of ranks yields instead the intergenerational elasticity (IGE), which we also provide results on in the Appendix. The closer β is to zero, the faster the regression to the mean and the higher is mobility.

Estimating intergenerational mobility in income ranks has recently gained in popularity (e.g., Chetty, Hendren, Kline and Saez, 2014). While individuals with zero income are omitted when estimating the IGE, and thus introducing potential sample selection bias, the IRP instead allows for the inclusion of zeros. This feature could be important if the labor-market attachment of sampled individuals varies systematically—such as when comparing men and women or time trends in the mobility of women.[13] Rank-based estimates have also been shown to be less sensitive to the attenuation and lifecycle biases that arise when using short-run income measures as proxies for lifetime income (Mazumder, 2016; Nybom and Stuhler, 2017).[14]

[12] For parents of most child cohorts, this setup implies that we use average annual non-missing income over child age 12-16. However, for parents to children born before 1955 (1956 in Sweden) we use incomes from successively older child ages, since we first observe incomes from 1967 (1968 in Sweden). For example, for US parents of those born 1952, we use average annual non-missing income over child age 15-19, and so on. Moreover, since the PSID becomes biennial from 1997, whereas in Sweden we instead have similar gaps prior to 1985, we extend the age range for parents of the youngest (oldest) cohorts in the US (Sweden) such that their income averages are based on the first five potentially observed income observations starting from child age 12.

[13] To get around the zero income issue, Mitnik and Grusky (2020) suggest that instead of estimating the IGE (i.e., the conditional expected log income of children), one could estimate the log value of children's expected income, conditional on parents' income. However, this measures a different parameter than the IGE, and its usage is not (yet) widespread in the literature.

[14] As Atkinson (1980) and Solon (1992) show, short-run measures are affected by transitory income variation, which results in attenuated estimates of β. Moreover, differences in short-run income tend to change systematically over the

Our main econometric specification is similar to the one used by Lee and Solon (2009). Separately for sons and daughters, as well as for the US and Sweden, we use least squares to estimate the regression:

$$y_{ict} = \alpha_t + \beta_t Y_{ic} + f(A_{ic}) + g(t - c - 40) + h(Y_{ic}(t - c - 40)) + u_{ict}, \tag{1}$$

where y_{ict} is the percentile ranked labor income in year t for child i in birth cohort c. The vector α_t contains calendar year fixed effects. The explanatory variable of interest is Y_{ic}, the percentile ranked long-run labor income of the parent(s) of child i, and its associated slope coefficient β_t is the IRP. In separate regressions, we use either the mother's, the father's, or their joint household income as Y_{ic}. Because our main purpose is to study time trends in intergenerational mobility, β_t varies by year. Standard errors are clustered at the individual (child) level.

The evolving structure of our panels makes it crucial to properly control for age dynamics. Rather than focusing on income at a fixed age, which results in very small samples for the PSID, we instead retain all income data from age 25-48 each year and include detailed age controls similar to Lee and Solon (2009). The regression includes functions that control for a quartic in parental age A_{ic} at the time parental income is observed, a quartic in child age $(t - c - 40)$, and interactions between a quartic in child age and parental income. The child's age, and thus β_t, is normalized to age 40 in each year t.[15]

The specification in equation (1) assumes that income differences between those with high- vs low-income parents follow a similar age profile over cohorts. The inclusion of year dummies allows the average height of the age-income trajectories to vary across years, but otherwise the coefficients of all variables involving child's age are assumed to be common across years. However, in sensitivity analyses we also provide alternative balanced-panel estimates using a narrower and fixed age range emulating a direct cohort analysis.

To concretely address the statistical significance of *changes* in mobility over time in the US, we estimate a modified version of our main specification in equation (1) where we interact parent income with three time period dummies—for early (1985-1995), middle (1996-2007), and late (2008-

lifecycle, and estimates are therefore sensitive to the age of income measurement (Jenkins, 1987; Haider and Solon, 2006). A common solution is to use multi-year averages of parental income to increase the signal-to-noise ratio and to measure mid-career income to minimize lifecycle bias (Nybom and Stuhler, 2016).

[15] While the evidence suggests that lifecycle bias from using current income as a proxy for lifetime income is minimized when incomes are measured at around age 40, we cannot fully exclude lifecycle effects for all years due to the changing age composition over time. The normalization merely affects the level of the estimates, not their variation over time.

2018) periods—rather than year dummies. Appendix table C.1 provides persistence estimates and standard errors for the early and late period, as well as the difference in these estimates.

2.3 Summary statistics

Table 1 provides descriptive statistics for our samples, separately by gender and time period in both generations and countries. For presentational purposes we aggregate the statistics for two subperiods, an early period (1985-1995) and a late period (2008-2019)[16], although we use the entire time period (1985-2019) in our main trends analysis. The early-period US sample includes just over 2200 children (split roughly equally between sons and daughters) with on average about eight annual income observations. The number of sampled individuals almost doubles for the late period, owing to the larger number of cohorts observed in the 25-48 age range in these years. The samples are obviously much larger in the population-wide Swedish data. For both countries, the samples are substantially larger in the later period due to the broader age composition.

While both countries display sizable gender gaps in labor-market outcomes, the magnitudes of those gaps differ markedly. Daughters in Sweden in the early period earned labor incomes that on average amounted to about 70% of the corresponding average for sons; this income ratio increased to 77% in the late period. For the US, the son-daughter income ratio starts much lower, at 49%, and increases to about 59% in the late period. The gender income gaps are even more substantial when comparing mothers and fathers: in Sweden the mother-father income ratio rose from about 41% to 60%, while in the US it rose from about 18% to 32%. Note that zeros are included when computing the income ratios.

The table also displays the well-established pattern of higher average years of schooling among women than men in the child generation, in both countries and time periods. Among the parents, however, fathers are slightly more educated than mothers in the early time period. But a qualitative country difference arises in the late period; while Swedish mothers gain an educational advantage over the fathers, we do not see the corresponding change in the US.

Table 1 also displays interesting country and time differences in employment. In Sweden, daughters are employed at a high and stable rate over time (at around 86%). This observation aligns with the known fact that female labor force participation reached a very high level in Sweden already in the 1980s and has since remained largely constant. Daughters in the US, on the other hand, increased their employment rates from around 66% to 75% between the two periods. Comparing

[16] These subperiods are of equal length for early and late periods with the PSID, which extends only to 2018.

mothers in Sweden and the US, we see increases in employment in both countries, though the rise is larger but from a much lower level in the US. The relatively larger employment rates of Swedish women is thus a partial explanation to the relatively smaller gender gaps in labor income compared to the US. For sons and fathers, employment rates were clearly higher, at around 90% in both countries, with a marginal decline over time.

Taken together, the table highlights several stylized facts that will serve as an important background to the remainder of the paper. First, gender gaps in labor income and employment are pervasive in both countries. Second, the gaps are generally larger in the US, both in the child and parent generations. Third, the gaps have narrowed over time and generations, with the exception of the roughly stable (and small) son-daughter employment gap in Sweden. We next turn to our main results on mobility time trends, to which these cross-country commonalities, as well as the differences, in the gender dynamics are central—they motivate why our two-country approach can be insightful and are key for interpreting the evidence on mobility trends.

3 Trends in intergenerational mobility

In this section, we present mobility trends for the US and Sweden. We first show aggregate trends in the IRP for all children (sons and daughters pooled) with respect to the household labor income of their parents. We then compare trends across genders (sons, daughters, mothers and fathers).

3.1 Aggregate trends for all children

Figure 1 shows estimates of the IRP for Sweden and the US, with each point representing an estimate of β_t from equation (1) for a given year t and each corresponding vertical bar showing the respective 95% confidence interval. We pool all children and relate their (individual) income ranks to the household income ranks of their parents, using (child) gender-by-cohort ranks. Because we pool sons and daughters, estimated persistence levels are slightly lower than prior work focusing on fathers and sons or household incomes in both generations. Using ranked incomes allows for the inclusion of very low/zero incomes and thus avoids the potential sample selection that is induced by the IGE. We can also see that for the US, the statistical uncertainty is smaller and the confidence intervals tighter compared to the IGEs (provided in Appendix Figure C.1).

The trends in terms of rank persistence indicate decreasing mobility for both countries. For Sweden (subfigure 1a), the IRP rose primarily during the 1990s, but exhibited subsequent stability

Table 1: Descriptive statistics

	Sweden				US			
	1985-95		2008-19		1985-95		2008-19	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Daughters								
Income	151522.5	83686.4	270406.7	175734.8	27859.2	30818.6	37216.2	38589.7
Age at income	31.7	4.6	36.6	7.1	31.9	4.6	35.3	6.7
Education	12.4	2.5	13.5	2.4	14.1	2.1	14.8	2
Employment	86.9	33.7	86	34.7	65.9	47.4	74.5	43.6
Birth year	1959	4.7	1977	8	1958.6	4.5	1977.7	7.5
Individuals		1009351		1827075		1158		2035
Observations		7976976		14390321		8511		7803
Sons								
Income	216259.6	129014.5	350678.3	266807.4	57045.4	51616	62731.7	80255.5
Age at income	31.7	4.6	36.5	7.1	32.1	4.5	35.4	6.6
Education	11.9	2.6	12.7	2.4	14	2.1	14.4	2
Employment	88.7	31.7	87.4	33.1	92.3	26.7	87.4	33.2
Birth year	1959	4.7	1977	8	1958.5	4.5	1977.5	7.4
Individuals		1065153		1931679		1081		1864
Observations		8405111		15232259		7734		6916
Mothers								
Income	107225.8	81480.5	164787.7	100865.1	13216.2	16005.4	25553.5	26711.5
Age at income	44.1	6.2	41.9	5.2	41.1	6	40.1	5.5
Education	9.5	2.8	11.4	2.9	12.4	2.5	13.7	2.2
Employment	72.2	36.1	84	30.6	38.6	42.4	61.5	41.5
Birth year	1931.6	8	1949.7	8.9	1931.9	7.6	1952.2	8.7
Individuals		1138607		1883320		1046		2026
Observations		16134822		29264375		15994		13992
Fathers								
Income	261246.7	159496.8	272055.6	181982.9	73486.6	50049.4	77705.6	89790.7
Age at income	47.1	6.6	44.7	5.8	44	6.4	42.5	5.8
Education	9.8	3.1	11.1	3	12.6	3.1	13.9	2.4
Employment	96.2	12.7	90.1	24.7	95.3	17.2	92.2	20.8
Birth year	1928.4	8.4	1946.9	9.3	1929.2	7.9	1949.5	9
Individuals		1079591		1803636		902		1749
Observations		15314676		28191919		13814		11990

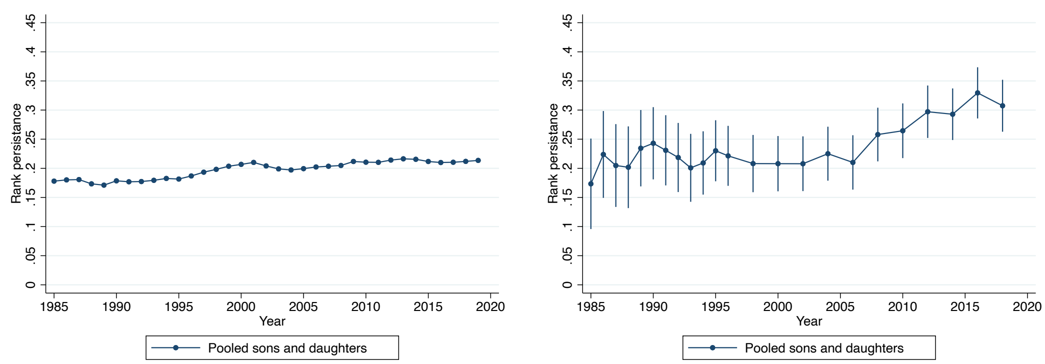
Notes: The statistics for income, age, birth year, and number of individuals or observations are based on the IRP estimation sample. The portion with non-missing education is used to compute the education and employment statistics; in the PSID we lose only 1 father with missing education.

during the 2000s. The results thus imply a long-run decrease in intergenerational mobility as measured by the IRP, with the latter increasing from around 0.17 in the late 1980s to around 0.22 in the late 2010s.

For the US (subfigure 1b), the point estimates are consistently about 0.20 or slightly higher until around 2005, increasing to around 0.30 for the most recent years.[17] This is similar to the change in rank persistence documented by Davis and Mazumder (2022) and Justman and Stiassnie (2021), though directly comparing magnitudes is complicated by their use of family incomes.[18]

Figure 1: Aggregate trends for all children (IRP)

(a) Sweden (b) United States



3.2 Trends by child and parent gender

We next move beyond the aggregate trends for all children and joint parental income and focus instead on different forms of gender-specific intergenerational persistence.

3.2.1 Sons and daughters

We first compare mobility trends of sons and daughters separately with respect to the household income rank of the parents. Figure 2 shows convergence over time in the levels of son-parent and daughter-parent persistence, in both the US and Sweden. Son-parent persistence increased slightly in both countries, but the change was small (and in the US not statistically significant).

Daughter-parent persistence increased more steadily in both countries. In Sweden (subfigure 2a), the IRP for daughters increased from about 0.15 in the late 1980s to about 0.20 in the 2010s.

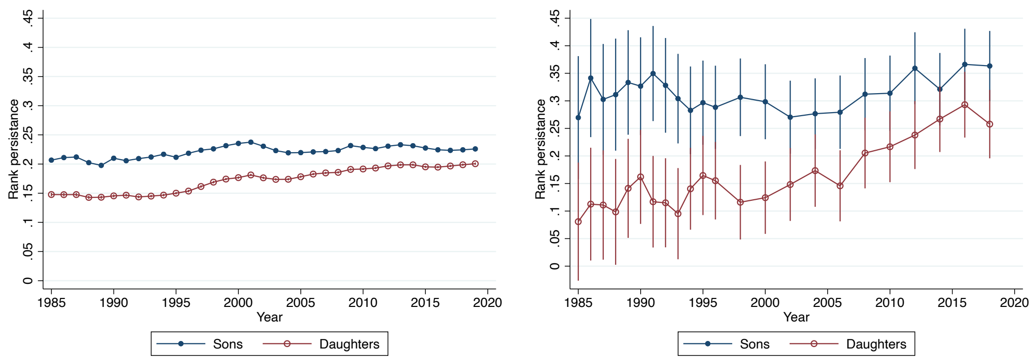
[17] The change is statistically significant, with a p-value=0.004 for the late minus early period difference (Table C.1).

[18] The results are also not at odds with studies finding no significant decline. Lee and Solon (2009) estimate the IGE up to year 2000, and for this time period our results indicate a similarly stable level of mobility. Chetty, Hendren, Kline and Saez (2014) include income data until 2012, but use a cohort approach with incomes measured at age 30.

In the US (subfigure 2b), the corresponding estimate increased from about 0.13 in the late 1980s to about 0.25 in the 2010s, and this change is statistically significant (p-value=0.001 in Table C.1).[19] Although the US estimates are imprecise, it is noteworthy that the son- vs daughter-parent persistence goes from being almost three times as high and significantly different in the 1980s, to about 25-35% higher and insignificantly different in the 2010s.

Figure 2: Trends by child gender

(a) Sweden (b) United States



3.2.2 Mothers and fathers

We next compare mobility trends of children (sons and daughters pooled) with respect to the individual income ranks of mothers and fathers separately. Figure 3 shows a striking pattern of strongly increasing child-mother persistence in both the US and Sweden. Child-father persistence also increased in both countries, but the change was more pronounced in the US than in Sweden.

Child-father persistence only increased marginally in Sweden (subfigure 3a), with an IRP of 0.18-0.19 in the 2010s. Child-mother persistence, on the other hand, more than doubled from about 0.07 to about 0.15. Thus, the father-child IRP went from being about 250% larger than the mother-child IRP to being around 25% larger in the most recent years.

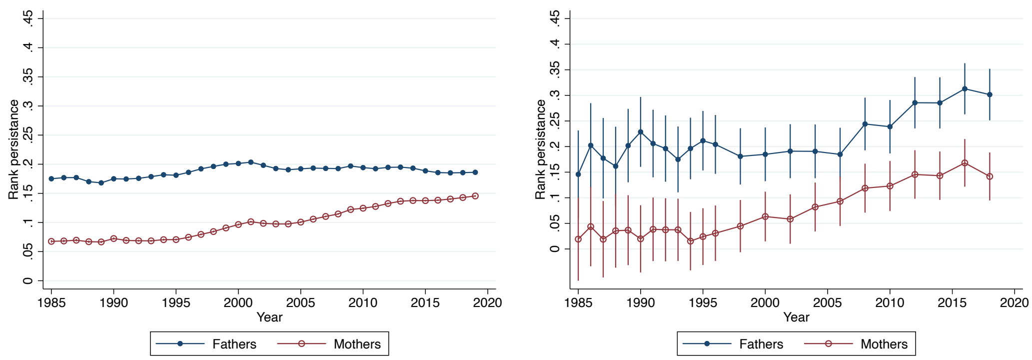
In the US (subfigure 3b), the child-father IRP rose more substantially than in Sweden, from about 0.20 to about 0.30. The mother-child IRP rose from less than 0.05 and being insignificantly different from zero in the 1980s and 1990s to almost 0.15 in the 2010s. These increases are statistically significant, for both fathers and mothers (p-values in Table C.1 are 0.004 and 0.0001,

[19]The low parent-daughter estimate in 1993 may be attributable to a particular issue with the 1994 survey. Kim et al. (1999) note that, due to an error, income information was not collected for 519 working wives in the 1994 survey; however, the vast majority of these were imputed by subgroup means and thus excluded from our analysis. Nonetheless, we estimate our main results excluding the 1994 survey and confirm that the trends are nearly identical to those in Figures 1–4 (results available upon request).

respectively). While the gap between the father-child and mother-child IRPs thus did not shrink much in absolute value, it did become much smaller in relative terms.

Figure 3: Trends by parent

(a) Sweden (b) United States



3.2.3 Gender-specific intergenerational persistence

As a final exercise, we consider trends in income persistence while distinguishing between the gender of both the children and the parents. Figure 4 shows trends in the father-son and father-daughter IRP (subfigure 4a for Sweden; subfigure 4b for the US) and in the mother-son and mother-daughter IRP (subfigure 4c for Sweden; subfigure 4d for the US). A number of interesting findings arise from this analysis.

First, the benchmark father-son association was largely stable over time in both countries. While there is a small uptick in the father-son IRP in the US in the last 10-15 years, the long-run change comparing the late 1980s with the 2010s is small and statistically insignificant. For both countries, we also see that the father-son IRP is substantially larger than the father-daughter IRP. However, the father-daughter IRP increased in both countries, such that this gap became smaller over time. In Sweden, the father-daughter IRP increased from around 0.13 to about 0.17. In the US the development was much more pronounced: for the early years, the father-daughter IRP was close to zero, while in the 2010s, the estimates are close to 0.25 and significantly different from the early-year estimates. In fact, the point estimate of the US father-daughter IRP was in the most recent years higher than the Swedish father-son IRP. Moreover, these results suggest that the increases in the father-child IRPs documented in Figure 3 in the previous subsection are primarily driven by the transmission between fathers and daughters as opposed to fathers and sons.[20]

[20]One explanation for this is that daughters' income became more informative over this time period. Another

The mother-child associations in subfigures 4c and 4d show a striking and qualitatively similar pattern of secularly increasing persistence in both countries, and with respect to both sons and daughters. In Sweden, both the mother-son and mother-daughter IRP estimates roughly double in size over time, although the mother-daughter IRP diverges from and is slightly higher than the mother-son IRP. In the US, the trend and the levels of the mother-daughter IRP are very similar to those of the mother-son IRP. For both sons and daughters, the IRP estimates grow from about 0-0.05 in the early years (and statistically indistinguishable from zero) to about 0.15 in the 2010s.

Thus, intergenerational income persistence appears to be partly gender specific, though with some differences across countries. For Sweden, income persistence is indeed stronger within gender (i.e., son-father and daughter-mother) than across gender (i.e., son-mother and daughter-father). In the US, fathers are generally more impactful (in a statistical sense) with the father-child IRPs being larger than the mother-child IRPs. In a relative sense, however, the father-son IRPs are substantially larger than the father-daughter IRPs, while the gap between mother-son and mother-daughter persistence is essentially zero.

The general pattern in Figure 4 is that, in both the US and Sweden, all measures of intergenerational income persistence involving women (daughters and/or mothers) have increased over time, while the commonly studied father-son persistence remained roughly stable. The patterns suggest that conventional studies that only look at recent trends in male-to-male transmission can miss some important dynamics pertaining to a large part of the population. More generally, trends in joint household income measures also miss this rapidly changing picture of mobility for women, despite potential underlying contributions to the aggregate trends. Of course, we cannot claim that the patterns of intergenerational mobility of women reflect a decrease in equality of opportunity—the increase in persistence involving women might, for example, be primarily due to an increase in the correspondence between their underlying skills and earnings, rather than an increase in the transmission of underlying skill. We explore this and the contributions of mothers and fathers to aggregate persistence in the next section. Regardless, the analyses do suggest that a wider perspective is important to fully grasp societal changes pertaining to intergenerational mobility.

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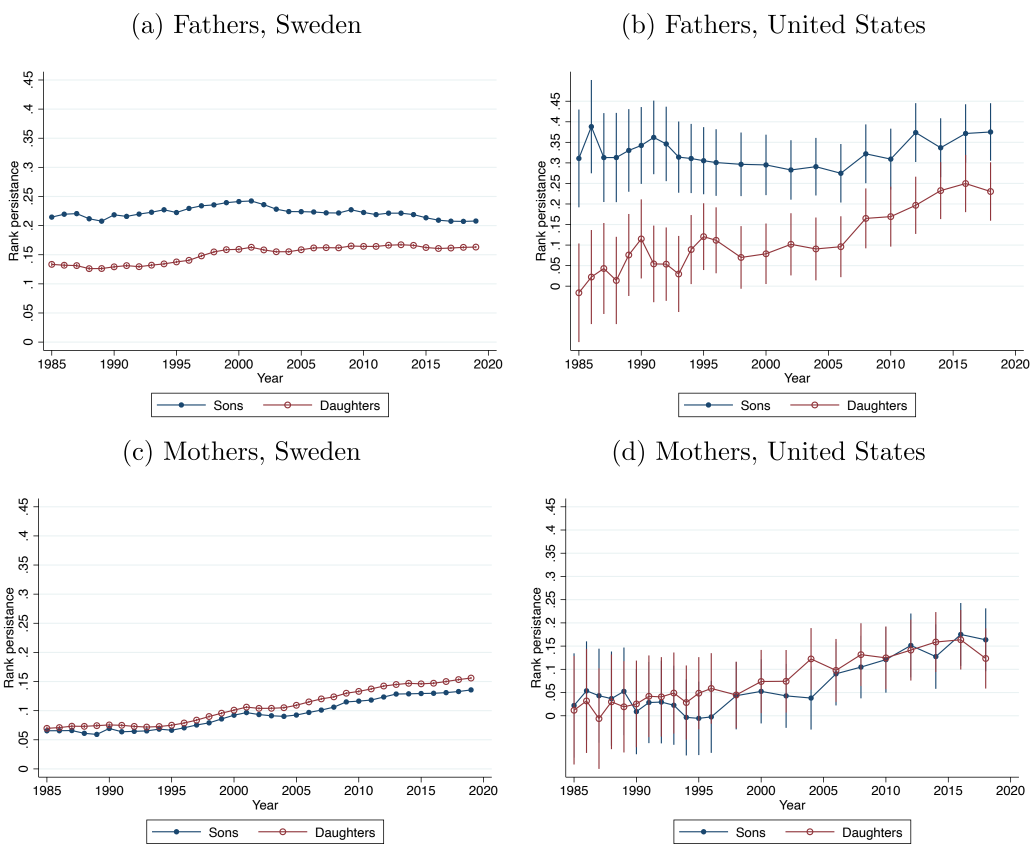
possibility is an occupational transmission mechanism, where father-son occupational persistence is unchanged but father-daughter occupational persistence increased (Hellerstein and Morrill, 2011).

Figure 4: Trends by parent and child gender



3.2.4 Robustness

Appendix A presents a set of tests that demonstrate the robustness of our findings to the inclusion of zero incomes and our decision to focus on yearly rather than cohort trends. We also document that our qualitative findings hold similarly when focusing on different ages of income measurement of the child generation. For many of our robustness checks, we focus on the Swedish data, given its larger samples and higher flexibility for performing certain types of tests.

Figure A.1 compares for Sweden the baseline trend in the IRP from our main analyses with the IRP trend using the intergenerational income elasticity (IGE) sample, which excludes zero and very low incomes. For all subgroups (sons/daughters, fathers/mothers) the IRP increases more over time when including zero incomes. Thus, structural changes on the labor market related to the prevalence of non-employment and individuals with very low incomes are either becoming increasingly important over time, or increasingly associated with parental income. However, the role of zero incomes for mobility trends appear similar across all subgroups. If anything, the IRP for more recent years is the most strongly underestimated when excluding zeros for sons and mothers (see subfigures A.1a and A.1d). For the US, Figure A.2 shows that the strongest sensitivity is in the mother-child trends where the IRP is roughly stable when we restrict to the IGE sample, compared to a fairly steep rise in our main analyses. This finding suggests that changes along the extensive margin of labor supply can explain much of the increase in mother-child persistence in the US.

We next check the sensitivity to a different type of sample selection in the PSID, examining whether including the Survey of Economic Opportunity (SEO) sample changes our results.[21] Using the combined SEO and SRC samples requires using sample weights, so this also sheds light on potential influences of attrition on our results. Reassuringly, the trends shown in Figure A.3 are nearly identical.

Figure A.4 shows trends from our main specification but using a tighter age interval of the included children (age 33-43 rather than age 25-48). When doing so, we focus specifically on prime-age incomes, and the mechanical changes in age composition over time becomes much smaller. The trends are very similar overall, with a somewhat stronger convergence in persistence between sons and daughters. The analysis thus suggests that our main findings are not driven by very young children, below age 33. Moreover, the results are reassuring for the generalizability of our main trends, since the analysis is closer in spirit to a pure cohort approach.

The analysis presented in Figure A.5 goes one step further by holding the age of income measurement of the children fully fixed, at various ages (age 29-31, age 34-36, age 39-41). A couple of observations stand out. First, the levels of the IRP are clearly higher when measuring incomes at age 34-36 or 39-41 compared to at age 29-31, which is in line with prior research on lifecycle effects (Haider and Solon, 2006; Nybom and Stuhler, 2016) and indicates that income mobility is overestimated when incomes are measured too early. The IRP levels in our main analysis are generally close to those at age 34-36 or age 39-41, which is reassuring given that rules-of-thumb in the literature are to measure incomes at about age 35-40 in order to approximate mobility in lifetime or long-run income. Importantly, the estimated *trends* are also similar to those in our main analysis when measuring incomes at a fixed age in mid-life. However, it is noteworthy that the estimated increase (decrease) in the IRP (mobility) becomes considerably smaller when incomes are measured at an early age (at 29-31). This finding suggests that parental-income related heterogeneity in age-income profiles has changed over time, and that early-age income differences are less

[21] The SEO sample was the other component of the PSID at the start in 1968, which oversampled low income households.

reflective of lifetime income differences in more recent years. The results further indicate that this change is strongest for women, with trends for mothers and especially daughters being the most sensitive to measuring incomes at a too early age.

4 Quantifying drivers of persistence

The role of mothers in the labor market and the household changed dramatically during our study period, and these changes were likely consequential for the determinants of intergenerational transmission. In addition, changes in terms of assortative mating and joint household decisions may have impacted not only measured maternal but also paternal persistence. We use a statistical framework to describe the roles of parental characteristics in shaping the observed trends in persistence. Decomposing the IRP into channels due to human capital, employment, and other income-determining traits, we study how these factors changed over time in Sweden and the US. The framework is akin to Lefgren, Sims and Lindquist (2012), which is a mechanical adaptation of Becker and Tomes (1979), though both focus on father-son transmission.[22] We extend the framework with an employment channel, a mechanism that likely is particularly important for women (e.g., Altonji and Dunn 2000), and with assortative mating of parents.

We start with a simple setup in Section 4.1, in which a parent begins with some level of human capital which subsequently affects employment. Incomes are then influenced by these human-capital based employment decision as well as orthogonal employment, human-capital, and other income-determining traits. To account for spouses, Section 4.2 extends the model by allowing for assortative mating. Here employment responses are allowed to also depend on the partner's human capital. In both models, income transmission occurs through the child's human capital, consistent with the aforementioned studies. We derive the IRP in terms of model parameters and decompose it into the various channels. The decompositions enable us to describe how the role of mothers and fathers in intergenerational transmission has changed over time in Sweden and the US.

4.1 Basic model

We assume child income (rank) is determined in sequentially according to four equations:

$$E_p = \phi_0 + \phi_1 H_p + \eta_{ep} \tag{2a}$$

[22] Miller and McIntyre (2020) is another related example, again focused on father-son persistence.

$$Y_p = \gamma + \theta_0 E_p + \theta_1 H_p + \eta_p \tag{2b}$$

$$h_c = \pi_0 + \pi_1 Y_p + \pi_2 H_p + \varphi_c \tag{2c}$$

$$y_c = h_c + u_c, \tag{2d}$$

In equation (2a), a parent starts with human capital H_p, which influences their employment, E_p, with ϕ_1 capturing the responsiveness of extensive-margin labor supply to own human capital. In particular for mothers, there could be multiple reasons for such a channel. Incentives to work are stronger for those with more human capital, both since they tend to earn higher wages and higher returns to experience (Blundell et al., 2016). Preferences or societal norms towards mothers working, as well as impacts of public policies, might also differ by human capital. This step is likely less pertinent to fathers. The residual term η_{ep} captures preferences and other idiosyncratic determinants of employment that are orthogonal to human capital.

Parent income (rank) is then determined by employment, human capital, and an idiosyncratic term.[23] Substituting equation (2a) into (2b) yields that human capital affects income both directly (θ_1) and indirectly through sorting into employment (via $\theta_0\phi_1$), with the latter employment sorting channel being of primary interest in our study of mothers. The parent influences child human capital through financial investment from own income (π_1) and from the (direct) transmission of human capital conditional on income (π_2) in equation (2c). Parental employment—conditional on income and human capital—does not directly affect the child. Like prior studies, child income is then a simple function of their human capital (equation (2d)).[24]

A sequence of substitutions yield a final equation for how parents influence child income:

$$y_c = \pi_0' + \left[\pi_1(\theta_0\phi_1 + \theta_1) + \pi_2\right] H_p + \pi_1\theta_0\eta_{ep} + \pi_1\eta_p + \varphi_c + u_c \tag{3}$$

where $\pi_0' = \pi_0 + \pi_1\gamma + \pi_1\theta_0\phi_0$ and the composite error elements φ_c and u_c are uncorrelated with parent characteristics. The gross influence of parental human capital on child's income is a function of both the productivity of financial investment (π_1) and the direct transmission of human capital (π_2). The former is scaled by the income returns to human capital (θ_1) and the product of the

[23]Because our aim is to decompose the IRP, we use as y_c and Y_p our measures of child and parent income *ranks* from above also in this section. Doing so avoids the level-to-rank transformation problem and simplifies the exposition considerably.

[24]Modeling parent influence on children's income through the channel of child's human capital was adopted in the original theory by Becker and Tomes (1979) and in subsequent studies, including those most closely related to ours that consider decompositions (Lefgren, Sims and Lindquist, 2012) or trends over time and place (Solon, 2004).

parameters governing the return to and sorting into employment ($\theta_0\phi_1$). The influence of parents' residual employment and income components, η_{ep} and η_p, is determined by π_1, with the former also being scaled by θ_0. Given this framework, we can decompose the IRP into parts due to parental human capital, an employment-human capital sorting channel, an orthogonal employment channel, and residual income[25]:

$$plim(\hat{\beta}) = \underbrace{\theta_1(\pi_1\theta_1+\pi_2)\frac{Var(H_p)}{Var(Y_p)}}_{\text{Human capital}} + \underbrace{(\theta_0\phi_1)\left[\pi_1(\theta_0\phi_1+2\theta_1)+\pi_2\right]\frac{Var(H_p)}{Var(Y_p)}}_{\text{Employment sorting}} + \underbrace{\pi_1\theta_0^2\frac{Var(\eta_{ep})}{Var(Y_p)}}_{\text{Employment } (\eta_{ep})} + \underbrace{\pi_1\frac{Var(\eta_p)}{Var(Y_p)}}_{\text{Resid inc } (\eta_p)} \tag{4}$$

4.1.1 Results for basic model

We estimate the model separately for mothers and fathers, for two time periods: an early period with child incomes observed 1985-1995 and a late period covering 2008-2019. We measure human capital using years of education, and E_p is an income-based measure of average employment status over multiple years.[26] We estimate a series of linear regressions to obtain the necessary parameter estimates. Appendix B.1 provides further details. Figure 5 provides a breakdown of the IRP into the channels in equation (4), for both mothers and fathers. Consistent with our main results, the mother-child IRP (subfigure 5a) for the early period is similarly low in Sweden and the US and rises substantially over time. Underlying the rising trends though, are country and time differences in the relative importance of mothers' characteristics.

Initially there are starkly different pictures of maternal transmission in Sweden and the US. Employment sorting dominates in the US, accounting for over 70% of the (small) IRP. In Sweden, the contribution is balanced with the human capital channel, each at about 20% of the IRP. The (residual) employment channel (orthogonal to human capital) is substantial in Sweden (40%), but minimal in the US (7%).

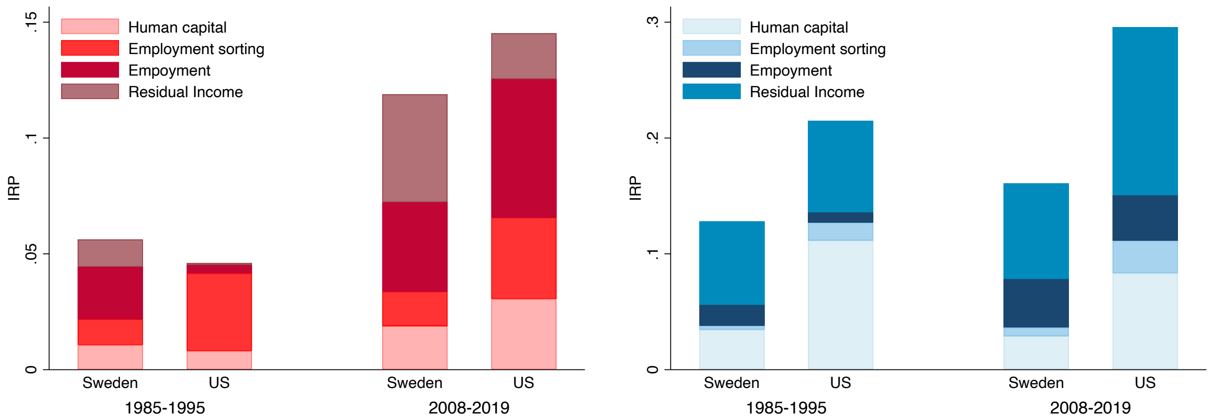
The disparity in the employment sorting channel is due to larger estimates of both the sorting parameter ϕ_1 and the direct transmission of maternal human capital π_2 in the US compared to

[25]Following equations (2a) and (2b), we include in the employment sorting channel all elements involving $\phi_1\theta_0$, with the remaining terms involving θ_1 or π_2 comprising the human capital component.

[26]An individual is employed if their annual income is above 20% of the annual median for prime-age men (age 25-55) in that year; E_p is then the average employment status over the five years in which income is measured. We also purge our measures of income, human capital, and employment from age and time effects. Using the main sample covering years 1985-2019, we regress each measure on a quartic in centered (at age 40) child age, a quartic in parent age, and year fixed effects. The estimations use all income observations in each time period, clustering by the parent.

Figure 5: IRP decompositions for separate mother and father models

(a) Mothers (b) Fathers



Notes: The height of each bar is the IRP. The underlying channels are the calculated elements of the decomposition equation (4). Appendix Table B.1 provides the numeric values and sample sizes.

Sweden. The growth in the residual employment and income channels are linked to the financial-resources parameter, π_1, which rises in both countries. However, both $\hat{\pi}_1$ and $\hat{\pi}_2$ are likely influenced by how H_p and Y_p correlate with income and human capital of the spouse (see the next subsection and Figure 6 below).

These contrasting pictures of mother's employment and income channels likely reflect country differences in women's labor market attachment. For the early period, mothers' incomes are primarily observed during the 1970s, when Sweden experienced a steep rise in female participation, a phenomenon that occurred slightly later in the US. Over time, the roles of maternal human capital, employment, and residual income in the US adjust to look more like the early period for Swedish mothers, consistent with the delayed rise in women's labor force participation. For Swedish mothers, on the other hand, growth in the income and human capital channels leads to convergence in the decomposition towards resembling that of (Swedish) fathers (subfigure 5b). The dominance of the income and human capital channels for fathers in both countries is driven by higher transmission from financial resources (π_1) as well as higher human capital returns (θ_2), despite weaker human capital transmission (π_2) compared to mothers.

The decompositions in Figure 5 demonstrate important differences in transmission along both gender and country lines. Employment is a key channel for mothers in both countries—though employment sorting becomes relatively less important once labor force participation has spiked. As expected, employment plays a much smaller role for fathers, though its importance increases slightly over time as male employment declines. In absolute terms, for fathers in both countries the contributions of the employment and residual income channels increased, while that for human capital declined. For mothers, on the other hand, all channels increased and contributed to rising mother-child persistence.

4.2 Extended model with assortative mating

Focusing on individual parents is a natural starting point given the large literature studying father-son income mobility. However, the parental characteristics we consider are inherently linked through assortative mating and joint household decisions. We thus extend our model to incorporate both elements. While several studies of mobility trends examine the implications of assortative mating in the child generation (Ermisch, Francesconi and Siedler, 2006; Davis and Mazumder, 2022; Holmlund, 2020), few have considered *parental* matching.[27] Assortative mating on human capital is linear and stable over time in both the US and Sweden, as shown in Figures 6a and 6b, which highlights the importance of accounting for parental sorting. Perhaps more intriguing though, is that despite very similar human capital matching, mother-father associations in *income* differ substantially (see Figures 6c and 6d). The relationship for Sweden is roughly linear and becomes more positive over time but for the US it is more non-linear and the slope of a fitted linear regression line changes from negative to marginally positive. We return to this in our discussion of the results.

We incorporate assortative mating in an initial stage of our model, and then extend the employment (2a) and child human capital (2c) equations to also reflect influences of both parents:

$$H_{sp} = \delta_0 + \delta_1 H_p + \eta_{sp} \tag{5a}$$

$$E_p = \phi_0 + \phi_1 H_p + \phi_2 H_{sp} + \eta_{ep} \tag{5b}$$

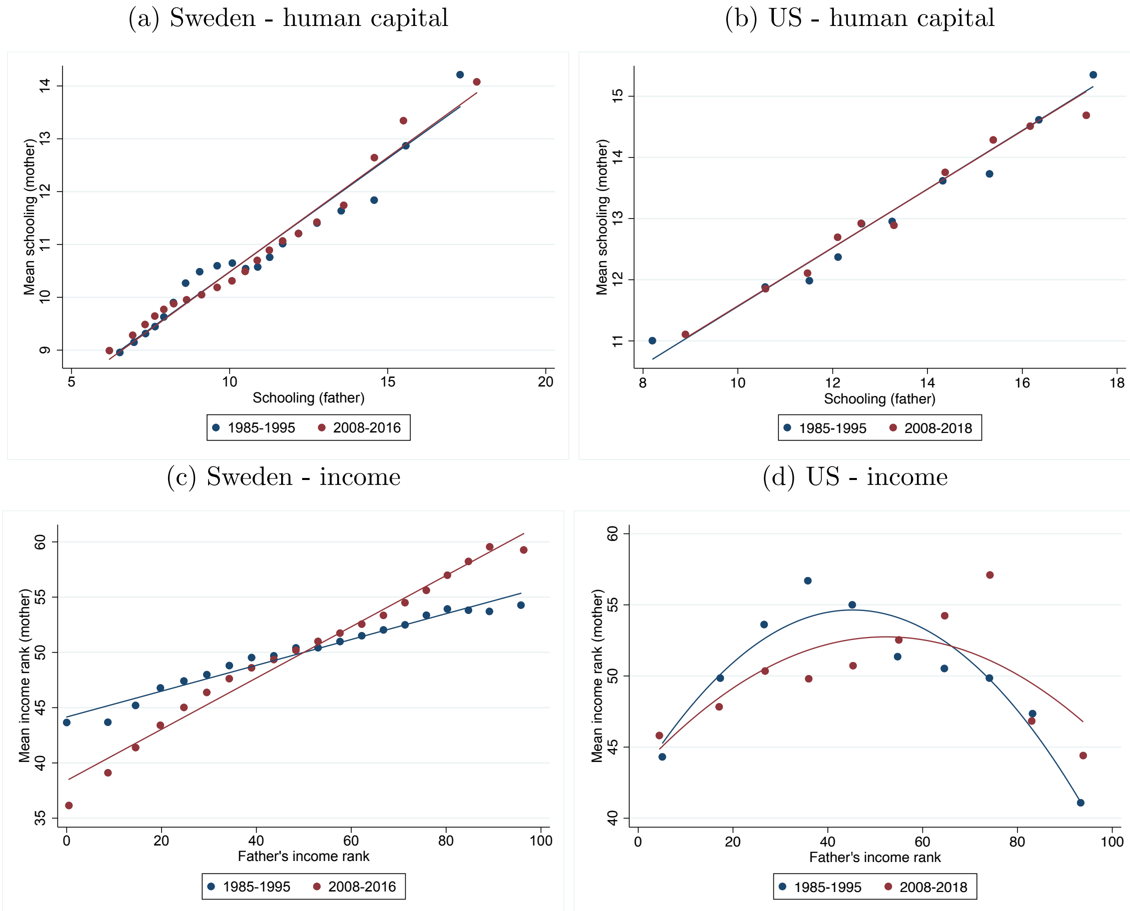
$$h_c = \pi_0 + \pi_1 Y_p + \pi_2 H_p + \pi_{1s} Y_{sp} + \pi_{2s} H_{sp} + \varphi_c. \tag{5c}$$

An individual chooses a spouse with some consideration of the person's human capital (equation (5a)). δ_1 measures assortative mating on human capital and η_{sp} is the idiosyncratic part of the spouse's human capital.[28] To reflect the joint nature of (mother's) labor supply decisions, employ-

[27] Bratsberg et al. (2022) study the role of parental assortative mating for various child outcomes in Norway, but not in the context of intergenerational mobility trends.

[28] The Eika, Mogstad and Zafar (2019) point about changes over time in $Var(H_p)$ is not of great concern here. We are not interested in δ_1 itself, rather in the proportion of the IRP attributable to assortative matching on human

Figure 6: Parental assortative mating in Sweden and the US



ment is now a function of the human capital of both parents according to ϕ_1 and ϕ_2 in equation (5b). η_{ep} is the idiosyncratic part of employment, now conditional on own and the spouse's human capital. Finally, child human capital depends on the income and human capital of both parents, meaning π_1 and π_2 now reflect transmission conditional on the spouse's characteristics (equation (5c)).

Following a sequence of substitutions similar to before, we obtain expressions for y_c and Y_p in

capital in our decomposition, $\left(\pi_{1s}\tilde{\theta}_s + \pi_{2s}\right)\tilde{\theta}_p\delta_1\frac{Var(H_p)}{Var(Y_p)}$. This simplifies to $\left(\pi_{1s}\tilde{\theta}_s + \pi_{2s}\right)\tilde{\theta}_p\frac{Cov(H_p,H_{sp})}{Var(Y_p)}$ because the $Var(H_p)$ terms cancel out. Changes in $Var(H_p)$ do play a role in the decomposition as can be seen in equation (6), but are not key drivers of the contributions of the assortative mating channel.

terms of model parameters and derive the probability limit of the OLS estimator of β:

$$\begin{aligned}plim\left(\hat{\beta}\right) = & \underbrace{\{\theta_0(\phi_1+\phi_2\delta_1)\left[\pi_1\theta_0(\phi_1+\phi_2\delta_1)+\pi_2\right]+2\pi_1\theta_1\theta_0(\phi_1+\phi_2\delta_1)\}\frac{Var(H_p)}{Var(Y_p)}}_{\text{Employment sorting}} \\ & +\underbrace{\theta_1(\pi_1\theta_1+\pi_2)\frac{Var(H_p)}{Var(Y_p)}}_{\text{Human capital}}+\underbrace{\pi_1\theta_0^2\frac{Var(\eta_{ep})}{Var(Y_p)}}_{\text{Employment }(\eta_{ep})}+\underbrace{\pi_1\frac{Var(\eta_p)}{Var(Y_p)}}_{\text{Resid Inc }(\eta_p)}+\underbrace{\left(\pi_{1s}\tilde{\theta}_s+\pi_{2s}\right)\tilde{\theta}_p\delta_1\frac{Var(H_p)}{Var(Y_p)}}_{\text{AM on Human Capital}} \\ & +\underbrace{\pi_{1s}\frac{Cov(\eta_{py},\eta_{spy})}{Var(Y_p)}+\pi_{1s}\tilde{\theta}_p\frac{Cov(H_p,\eta_{spy})}{Var(Y_p)}+(\pi_{1s}\tilde{\theta}_s+\pi_{2s})\frac{Cov(H_{sp},\eta_{py})}{Var(Y_p)}+\pi_1\theta_0^2\phi_2^2\frac{Var(\eta_{sp})}{Var(Y_p)}}_{\text{Other assortative mating/spouse related elements}}\end{aligned} \tag{6}$$

The decomposition in (6) consists of six components. Apart from the four components of the basic model from above, it also includes assortative mating on human capital and a component capturing other spousal cross-correlations between residual income determinants and human capital.[29] See Appendix B.2 for details.

4.2.1 Results for the extended model with assortative mating

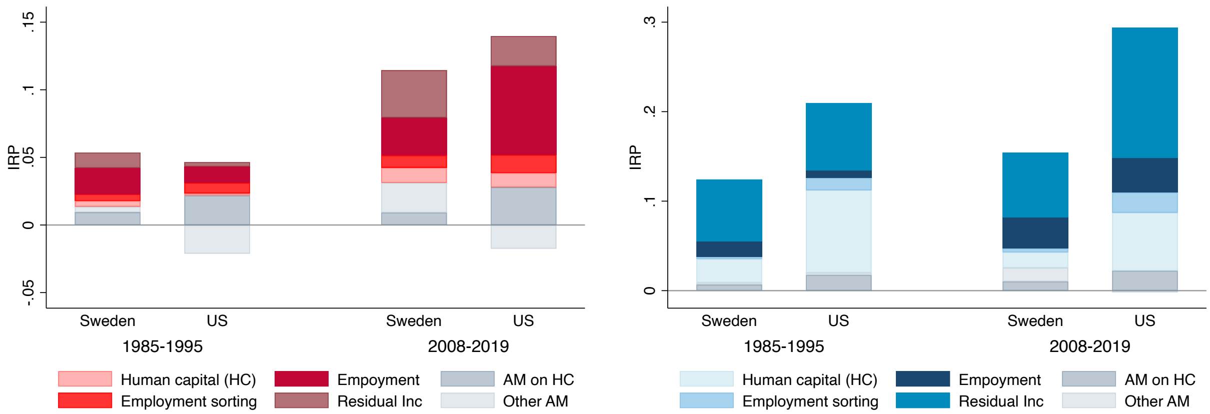
Intergenerational transmission now explicitly depends on the income and human capital of both the mother and the father, yet $\hat{\pi}_1$ (financial investment) remains roughly similar in magnitude as in the simple model. But over time, $\hat{\pi}_1$ exhibits some increases for mothers and fathers, suggesting that financial investment may be an increasingly important transmission mechanism. In contrast, conditioning on the spouse substantially reduces $\hat{\pi}_2$ (human-capital transmission) for mothers, with more modest declines for fathers. The over-time changes differ by parent, rising for mothers but declining for fathers.

The relative roles of mother's characteristics change substantially when fathers are incorporated, reflecting in part the aforementioned declines in π_2. Figure 7 shows the decompositions from equation (6). Mother's human capital and, to a greater extent, employment *sorting*, account for far less in both countries in both time periods. This shift seems to largely play out in the form of an increased role for employment accompanied by a rise in the role of residual income, with both changes more extreme for the US. In fact, the changes in each relative contribution compared to the simpler model are minimal for Swedish mothers in the late period. The US decomposition in the later period still approaches that of the early period for Sweden, consistent with the delayed

[29] To simplify notation, the human capital parameters are aggregated in $\tilde{\theta}_p = \theta_0(\phi_1+\phi_2\delta_1)+\theta_1$ and the combined non-human capital income is denoted $\eta_{py} = \theta_0\phi_2\eta_{sp}+\theta_0\eta_{ep}+\eta_p$. For spouses, $\tilde{\theta}_{sp}$ and η_{spy} are the analogous elements based on their respective equations for sorting, employment, and income.

Figure 7: IRP decompositions for extended model with assortative mating

(a) Mothers (b) Fathers



Notes: The height of each bar is the IRP. The underlying channels are the calculated elements of the decomposition equation (6): Human capital (HC), Employment sorting, Employment, Residual income, Assortative mating (AM) on HC, and Other AM related elements. Appendix Table B.3 provides the calculated values and sample sizes.

increase in female labor force participation. In terms of father-child persistence, there is little change in the relative roles of different components compared to the basic model or considering changes over time.

We next turn to the role of assortative mating, as captured by the last two components of equation (6). Only in Sweden do we find the expected result that aggregate assortative mating accounts for more of the IRP for mothers (approximately 25%) than for fathers (7% to 17%). In fact, the role of aggregate assortative mating is negligible for mothers in the US, accounting for only 2% and 8% in the early and late periods, respectively. Visually though, Figure 7 shows that assortative mating *is* important for US mothers, but in a distinct manner. Explicitly considering the two components of marital sorting—spousal human capital matching and other spousal correlations—reveals important heterogeneity in the nature of assortative mating, consistent with the country differences shown in Figure 6. The contribution of assortative mating on human capital is actually much larger in the US than in Sweden. Conversely, the other spousal correlations ("Other AM")—capturing spousal income correlations conditional on the human-capital matching—is *negative* in the US and of the same magnitude as the human capital matching. In our accounting exercise, this cancels out the positive contribution of human capital matching.[30]

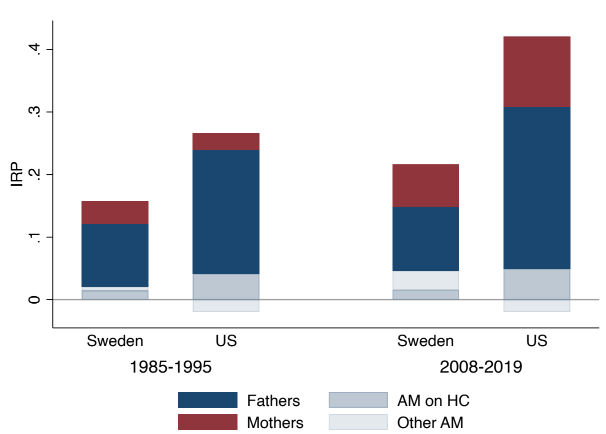
[30]Note that this negative sorting influences the father-child IRP differently, since the multiplicative parameters on the (similar) covariances differ. The multiplicative parameter for mothers π_{1s} (the financial investment transmission for fathers) is much larger than π_1, the corresponding one relevant for fathers. Thus, the negative "sorting" related to unobservable income determinants plays a much larger role in (reducing) the mother-child IRP than the father-child

This extended model thus not only gives a more detailed picture of the roles of mother's characteristics but also provides important insights on the role of parental assortative mating. Assortative mating is typically thought to boost intergenerational persistence, which is what we observe in Sweden even with a simple mediating-factor type analysis where we condition our main trends on father's income (see Appendix Figure C.2a). For the US, however, there is no such aggregate effect, despite strong underlying marital sorting (Appendix Figure C.2b). However, the decomposition exposes both negative and positive contributions to the mother-child IRP of marital sorting. Nonetheless, similar to our results for the basic model, the results in Table B.3 for the extended model also show that the absolute contribution of each characteristic of mothers rises over time in both countries, jointly driving the growth in mother-child persistence.

4.2.2 Persistence with respect to parent household income

We also decompose the IRP with respect to the joint household income of the parents, as such measures are often used in studies of mobility trends.[31] Our primary interest is in the aggregate contribution of mothers relative to that of fathers, as well as the two assortative mating dimensions.[32]

Figure 8: Decomposition of IRP for parent household income



Notes: The height of each bar is the IRP. The channels shown include Mother's characteristics, Father's characteristics, assortative mating on human capital (AM on HC), and other assortative mating related elements (Other AM).

IRP.

[31]In our main analyses of trends, we used the ranks of the average of mother and father income to avoid changes in the variance of the average measure from driving trends over time. Here, we instead use the average of mother and father income ranks, as this greatly simplifies the algebraic derivations for the decomposition. Thus, the levels of estimates differ slightly from the main results.

[32]The relative importance of each underlying characteristic of a parent is unchanged, which can be seen in the detailed decomposition equation and results in Appendix B.2.

Figure 8 shows that the IRP with respect to parental household income is higher than the IRPs for the individual incomes of mothers, and roughly similar to those of fathers, consistent with prior studies. Similar to the trends in Section 3, the IRP rises over time. Importantly, fathers account for large, but declining, shares of the IRP, while the contribution of mothers grows substantially, and especially so in the US. The aggregate role of mothers' characteristics is initially very small in the US, but rises to roughly 30% in both countries. Finally, a substantial—and changing—role of parental assortative mating is again evident. Human capital sorting accounts for a declining share in both countries. The other parental assortative mating channel expands in Sweden and the negative offsetting effect becomes (relatively) less influential in the US.[33] The net role of the two assortative mating components increases to just over 21% of the IRP in Sweden and declines slightly to 7.4% in the US. The evolution of parental assortative mating along with rising maternal persistence are both key to the observed increase in persistence with respect to household income.

4.3 A rising impact of mothers?

Our decomposition showed that underlying the rising IRPs in Section 3 are dramatic changes in the relative contributions of mother's employment, human capital, and income. The variation in these channels across time, country, and gender are all consistent with women's changes in labor supply being a key factor driving rising maternal persistence. These results are interesting, yet leave one question unanswered: to what extent is the rising persistence due to a rising causal impact of mother's income versus declining noise in how mother's income reflects her underlying permanent status? We next provide suggestive evidence on these competing explanations using a measurement-error framework.

It is well recognized that using short-run (parent) incomes as proxies for lifetime income attenuates estimates of intergenerational persistence. Under classical errors, short-run income in t is the sum of lifetime income and a transitory error, $Y_{it} = Y_i + e_{it}$, and the attenuation bias increases with the importance of the transitory income variance, $Var(e_{it})$.[34] Hence, the rising persistence of mothers might be due to a concurrent decrease in $Var(e_{it})$. But for mothers there may be an additional layer of error, if even long-term incomes inaccurately capture underlying socio-economic status. In other words, Y_i itself might be a noisy proxy for true status, Y^*, according to $Y_i = Y_i^* + u_i$

[33]The less prominent role of negative spousal correlations here compared to the maternal persistence decomposition for the US reflects the reduced importance found for fathers.

[34]Lifecycle effects are also well established sources of bias, which we ignore here as we focus on parental incomes measured at prime stages of their careers.

(Vosters and Nybom, 2017; Braun and Stuhler, 2018). Thus, changes in $Var(u_i)$ might also affect trend estimates. After substituting for Y_i, we have

$$Y_{it} = Y_i^* + u_i + e_{it}, \tag{7}$$

where we assume that the additive errors are classical and uncorrelated with each other.

With this model, there are two sources of error to consider: the "status error" u_i and the "income error" e_{it}.[35] We use two instrumental variables (IV) approaches to address each error in turn. In addition, correlations between Y^* and spousal characteristics (e.g., income) may change over time, and thus affect estimated IRPs of (individual) parents (as shown in our decomposition). In our IV approaches, such correlations could violate the instrument exclusion restrictions (and to differing extents over time) so we also estimate specifications conditional on the spouse's income and human capital. Each specification thus mitigates bias from e_{it}, u_i, and/or parental sorting to varying degrees, and with various limitations.

The first approach addresses the "income error" e_{it}. One can use another (noisy) short-run income observation Y_{it+s} as an instrument for the mis-measured one Y_{it}, which eliminates the bias if e_{it} and e_{it+s} are uncorrelated (Nybom and Stuhler, 2017; Altonji and Dunn, 1991).[36] We use parent incomes about 4-5 years apart with the "endogenous" income measured when the child is age 16 and with annual incomes at age 12 and 21 as possible instruments. If changes in transitory variation are driving the rising IRPs for mothers, the error-corrected estimates in the early and late periods should be similar. However, this is not what we find. Table 2 shows consistently large over-time changes in all specifications; in many cases, the error-corrected estimates actually rise more than the baseline IRP.

Turning now to test for the importance of the "status error" u_i, we use a different IV approach. Under certain conditions, instrumenting for income using education or other non-transitory income determinants can eliminate attenuation biases (Zimmerman, 1992). But there are a few caveats. First, any (positive) direct effect of maternal education on child income leads to upward bias. Second, within-variation in income (e.g., within education groups) is fully abstracted from. To get at the "status error" for mothers, the effectiveness of this approach is also limited by, for example, all women having generally lower returns to education due to u_i. Therefore, we construct *potential*

[35] The attenuation factor in the OLS estimate of the IRP is $Var(Y^*)/[Var(Y^*) + Var(u) + Var(e)]$.

[36] We abstract from the fact that if the errors are serially correlated, the bias diminishing effects of both averaging and the IV approach will be smaller.

Table 2: Exploring changes in Mother's IRP

Instrument(s)	Spec.	Sweden 1985-1995	Sweden 2008-2019	Sweden Change	US 1985-1995	US 2008-2018	US Change
OLS (baseline)	1	.052	.114	.062	.024	.122	.098
Income, child age 12	1	.052	.131	.079	.014	.125	.111
Income, child age 21	1	.081	.177	.096	.077	.18	.103
Income, child age 12	2	.033	.108	.075	-.021	.07	.091
Income, child age 21	2	.06	.156	.096	.011	.115	.104
Income, child age 12	3	.034	.081	.047	.004	.115	.111
Income, child age 21	3	.052	.121	.069	.026	.132	.106
Educ, employ	1	.062	.116	.054	.116	.14	.024
Educ, employ	4	.044	.079	.035	.047	.108	.061

Notes: All specifications use the pooled child sample (sons and daughters) and relate their annual income rank within the assigned time period to the income rank of their mother. All included variables have been residualized with respect to age and year using the full-period main sample, as described in Section 4. Row 1 shows the baseline IRP using OLS. Rows 2-7 show IV estimates using parent income at age 12 or 21 as IV for income at age 16. Rows 8-9 use potential income based on education, employment status and their interaction, with the returns to those characteristics estimated using the sample of fathers. Specification 1 (see col. 2) uses no controls; 2 adds mother's education as control; 3 adds mother's education and father's income and education as controls; 4 controls for father's income and education in the second stage.

incomes of mothers using their observed characteristics combined with estimated earnings returns of the corresponding *fathers*, so essentially a two-sample IV (TSIV) using the fathers in the first stage. We use as instruments years of education, employment, and their interaction, and then use our measures of potential income to estimate the IRP.[37]

For both countries, the IRPs (row 8, spec. 1) are larger using our measure of potential income, consistent with some role for the "status error" (i.e., $Var(u_i) > 0$). But for Sweden the levels are only slightly higher than the baseline IRP, and the over-time increase is only marginally smaller in magnitude. For the US, estimates increase more using the IV, and especially so for the early time period, resulting in a much smaller over-time increase. This is consistent with incomes increasingly reflecting underlying status explaining much of the trend for the US: with the estimates taken at face value, this form of measurement error explains roughly 75% of the increased persistence. The higher IV estimates can also reflect an additional causal effect that maternal education has on child adult incomes, which might then be larger in the US.[38] Regardless, the findings are in line with our

[37] Holmlund (2020) uses a similar approach to compute potential incomes of women. Note that our predicted income ranks will have a different variance than actual ranks, so we standardize the predicted measure to have the same variance as income ranks, thus avoiding mechanical differences in the IRP.

[38] We can also consider the corresponding TSIV estimates for fathers (see Table C.2), which are generally similar to or lower than the baseline IRPs, and considerably lower for the later time period. A possible explanation is that

decomposition analysis; in that model, the association between a mother's human capital and her income is approximated by $\tilde{\theta}_p$, which rises substantially for US mothers but remains roughly steady for Swedish mothers. The IV estimates of the IRP become lower when conditioning on father's characteristics in the second stage (see bottom row), and the change over time is slightly smaller for Sweden but larger for the US.[39]

We draw three suggestive conclusions from this exercise. First, it appears that the "status error" u_i is very important for US mothers, and much of the increase in the IRP may be attributable to a growing link between mothers' income and underlying human capital or status. Second, parental sorting can potentially explain some of the increase in the IRP of Swedish but not US mothers, echoing the results from the model decomposition. Lastly, none of our tests wipe out all of the increase in persistence, indicating that at least some of the baseline trend might be due to an increasing causal impact of mothers.

5 Conclusions

While there is emerging evidence on differences in income mobility between sons and daughters, very little research exists on the role of mothers. Our study fills this gap in the literature. We highlight that father-son evidence does not necessarily depict intergenerational mobility that is informative for women. As we show, intergenerational income mobility (or inversely, persistence) has evolved in a markedly different ways for men and women since the mid-1980s, in both Sweden and the US. Persistence involving mothers and/or daughters increased dramatically over time while father-son associations remained largely stable. Furthermore, mother-child persistence is rising at similar rates and levels in Sweden and the US, in contrast to the well-established cross-country difference in mobility for fathers and sons. We also point to the role of women in declining aggregate mobility during recent decades. While our results are primarily descriptive, they support the idea that changes in intergenerational transmission among women are crucial to understand the recent decline in income mobility at the household level.

An examination of the drivers of mother-child persistence divulges notable country differences

within-group variation—income differences conditional on education and employment—which the TSIV abstracts from, plays an increasingly important role for father-child transmission. Moreover, the IV estimates for fathers are not consistent with the instruments having an independent positive effect (i.e., failed exclusion restriction), perhaps lending credence to the interpretation that the larger IV estimates for mothers are due to a decreased "status error".

[39] This is also consistent with our decomposition, as adjusting for this type of spousal sorting has a somewhat different influence in the US because it captures sorting on underlying characteristics (e.g., education), which is stronger than with respect to income in the US.

in the relative contributions of human capital, employment and (parental) spousal sorting, as well as in their evolution over time. The more pronounced role of employment in Sweden coincides with an earlier rise in labor force participation of women, with US women following suit later on. Our decomposition further exposes country differences in the influence of assortative mating. The nonlinearity in mother-father income associations unique to the US shows that there is pressure for women married to high income men to reduce labor supply, whether due to cultural norms or structural components of labor market. If this spousal cross effect weakens in the US, our results predict further declines not only in mobility with respect to mothers, but potentially also with respect to aggregate household income measures.

In general, our paper shows that a narrow focus on traditional measures can fail to capture important social-mobility dynamics in a society, and that it is essential to account for the importance of mothers' income or human capital for their children, even descriptively, rather than relying solely on studies of men. Women's identities are evolving to put more weight on labor market outcomes and economic independence is increasingly important, and not just for single mothers. Higher divorce rates, delayed partnership formation, and a rising prevalence of partnership formation without complete pooling of resources mean women's individual financial viability has become far more salient than for earlier cohorts of women.All these factors can have important implications for income mobility of women and their children, and are not necessarily detectable in our usual persistence estimates. After all, "Women's increased involvement in the economy was the most significant change in labor markets during the past century" (Goldin, 2006).

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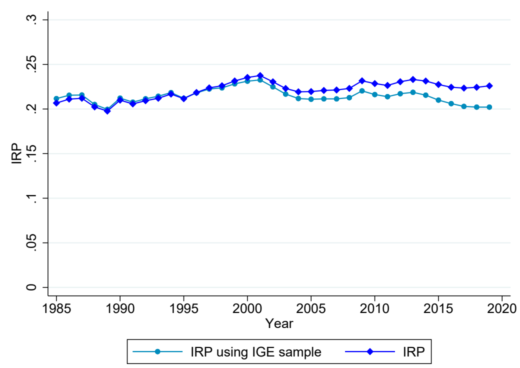
Appendix

A Robustness tests

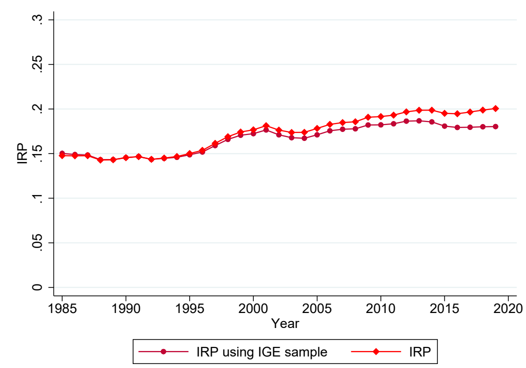
A.1 Sample selection and the influence of zero incomes

Figure A.1: Sample selection analysis: sensitivity to zeros (Sweden)

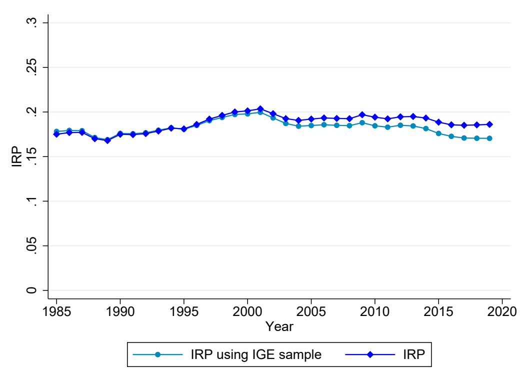
(a) Sons w.r.t. combined parental income



(b) Daughters w.r.t. combined parental income



(c) All children on father's income



(d) All children on mother's income

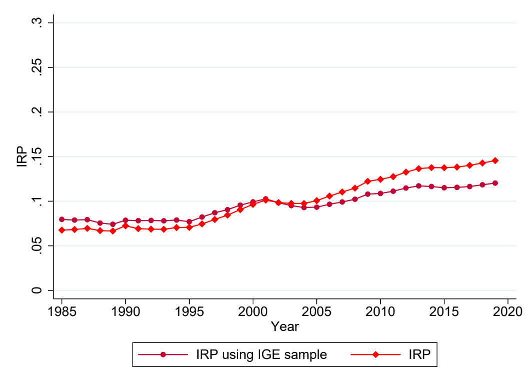
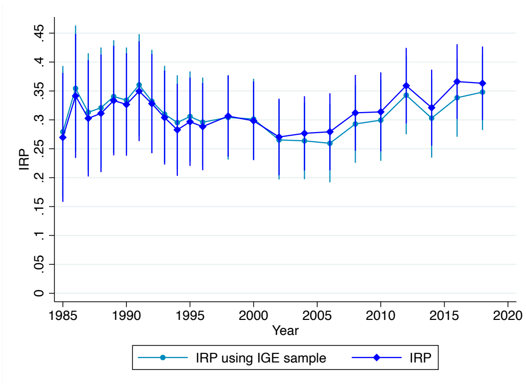
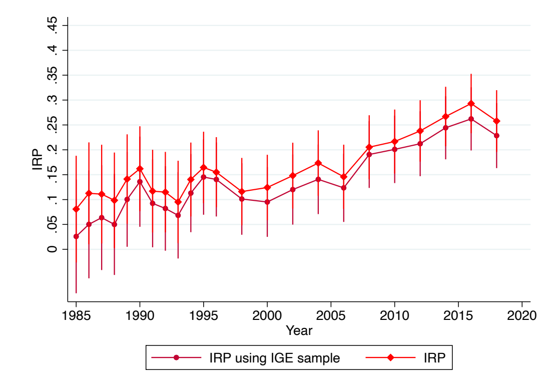


Figure A.2: Sample selection analysis: sensitivity to zeros (US)

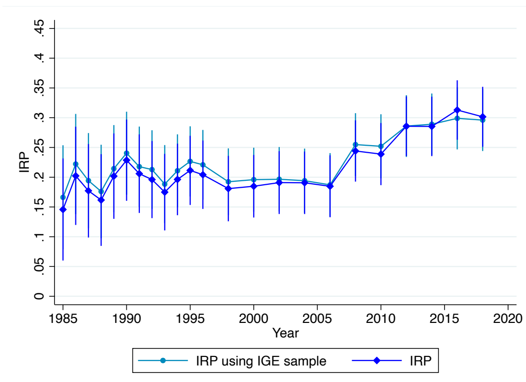
(a) Sons w.r.t. combined parental income



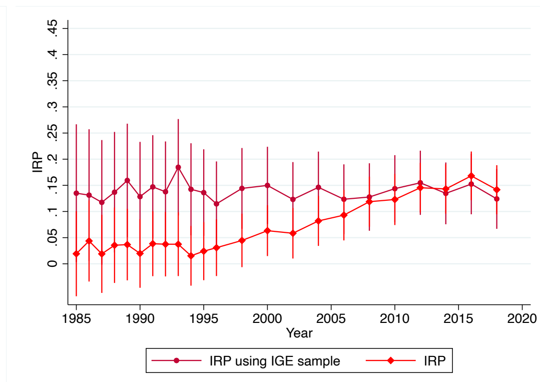
(b) Daughters w.r.t. combined parental income



(c) All children on father's income



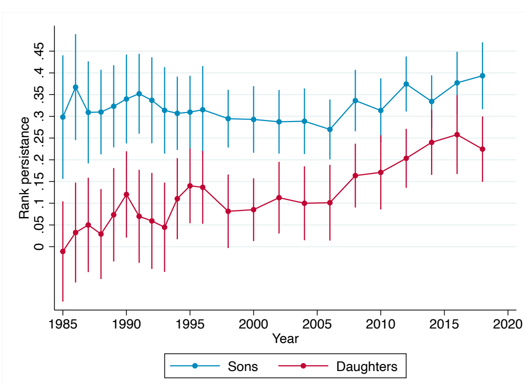
(d) All children on mother's income



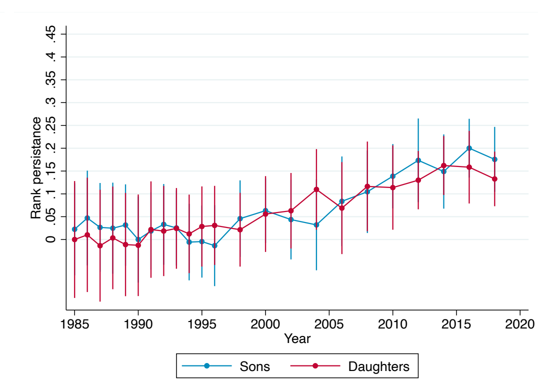
A.2 Sample selection and the combined PSID sample

Figure A.3: Sample selection analysis: US results for combined SRC and SEO sample

(a) Father's income



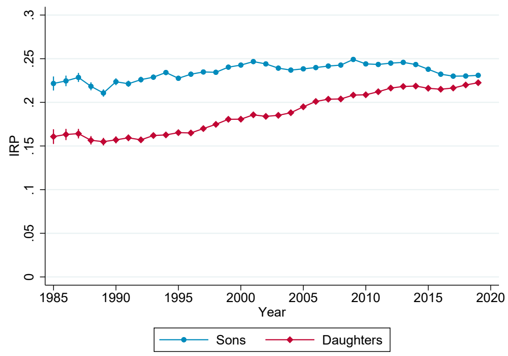
(b) Mother's income



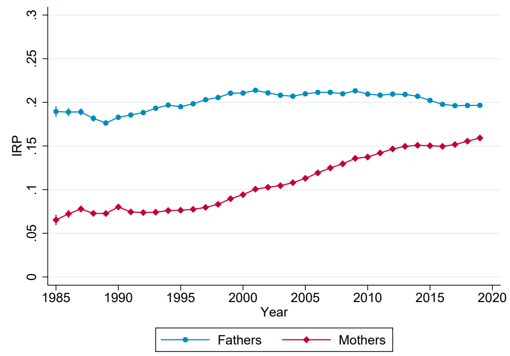
A.3 Main specification for prime-aged children age 33-43

Figure A.4: Child-generation aged 33-43 (Sweden)

(a) Sons and daughters on combined parental income



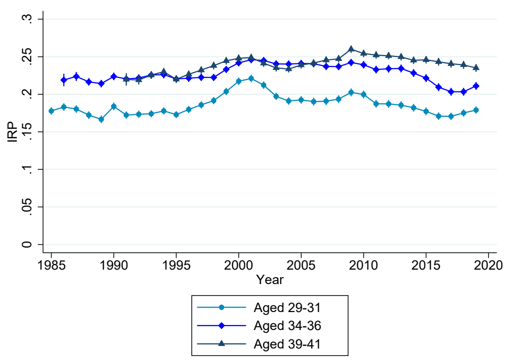
(b) Sons and daughters pooled on father's and mother's income



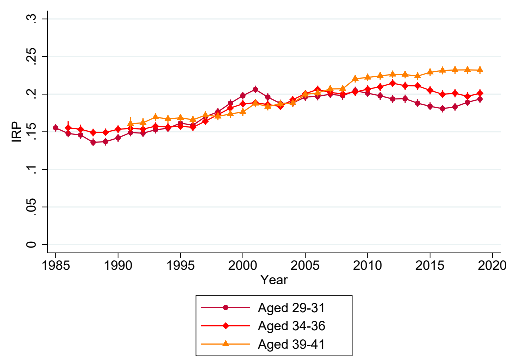
A.4 Different child ages

Figure A.5: Trends for different child ages at income measurement (Sweden)

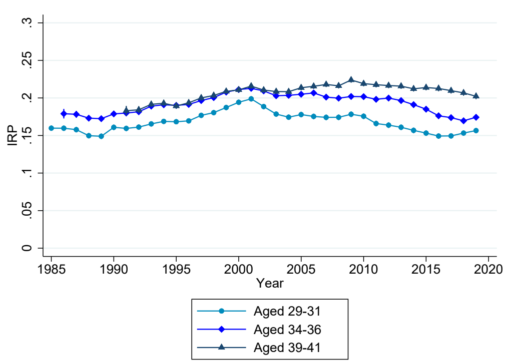
(a) Sons on combined parental income



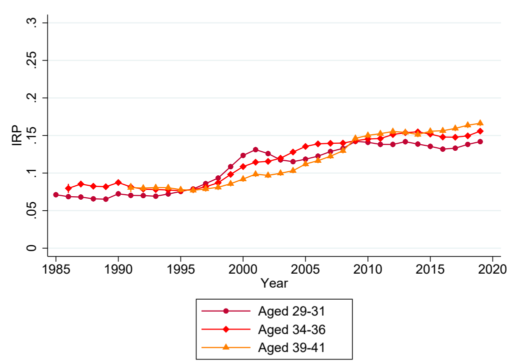
(b) Daughters on combined parental income



(c) Sons and daughters pooled on father's income



(d) Sons and daughters pooled on mother's income



Note: Child-generation aged 29-31 (years 1985-2019); 34-36 (1986-2019); 39-41 (1991-2019) and no child age controls in the regressions.

B Decomposition models

B.1 Basic model

B.1.1 Model estimation

Throughout estimation, we use the residualized measures described in the main text (with age and year effects partialled out). We first estimate the employment equation (2a), saving both the coefficient estimate for ϕ_1 and the residuals (as an estimate of $\hat{\eta}_{ep}$). Next, using these residuals, $\hat{\eta}_{ep}$, as a regressor, we estimate

$$Y_p = \gamma' + (\theta_0\phi_1 + \theta_1)H_p + \theta_0\eta_{ep} + \eta_p, \tag{B.1}$$

obtained by substituting (2a) into (2b) and rearranging. From this regression, we save the residuals as an estimate of $\hat{\eta}_p$ and obtain the coefficient on η_{ep} as an estimate of $\hat{\theta}_0$. With this, we can use the coefficient on H_p, which is an estimate of $(\widehat{\theta_0\phi_1 + \theta_1})$ to then compute $\hat{\theta}_1 = (\widehat{\theta_0\phi_1 + \theta_1}) - \hat{\theta}_0\hat{\phi}_1$.

To obtain estimates of the intergenerational transmission parameters, π_1 and π_2, we estimate a version of equation (3), rearranged here for the sake of clarity in describing our approach:

$$y_c = \pi_0' + [\pi_1(\theta_0\phi_1 + \theta_1) + \pi_2]\, H_p + \pi_1\, [\theta_0\eta_{ep} + \eta_p] + \varphi_c + u_c. \tag{B.2}$$

For estimation, we first create a new variable equal to $[\hat{\theta}_0\hat{\eta}_{ep} + \hat{\eta}_p]$, in order to restrict the coefficients on $\hat{\theta}_0\hat{\eta}_{ep}$ and $\hat{\eta}_p$ to be the same ($\hat{\pi}_1$). We then save the coefficient on this new variable as $\hat{\pi}_1$. With our estimate of $\hat{\pi}_1$, we then compute $\hat{\pi}_2 = [\pi_1(\theta_0\widehat{\phi_1 + \theta_1}) + \pi_2] - \hat{\pi}_1(\hat{\theta}_0\hat{\phi}_1 + \hat{\theta}_1)$.

The variances used in the decomposition are straightforward to compute using the measures or constructed variables (e.g., calculating the variance of $\hat{\eta}_p$). The decomposition elements in equation (4) are then calculated using the estimated parameters and variances.

B.1.2 Decomposition results

Table B.1: IRP decompositions: Separate mother and father models

	Sweden		US	
	1985-95	2008-19	1985-95	2008-18
Mothers: IRP	.056	.119	.046	.145
(1) Human capital channel	.022	.034	.042	.066
(2) Employment channel	.022	.038	.003	.06
(3) Residual income channel	.012	.047	.001	.02
(1a) Human capital only	.011	.019	.008	.031
(1b) Employment-human capital	.011	.015	.034	.035
Mothers #	997223	1858455	1046	2026
Children #	1852582	3677112	2192	3720
Obs #	14126335	29109601	15994	13992
Fathers: IRP	.128	.161	.215	.296
(1) Human capital channel	.038	.036	.127	.111
(2) Employment channel	.018	.042	.009	.039
(3) Residual income channel	.072	.082	.079	.145
(1a) Human capital only	.035	.029	.112	.083
(1b) Employment-human capital	.003	.007	.015	.028
Fathers #	845415	1741880	901	1749
Children #	1589552	3487889	1875	3155
Obs #	24609845	27842712	13803	11990

Notes: The quantities (1a), (1b), (2), and (3) are the calculated elements of the decomposition equation (4), and thus sum to the IRP. Parts (1a) and (1b) sum to the quantity in (1).

B.1.3 Parameter estimates

Table B.2: Parameters: Separate mother and father models

	Sweden		US	
	1985-95	2008-19	1985-95	2008-18
Mothers: IRP	.056	.119	.046	.145
ϕ_1	.026	.022	.032	.038
θ_0	62.673	59.095	60.313	59.583
θ_1	1.842	2.399	.466	2.269
$\tilde{\theta}_p$	3.459	3.72	2.401	4.541
π_1	.038	.098	.005	.089
π_2	.576	.596	2.39	2.454
$Var(H_p)$	7.259	7.616	5.89	4.25
$Var(\eta_{ep})$	.122	.091	.17	.159
$Var(\eta_p)$	251.432	383.192	161.031	186.971
$Var(Y_p)$	815.595	804.851	815.097	838.802
Fathers: IRP	.128	.161	.215	.296
ϕ_1	.003	.008	.01	.018
θ_0	85.96	62.523	48.488	56.971
θ_1	4.083	3.349	4.634	5.123
$\tilde{\theta}_p$	4.318	3.84	5.122	6.175
π_1	.117	.149	.125	.247
π_2	.206	.283	1.529	1.182
$Var(H_p)$	9.565	8.887	8.974	5.394
$Var(\eta_{ep})$	.016	.058	.024	.04
$Var(\eta_p)$	474.681	443.71	494.933	475.596
$Var(Y_p)$	773.191	800.135	786.197	810.731

B.2 Model with assortative mating

B.2.1 Further details on model

A parent starts with some human capital and then chooses a spouse with some human capital H_{sp} according to equation (5a) in the main text. Subsequently, employment status, E_p, is influenced by the human capital of both parents as in equation (5b). Substituting for H_{sp} in the employment equation and rearranging, we get:

$$E_p = (\phi_0 + \phi_2\delta_0) + (\phi_1 + \phi_2\delta_1)H_p + \phi_2\eta_{sp} + \eta_{ep} \tag{B.3}$$

Parental income still follows (2b), so substituting equation (B.3) in for E_p and defining $\gamma' = \gamma + \theta_0(\phi_0 + \phi_2\delta_0)$ gives us:

$$Y_p = \gamma' + [\theta_0(\phi_1 + \phi_2\delta_1) + \theta_1]\, H_p + \theta_0\phi_2\eta_{sp} + \theta_0\eta_{ep} + \eta_p \tag{B.4}$$

To simplify notation in what follows, we aggregate the human capital effects by defining $\tilde{\theta}_p = \theta_0(\phi_1+\phi_2\delta_1)+\theta_1$

and combine the part of parental income orthogonal to human capital by denoting $\eta_{py} = \theta_0\phi_2\eta_{sp} + \theta_0\eta_{ep} + \eta_p$.

Similar to parents, analogous equations for spouses are also defined for sorting ($H_p = \delta_{0s} + \delta_{1s}H_{sp} + \eta_{ss}$), employment ($E_{sp} = \phi_{0s} + \phi_{1s}H_{sp} + \phi_{2s}H_p + \eta_{es}$) and income ($Y_{sp} = \gamma_s^{'} + \tilde{\theta}_s H_{sp} + \eta_{spy}$).

Child human capital depends on the human capital and income of both parents, as shown in equation (5c). The income of the child still follows (2d), so plugging (5c) into this and substituting for parent and spouse incomes, we can write

$$y_c = \pi_0' + \left(\pi_1\tilde{\theta}_p + \pi_2\right) H_p + \pi_1\eta_{py} + \left(\pi_{1s}\tilde{\theta}_s + \pi_{2s}\right) H_{sp} + \pi_{1s}\eta_{spy} + v \tag{B.5}$$

where the error term $v = \varphi_c + u_c$ is uncorrelated with parental characteristics and $\pi_0' = \pi_0 + \pi_1\gamma^{'} + \pi_{1s}\gamma_s^{'}$.

With this last expression for y_c and the parent income equation in (B.4) we derive the probability limit of the OLS estimator of β shown in equation (6).

B.2.2 Additional decompositions

Because combined parent income measures are used frequently, we also derive the probability limit of regression parameter relating child income rank to average parent income (specifically, the average of mother and father ranks):

$$\begin{aligned}
plim\ \hat{\beta}_{avg} = & \underbrace{0.5\left\{\left(\pi_1\tilde{\theta}_p + \pi_2\right)\tilde{\theta}_p\frac{Var(H_p)}{Var(\bar{Y}_p)} + \pi_1\theta_0^2\frac{Var(\eta_{ep})}{Var(\bar{Y}_p)} + \pi_1\frac{Var(\eta_p)}{Var(\bar{Y}_p)}\right\}}_{\text{Parent characteristics}} \\
& \underbrace{0.5\left\{\left(\pi_{1s}\tilde{\theta}_s + \pi_{2s}\right)\tilde{\theta}_s\frac{Var(H_{sp})}{Var(\bar{Y}_p)} + \pi_{1s}\theta_{0s}^2\frac{Var(\eta_{sp})}{Var(\bar{Y}_p)} + \pi_{1s}\frac{Var(\eta_s)}{Var(\bar{Y}_p)}\right\}}_{\text{Spouse characteristics}} \\
& + \underbrace{0.5\left\{\left(\pi_{1s}\tilde{\theta}_s + \pi_{2s}\right)\tilde{\theta}_p\delta_1\frac{Var(H_p)}{Var(\bar{Y}_p)} + \left(\pi_1\tilde{\theta}_p + \pi_2\right)\tilde{\theta}_s\delta_{1s}\frac{Var(H_{sp})}{Var(\bar{Y}_p)}\right\}}_{\text{AM on Human Capital}} \qquad \text{(B.6)} \\
0.5 & \left\{\underbrace{\begin{aligned} & +\pi_1\frac{Cov(\eta_{py},\eta_{spy})}{Var(\bar{Y}_p)} + (\pi_1\tilde{\theta}_p + \pi_2)\frac{Cov(H_p,\eta_{spy})}{Var(\bar{Y}_p)} + \pi_1\tilde{\theta}_s\frac{Cov(H_{sp},\eta_{py})}{Var(\bar{Y}_p)} + \pi_{1s}\theta_{0s}^2\phi_{2s}^2\frac{Var(\eta_{ss})}{Var(\bar{Y}_p)} \\ & + \pi_{1s}\frac{Cov(\eta_{py},\eta_{spy})}{Var(Y_p)} + \pi_{1s}\tilde{\theta}_p\frac{Cov(H_p,\eta_{spy})}{Var(Y_p)} + (\pi_{1s}\tilde{\theta}_s + \pi_{2s})\frac{Cov(H_{sp},\eta_{py})}{Var(Y_p)} + \pi_1\theta_0^2\phi_2^2\frac{Var(\eta_{sp})}{Var(Y_p)}\end{aligned}}_{\text{Other assortative mating/spouse related elements}}\right\}
\end{aligned}$$

B.2.3 Model estimation

Estimation of the extended model in 4.2 is very similar to that for the individual model in Section 4.1. Since outcomes for both parents are included in several of the equations, the initial regressions to residualize each parental outcome measure include the same set of controls, which now include quartics in both mothers' age and fathers' age along with the child age controls and year effects. The residualized measures are used to estimate a sequence of regressions.

We begin by estimating the assortative mating equation in (5a), saving both the estimate of the mating coefficient δ_1 and the residuals, η_{sp}. The residuals then serve as a regressor in estimation of the employment equation in (B.3), with the associated coefficient estimate providing an estimate of ϕ_2. The coefficient estimate on H_p gives an estimate of $(\phi_1 + \phi_2\delta_1)$, so we can now calculate $\hat{\phi}_1 = (\widehat{\phi_1 + \phi_2}\delta_1) - \hat{\phi}_2\hat{\delta}_1$. The residuals from this regression serve as an estimate of η_{ep}. Next we estimate the parent income equation in (B.4), rearranged here to illustrate that creating a new variable equal to $\hat{\phi}_2\hat{\eta}_{sp} + \hat{\eta}_{ep}$,

$$Y_p = \gamma' + [\theta_0(\phi_1 + \phi_2\delta_1) + \theta_1] H_p + \theta_0 [\phi_2\eta_{sp} + \eta_{ep}] + \eta_p \tag{B.7}$$

facilitates the corresponding coefficient serving as an estimate of θ_0. Using the coefficient estimate on H_p as an estimate of the quantity $[\theta_0(\phi_1 + \phi_2\delta_1) + \theta_1]$ and our estimates $\hat{\delta}_1$, $\hat{\phi}_1$, $\hat{\phi}_2$, and $\hat{\theta}_0$, we can calculate the remaining unknown, θ_1.

Because we will also be using parameters and residuals from the corresponding equations for a parent's spouse, we repeat all of the steps up to this point from the perspective of the spouse to obtain the respective parameters and residuals.

After obtaining estimates of the parameters and residuals in the parent and spouse income, employment and mating equations, we turn to estimating the intergenerational transmission parameters, π_1, π_2, π_{1s}, and π_{2s}. We create new variables $\hat{\eta}_{py} = \hat{\theta}_0\hat{\phi}_2\hat{\eta}_{sp} + \hat{\theta}_0\hat{\eta}_{ep} + \hat{\eta}_p$ and $\hat{\eta}_{spy} = \hat{\theta}_{0s}\hat{\phi}_{2s}\hat{\eta}_{ss} + \hat{\theta}_0\hat{\eta}_{es} + \hat{\eta}_s$. With these constructed variables in a rearranged version of the child income equation in B.5,

$$y_c = \pi_0' + \left(\pi_1\tilde{\theta}_p + \pi_2\right) H_p + \pi_1\eta_{py} + \left(\pi_{1s}\tilde{\theta}_s + \pi_{2s}\right) H_{ps} + \pi_{1s}\eta_{spy} + v \tag{B.8}$$

we can now estimate the remaining parameters. The estimates, $\hat{\pi}_1$ and $\hat{\pi}_{1s}$, are obtained from the coefficients on the constructed variables, $\hat{\eta}_{py}$ and $\hat{\eta}_{spy}$, respectively. An estimate of $\tilde{\theta}_p = \theta_0(\phi_1 + \phi_2\delta_1) + \theta_1$ is easily calculated using the estimates of the underlying parameters, and similarly for $\tilde{\theta}_{sp}$. Then we can obtain $\hat{\pi}_2 = \pi_1\widehat{\tilde{\theta}_p + \pi}_2 - \hat{\pi}_1\hat{\tilde{\theta}}_p$, and similarly for $\hat{\pi}_{2s}$.

For the decomposition in equations (6), we use the parameter estimates along with estimates of the variances.

B.2.4 Decomposition results

Table B.3: IRP decompositions: Model with assortative mating

	Sweden		US	
	1985-95	2008-19	1985-95	2008-18
Mothers: IRP	.054	.114	.025	.122
Own Characteristics	.04	.083	.025	.112
(1) Human capital channel	.009	.02	.009	.024
(2) Employment channel	.019	.028	.012	.066
(3) Residual income channel	.011	.035	.003	.022
(1a) Human capital only	.004	.011	.002	.011
(1b) Employment-human capital	.005	.009	.008	.013
AM / Spouse Characteristics	.014	.031	.001	.01
(4) AM on Human capital	.009	.009	.022	.028
(5) Other AM, spouse char.	.004	.022	-.021	-.018
Fathers: IRP	.124	.154	.21	.292
Own Characteristics	.115	.129	.19	.272
(1) Human capital channel	.029	.022	.106	.087
(2) Employment channel	.017	.035	.009	.038
(3) Residual income channel	.069	.072	.075	.146
(1a) Human capital only	.026	.017	.092	.065
(1b) Employment-human capital	.003	.004	.014	.023
AM / Spouse Characteristics	.009	.026	.02	.02
(4) AM on Human capital	.007	.01	.017	.022
(5) Other AM, spouse char.	.002	.015	.003	-.002
Mothers #	822118	1729375	872	1652
Fathers #	811557	1713515	871	1646
Children #	1525143	3425551	1828	2976
Obs #	11103783	27406842	13552	11263

Notes: The quantities (1a), (1b), (2), and (3) are the calculated elements of the decomposition equation (6), and thus sum to the IRP. Parts (1a) and (1b) sum to the quantity in (1).

Table B.4: Decomposition of IRP for average parent income measure

	Sweden		US	
	1985-95	2008-19	1985-95	2008-18
IRP	.158	.216	.246	.401
Mother's characteristics (%)	23.5	31.4	10.7	28
Father's characteristics (%)	63.6	47.4	80.5	64.7
Assortative mating (AM) (%)	13	21.2	8.8	7.4
AM on human capital (%)	9.1	7.2	16.8	12.3
Other AM, spouse char. (%)	3.9	14	-8	-4.9

Notes: The numbers shown are the percent of the IRP attributable to a particular channel.

B.2.5 Parameter estimates

Table B.5: Parameters: Model with assortative mating

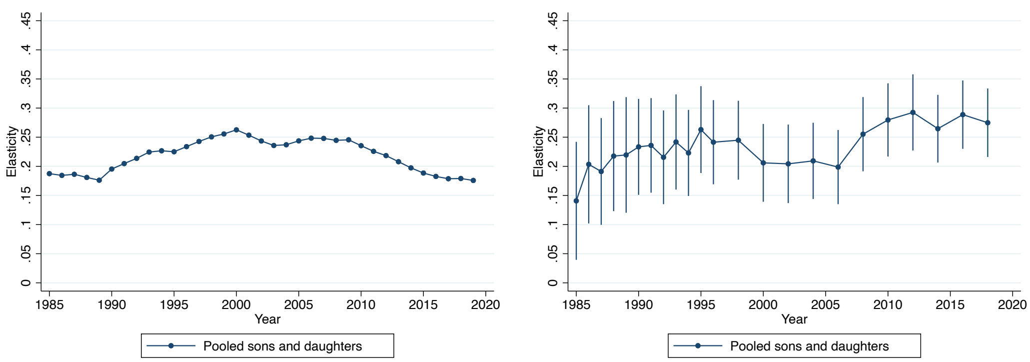
	Sweden				US			
	Fathers		Mothers		Fathers		Mothers	
	1985-95	2008-19	1985-95	2008-18	1985-95	2008-19	1985-95	2008-18
IRP	.124	.154	.054	.114	.21	.292	.025	.122
π_1	.111	.127	.034	.073	.118	.245	.016	.097
π_2	.085	.057	.177	.305	1.247	.655	.598	.73
π_{1s}	.034	.073	.111	.127	.016	.097	.118	.245
π_{2s}	.177	.305	.085	.057	.598	.73	1.247	.655
$Var(Y_p)$	752.809	771.353	800.773	791.657	772.522	790.603	788.739	829.397
$Var(H_p)$	9.402	8.656	7.456	7.542	8.756	5.25	5.279	4.051
$Var(\eta_{ep})$	.016	.055	.117	.086	.023	.038	.164	.157
$Var(\eta_p)$	470.144	439.829	264.19	383.555	492.006	470.093	164.067	189.104
$Var(\eta_{sp})$	5.729	5.917	7.224	6.791	3.264	2.856	5.415	3.701
$Var(\eta_{py})$	586.953	654.325	716.225	688.568	548.214	594.095	762.889	755.205
$Var(H_{sp})$	7.456	7.542	9.402	8.656	5.279	4.051	8.756	5.25
$Var(\eta_{ss})$	7.224	6.791	5.729	5.917	5.415	3.701	3.264	2.856
$Var(\eta_{es})$	.117	.086	.016	.055	.164	.157	.023	.038
$Var(\eta_s)$	264.19	383.555	470.144	439.829	164.067	189.104	492.006	470.093
$Var(\eta_{spy})$	716.225	688.568	586.953	654.325	762.889	755.205	548.214	594.095
$Cov(H_p, \eta_{spy})$	-.451	3.582	4.49	5.981	-5.044	-4.959	5.713	4.103
$Cov(H_{sp}, \eta_{py})$	4.49	5.981	-.451	3.582	5.713	4.103	-5.044	-4.959
$Cov(\eta_{py}, \eta_{spy})$	17.746	100.974	17.746	100.974	-75.586	-35.854	-75.586	-35.854
θ_0	85.67	62.162	62.107	59.526	48.781	57.038	60.341	59.685
θ_1	3.978	3.266	1.857	2.442	4.56	5.121	.422	2.278
$\tilde{\theta}_p$	4.2	3.677	3.367	3.697	5.061	6.118	2.213	4.28
ϕ_1	.003	.004	.026	.021	.007	.016	.04	.047
ϕ_2	0	.006	-.004	0	.007	.002	-.013	-.022
ϕ_{1s}	.026	.021	.003	.004	.04	.047	.007	.016
ϕ_{2s}	-.004	0	0	.006	-.013	-.022	.007	.002
δ_1	.429	.433	.54	.497	.48	.477	.796	.618
δ_{1s}	.54	.497	.429	.433	.796	.618	.48	.477
θ_{0s}	62.107	59.526	85.67	62.162	60.341	59.685	48.781	57.038
θ_{1s}	1.857	2.442	3.978	3.266	.422	2.278	4.56	5.121
$\tilde{\theta}_s$	3.367	3.697	4.2	3.677	2.213	4.28	5.061	6.118

C Additional trends results

We also provide aggregate trends in the IGE for comparison to prior studies, shown in Figure C.1. For our measure of log earnings, we exclude outlier observations for which annual earnings are lower than USD100 (in 1967 prices). Similar to our aggregate measure for the IRP, here we take the log of the average (of parents) or annual (of children) earnings. We pool all children and relate their (individual) log earnings to the log combined earnings of their parents. Because we pool sons and daughters, estimated persistence levels are slightly lower than prior work focusing on fathers and sons or household incomes. Each point in the graph represents an estimate of β_t from equation (1) for a given year t.

Figure C.1: Aggregate trends for all children (IGE)

(a) Sweden   (b) United States



For Sweden (subfigure C.1a), the IGE rose during the 1990s, when a deep recession hit the country and earnings inequality rose rapidly. However, the IGE fell and mobility increased during the 2000s, and was by the end of the period at a similar level as in the late 1980s. While we thus see variation over time, there is not much evidence of a long-run change in intergenerational mobility as measured by the IGE.

For the US (subfigure C.1b), we see signs of an increasing IGE but with substantial statistical uncertainty. The point estimates are consistently between 0.20-0.25 for much of the time period, but then settle in closer to 0.30 after 2010. Overall, the US results are thus consistent both with studies that fail to find a significant change in mobility (Lee and Solon, 2009; Chetty, Hendren, Kline and Saez, 2014) and those that indeed find an increase (decrease) in the IGE (mobility) (e.g., Justman and Stiassnie, 2021).

Because the IGE and IRP estimates based on the PSID are relatively imprecise, we also obtain estimates from a modified version of our main specification where we interact parent income with three time period dummies—for early (1985-1995), middle (1996-2007), and late (2008-2018) periods—rather than year dummies. Table C.1 provides the estimates, the late minus early change in the estimates, and the p-value for the statistical significance of these changes.

Table C.1: Statistical significance of changes in US persistence from early to late period

Persistence measure	Time period	Estimate	Std. Err.	Difference	Std. Err.	p-value
IGE (parent-child)	1985-95	.228	.035	.055	.034	.1072
	2008-19	.283	.025			
IRP (parent-child)	1985-95	.218	.027	.075	.026	.0044
	2008-19	.293	.019			
IRP (parent-daughter)	1985-95	.128	.037	.121	.037	.0009
	2008-19	.249	.026			
IRP (parent-son)	1985-95	.313	.04	.027	.037	.4727
	2008-19	.34	.027			
IRP (father-child)	1985-95	.196	.03	.084	.029	.0038
	2008-19	.28	.021			
IRP (mother-child)	1985-95	.029	.029	.11	.028	.0001
	2008-19	.139	.02			
IRP (father-daughter)	1985-95	.067	.042	.146	.041	.0004
	2008-19	.213	.03			
IRP (father-son)	1985-95	.328	.042	.019	.04	.6343
	2008-19	.347	.03			
IRP (mother-daughter)	1985-95	.033	.041	.109	.039	.0059
	2008-19	.141	.028			
IRP (mother-son)	1985-95	.02	.041	.117	.039	.0029
	2008-19	.137	.028			

Notes: Estimates by period are from estimating our main specification modified to estimate β_t for three time periods $t = 1985-95, 1996-2007, 2008-2019$ rather than each year. The difference is the late minus early period estimate, and the last two columns contain the standard error of this difference and the p-value for whether the difference is statistically significant.

Figure C.2: Trends in mother-child IRP, unconditional and conditional on fathers' income or schooling

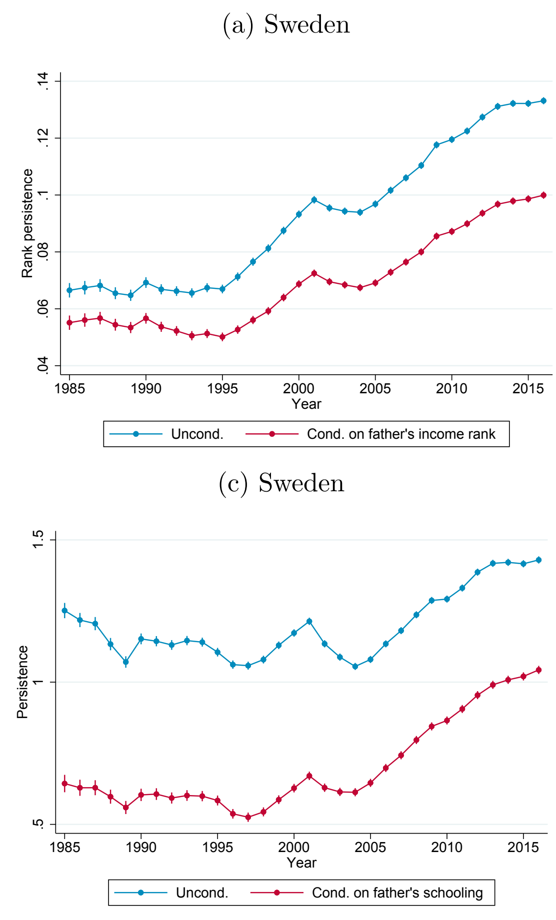


Table C.2: Exploring changes in Father's IRP

		Sweden			US		
Instrument(s)	Spec.	1985-1995	2008-2019	Change	1985-1995	2008-2018	Change
OLS (baseline)	1	.125	.157	.032	.217	.295	.078
Income, child age 12	1	.145	.188	.043	.236	.335	.099
Income, child age 21	1	.154	.201	.047	.241	.347	.106
Income, child age 12	2	.137	.178	.041	.138	.284	.146
Income, child age 21	2	.148	.195	.047	.154	.305	.151
Income, child age 12	3	.13	.155	.025	.128	.294	.166
Income, child age 21	3	.143	.167	.024	.149	.303	.154
Educ, employ	3	.086	.112	.026	.22	.235	.015
Educ, employ	4	.072	.08	.008	.17	.19	.02

Notes: All specifications use the pooled child sample (sons and daughters) and relate their annual income rank within the assigned time period to the income of their father. All included variables have been residualized with respect to age and year using the full-period main sample, as described in Section 4. Row 1 shows the baseline IRP using OLS. Rows 2-7 show IV estimates using parent income at age 12 or 21 as IV for income at age 16. Rows 8-9 use predicted income based on education, employment status and their interaction. Specification 1 (see col. 2) uses no controls; 2 adds father's education as control; 3 adds father's education and mother's income and education as controls; 4 controls for mother's income and education in the second stage.