NBER WORKING PAPER SERIES

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Working Paper 33023
http://www.nber.org/papers/w33023

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2024

This research was supported in part by an anonymous funder, the ROCKWOOL Foundation, and NIH grant NICHD R37HD065072. The views expressed in this paper are solely those of the authors and do not necessarily represent those of the funders or the official views of the National Institutes of Health. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 33023
October 2024
JEL No. D31, I24, I30

ABSTRACT

This paper studies intergenerational mobility—the transmission of family influence. We develop and estimate measures of lifetime resources motivated by economic theory that account for differences in life-cycle trajectories, and uncertainty about future income. We identify the effects of parents' resources on child outcomes through policy shocks at different childhood ages that affect family investments. Parents' expected lifetime resources are stronger predictors of child outcomes than the income measures traditionally used in the literature on social mobility. Moreover, while effects estimated through exogenous variation in parents' expected lifetime resources are smaller in magnitude than their correlational counterparts, they are still sizable and largest in early childhood. The paper illustrates how integrating key insights from different literatures when studying intergenerational mobility allows for a better understanding of the importance of factors such as the family's role, changes in individual life cycles across generations, and the expectations and trajectories individuals face across their lifetimes.

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1 Introduction

This paper studies the transmission of family influence between parents and their children. We present measures of lifetime resources allowing us to study the relationship between parents' resources and child outcomes at crucial stages of children's lives. We incorporate exogenous shocks to parents' resources that allow us to identify the effects of expected resources on children's later outcomes.

The conventional approach to measuring social mobility estimates intergenerational elasticities (IGEs) of income following the pioneering work of Becker and Tomes (1979, 1986) and the sociologists who preceded them (Blau and Duncan, 1967; Blau et al., 1994; Hauser and Featherman, 1976). This approach treats childhood as a single-stage in a three-stage overlapping generations model that is followed by adulthood (when parents invest in children) and retirement. This literature i) ignores uncertainty and abstracts from timing considerations within the various stages of the life cycle, ii) focuses on *realized* lifetime resources across generations often measured over shorter time spans to proxy lifetime incomes due to data limitations, iii) emphasizes the role of measurement errors and alignment of ages across generations,[1] iv) relies on implicit assumptions of stationarity or limited forms of nonstationarity to characterize life cycles across generations,[2] and v) is largely correlational in nature.

Another strand of literature measures the correlates of successful lives—e.g., education, health, and participation in crime—across generations.[3] Recent research on human development (e.g., Cunha and Heckman, 2007; Heckman and Mosso, 2014) demonstrates the importance of critical and sensitive periods in shaping lifetime skills. In the presence of imperfect capital markets, the timing

[1]Focus has been on attenuation bias due to measuring income over short age intervals and life-cycle bias if income is not measured at ages that approximate lifetime income flows captured by Mincer's (1974) notion of the "overtaking age" (see Mazumder, 2005; Solon, 1992; Willis, 1986, for discussion of alignment).

[2]Nybom and Stuhler (2024) is an important recent exception.

[3]The first strand is connected with the second strand because parental lifetime resources help determine the resources available to invest in children. Conventional one-period-lifetime models of family influence, like Becker and Tomes (1979, 1986) and Solon (2004), provide a tight link between the two approaches.

of parental income plausibly affects parental investments in children.[4] Recognizing the importance of child investment at early ages on child lifetime outcomes, it is the resources of parents at those ages that are relevant to the transmission of family influence.

This paper unites and extends these two strands of literature on social mobility in several ways: We motivate, formulate, and estimate expected lifetime resources to analyze intergenerational dependence. We analyze the *expected present discounted value of future income* (*PDV*), which recognizes that the timing of key life events differs greatly across generations and individuals, and the updating of relevant information over the lifecycle. In doing so, we explicitly account for agent information sets about current and future resources that govern child investment decisions and *ex ante* measures of lifetime resources. We estimate information sets by age to account for the evolution of uncertainty and its consequences. The crucial distinction between *ex post* and *ex ante* measures is absent from previous studies. Realized lifetime incomes are measures of lives well lived. However, expected lifetime incomes at different ages are measures of resources available for consumption and child investment at those ages. A life well endowed at age 35 may not be one well endowed at age 50. As individuals progress through life, expected incomes are the relevant measures of age-by-age command of resources, thus, of interest in itself.

We compare results based on commonly used proxy measures with those based on actual lifetime resources (*ex post*) and find that this leads to substantial differences in the magnitude of estimated social mobility in both relative and absolute terms. Using rich Danish register data spanning 40 years, we find that frequently used measures of realized incomes substantially underestimate lifetime intergenerational persistence. For example, the intergenerational dependence measured by log-log regressions (IGE) is 0.29 for snapshot measures of realized wage income but around 0.50 when considering expected lifetime resources and 0.40 when considering realized lifetime resources. This pattern holds for alternative measures of intergenerational income mobility such as Pearson correla-

[4]See Cunha and Heckman (2007) and Caucutt and Lochner (2020). Related, Carneiro et al. (2021) find that parental income in early childhood is a better predictor of children's prospects than parental income in middle childhood.

tions and rank-rank measures.[5]

Ex ante lifetime measures of parental resources also better predict child cognitive skills, education, crime, and teenage pregnancy compared to measures of realized parental income averaged over 40 years. They do so because they better proxy the resources parents act on when they make investment decisions, while also accounting for the substantial intercohort changes in educational attainment and family formation, which causes income measured over fixed age ranges across cohorts to be inaccurate proxies of individual expectations of lifetime resources at the ages where they are computed.[6]

Having documented the importance of integrating individual and family life-cycle income dynamics and updating of information when studying social mobility, we utilize yearly variation in income-tax schedules, interest rates, and income transfer rates throughout childhood to draw three main conclusions. First, the effects of parental resources at a given age of the child are 20-30% lower than the corresponding OLS estimates. For example, the OLS and corresponding IV estimates of the IGE for parental resources measured at ages 0–4 of the child are 0.51 and 0.42, respectively. Thus, while correlational evidence overstates the actual effects of parental resources, the underlying impact identified through plausible exogenous variation in parents' resources is still stronger than earlier IGE estimates based on the conventional income measures using Danish

[5]See Aaronson and Mazumder (2008); Corak (2006); Corak and Heisz (1999); Mazumder (2005); Solon (1992) for examples of studies focusing on the alignment of incomes across generations. Black and Devereux (2011) and Jäntti and Jenkins (2015) review the literature on intergenerational income mobility and Deutscher and Mazumder (2023) review different measures commonly used. There are additional related studies that focus on other dimensions of intergenerational persistence, such as wealth (Boserup et al., 2017; Charles and Hurst, 2003), consumption expenditures (Charles et al., 2014; Waldkirch et al., 2004), occupations (Bello and Morchio, 2017; Corak and Piraino, 2011), incarceration and criminal behavior (Dobbie et al., 2018; Meghir et al., 2012), health (Björkegren et al., 2019; Johnston et al., 2013), and employment and welfare dependency (Li and Goetz, 2019; Lo Bello and Morchio, 2020).

[6]Focusing on expected lifetime resources also shapes estimated absolute upward mobility with upward mobility being almost as large for children from affluent background as it is for children from disadvantaged background.

data (see e.g., Landersø and Heckman, 2017).

Second, children's expected lifetime resources and years of completed schooling are most sensitive to parents' expected lifetime resources in early childhood. Yet, while the importance of parental resources declines as a child ages, family resources remain important even in adolescence.

Finally, there are important differences in IV estimates across both parental income levels and child gender. The effects of parents' expected lifetime resources on children's expected lifetime resources are largest for children from high-income families and for males. These results illustrate a strong persistence in economic resources across generations in affluent families and speak to the role of gender differences in the labor market as a mediator of how the transmission of family influence manifests.

Our paper integrates key insights from different economic literatures. We demonstrate the importance of factors such as the role of the family, changes in individual life cycles across generations, and the expectations and trajectories individuals face across their lifetimes in studying intergenerational mobility .

This paper unfolds as follows: Section 2 defines our lifetime measures. Section 3 describes our data. Section 4 explains the identification and estimation procedures. Section 5 documents cohort differences in life cycles and compares the predictive properties the paper's measures of parental resources. Section 6 presents our estimates of intergenerational mobility including IV results based on policy innovations. Section 7 extends the analysis by presenting results for children's educational attainment, by subgroups, and for absolute mobility. Section 8 concludes. An appendix for online publication presents supporting technical and empirical arguments.

2 Our Measures of Lifetime Resources

One novelty of this paper is that we introduce life cycle, stage–specific measures of resources that adjust for agent uncertainty by estimating agent information sets that computation of the PDV that serves to determine child investment decisions. We focus on expected PDVs, which represent the discounted future cash flows. We focus on how these allow us to better account for lifecycle dynamics within and across generations to improve the estimates of intergenerational transmission of family influence.

We analyze estimates using two different versions of lifetime resources: *ex ante* and *ex post* (anticipated and realized, respectively). The *ex ante* measure of resources is what enters parents' decision rule about investing in children at age a and their expectations about the future at that age. In contrast, the *ex post* measure is consistent with perfect foresight. In practice, parents do not know their lifetime income when their children are young. Yet, this is the implicit assumption in a vast literature on intergenerational mobility.

This section introduces our measures. In Sections 5 and 6, we show that distinguishing between *ex ante* and *ex post* measures matters empirically.

2.1 Measures of Expected Lifetime Resources

We think of individual income evolving according to a general function that maps their known information at age a, X_a, as well as a shock, ε_a, to their income, y_a:

$$y_a = g(X_a) + \varepsilon_a. \tag{1}$$

Their information set $\mathcal{I}_a$ comprises their knowledge of their future expected returns given their current information X_a plus the realized shock ε_a. Thus, the expected present discounted value at age a is

$$E(PDV_a) = \sum_{k>a} \beta^{k-a} \mathbb{E}_a[g(X_k) + \varepsilon_k | \mathcal{I}_a] \tag{2}$$

Here we make no assumptions about ε_k. We discuss restrictions we place in Section 4 when we discuss estimation.

Expected PDV

Given the information set $\mathcal{I}_{i,t}$ available to individual i in period t, the expected PDV is

$$
\begin{aligned}
E(PDV_{i,t}) &= \mathbb{E}_{i,t}\left[\sum_{\tau=1}^{T-t} \beta^{\tau} y_{i,t+\tau} \middle| \mathcal{I}_{i,t}\right] \\
&= \mathbb{E}_{i,t}\left[\beta(y_{i,t+1} + \text{PDV}_{i,t+1}) \middle| \mathcal{I}_{i,t}\right]
\end{aligned} \tag{3}
$$

where β is a fixed discount factor, and $y_{i,t}$ is income in period t. The expected PDV is individual i's expected present value of future income flows measured at period t. This measure improves on the way income has been measured in the previous literature, by considering a full life-cycle perspective and by allowing for differences in age profiles across generations and individuals.

For example, later generations, on average, acquire more formal education. This means that they are more likely to have lower incomes at younger ages than their parents who do not attend college, compensated by higher (and steeper) income profiles when entering the labor market after completing their higher education. We show evidence on these patterns across generations in Section 5.2. The expected PDV takes into account that more highly educated individuals face steeper expected income profiles and that income profiles have changed across generations. We also report a realized lifetime version of Equation (3)

$$
PDV_{i,t} = \sum_{\tau=1}^{T-t} \beta^{\tau} y_{i,t+\tau} \tag{4}
$$

Observing the full life cycle is, however, only possible for parents. Therefore, when we estimate intergenertional income mobility, we consider the association between parents' realized PDV and children's expected PDV.

2.2 Instruments for Expected Lifetime Resources

We lack data on precise measures of child investment at each age. However, we draw on an established literature that relates investment in children at age a to the resources of the family at that age (see, e.g., Becker and Tomes, 1979, 1986; Caucutt and Lochner, 2020; Solon, 1992). We relate child outcomes to our measures of family resources at each age of the child. There are many sources of intergenerational dependence in income flows: pure income effects, correlated ability and cultural values are among many. To isolate pure income effects. We develop and apply instrument.

We compute the updates to the expected PDV at each age after the realization of policy changes. To instrument for parental expected lifetime income, we construct instruments based on how much these policy changes affect parent's after-tax income. The policy variations we consider here include all year-to-year income-tax changes at national and local level, year-to-year changes to transfer rates (such as social assistance), and year-to-year changes to interest rates. Appendix Section A describes these in detail.

To gain intuition about our approach, consider the major tax reform in Denmark in 1987. We note that changes in log parental after-tax income in 1987 (right after the tax reform), $log(Y_{87})$, are partly attributable to the different tax schemes in 1986 and 1987. Post-reform parental income can be decomposed into two components, a component that is exogenously induced by the tax changes and a residual component. To capture the exogenous changes due to the tax reform, we form a ratio $\Delta_{Y_{86}}^{T_{87}} = log\left(\frac{Y_{86}|T_{87}}{Y_{86}|T_{86}}\right)$, where $Y_t|T_{t'}$ is the counterfactual after-tax income at time t if the tax scheme of the year t' was in place (t and t' are equal to 1986 and 1987 respectively in the example illustrated above for the 1987 tax reform). Let $\mathcal{Y}$ denote pre-tax total income and $T_t(.)$ denotes the tax scheme that was in place in year t, so $Y_t|T_t = \mathcal{Y}_t - T_t(\mathcal{Y}_t)$ is the after-tax income in year t and $Y_t|T_{t'} = \mathcal{Y}_t - T'_t(\mathcal{Y}_t)$ is the counterfactual after-tax income in year t assuming $T_{t'}$ (the tax scheme of the year t') was enacted in year t. Using Δ terms as our instruments, we obtain instrumentals. We assume stationary expectations about tax cuts, i.e., that they are expected to last forever.

We extend this approach and compute instruments for all years and other policy changes. We construct policy instruments by combining updates to the following policies in year t: tax policy (T), interest rate (r), public transfer scheme (S). For tax policy, the policy update for year t is calculated as: $\Delta_t^T = (Y_t|T_{t+1}) - (Y_t|T_t)$ where Y_t denotes after-tax income in year t and T_t denotes tax scheme in year t. Likewise, for interest rate update, we calculate the update as: $\Delta_t^r = (Int_t|r_{t+1}) - (Int_t|r_t)$ where Int_t denotes net interest income in year t and r_t denotes real interest in year t, and updates linked to changes in aggregate monetary policy. Policy update for public transfer income (social cash assistance, unemployment benefits and child assistance) is calculated as: $\Delta_t^S = (Soc_t|S_{t+1}) - (Soc_t|S_t)$ where Soc_t denotes the public transfer income received in year t and S_t denotes public transfer scheme in year t.[7]

After calculating each component at time t, we calculate the combined policy instrument as:

$$\Delta_t = log(Y_t + \Delta_t^T + \Delta_t^r + \Delta_t^S) - log(Y_t) \tag{5}$$

To compute our policy instruments, we exploit the changes in policies across two consecutive years t and $t+1$. Changes in taxes from year t to $t+1$ are used as instrument for expected PDV measured in year $t+1$. We construct the policy instrument at both paternal and household levels. At the household level, we calculate each component of the instrument ($\Delta_t^T, \Delta_t^r, \Delta_t^S$) separately for fathers and mothers and aggregate these two components in the first logged term in Equation (5) to calculate the household level policy innovation. This approach is valid because Danish income tax are based on individual filing with a few within household deductions and allowances. A concern may be that parents' respond to policies between year t and $t+1$ in terms of e.g., changes in labor supply, which would in turn affect their future expected income. Therefore, as a robustness check, we also compute instruments using a 2-year lag, which mitigates this concern.[8] These results mimic the patterns in our main specification.

[7]We observe year-by-year changes in public transfer income rates during our observation period. We specifically focus on the following benefits: cash assistance benefits (which is applicable for people experiencing social incidences –such as illness, unemployment, and end of cohabitation– and cannot support themselves or their family, and the need for support cannot be met by other benefits like unemployment benefit), child allowances (paid until the quarter the child reaches 18), and unemployment benefits (based on the 12 months in which one had the highest income within the past 24 months, with a maximum amount based on insurance status).

[8]We compute them as $\tilde{\Delta}_t = log(Y_t + \tilde{\Delta}_t^T + \tilde{\Delta}_t^r + \tilde{\Delta}_t^S) - log(Y_t)$ where $\tilde{\Delta}_t^T = (Y_t|T_{t+2}) - (Y_t|T_t)$ is for tax changes, $\tilde{\Delta}_t^r = (Int_t|r_{t+2}) - (Int_t|r_t)$ takes into account interest rate changes, and $\tilde{\Delta}_t^S = (Soc_t|S_{t+2}) - (Soc_t|S_t)$ captures changes to public transfer income from year t to $t+2$. Appendix F.1 presents the results.

3 Our Data

We use full population administrative register data from Denmark in the years 1980 through 2019. The data contain unique identifiers of individuals, which enable us to combine information on a wide range of different outcomes across the lifetime. The data also include unique identifiers of parents and spouses, allowing us to link families throughout the entire period. In addition to information on income, assets, and liabilities of children and their parents, we also add information on completed education, household structure and demographic characteristics, 9th-grade exam scores, and crime. Appendix B provides a detailed description of all of the data sources and definitions we use.

Our main sample consists of children born in 1981 and 1982 for whom we can establish a link to parents. We observe the birth cohorts of 1981 and 1982 from birth to age 38 and 37, respectively (in 2019). We have information on their parents in all years between 1980 and 2019.[9]

Measuring Income

For the main analyses in this paper, our specifications using log income exclude individuals with zero or negative average income for the age range over which we measure their income. We restrict the sample to children born in Denmark. We start with a sample of 105,953 native Danes who did not migrate, whose parents did not migrate, and for whom we can establish links with their parents. This reduces to 100,344 when dropping observations with zero or negative values of resources, and reduces further to 98,686 when we drop children with fewer than three observations. We measure children's income at ages 30–35 in the years 2011–2016 and 2012–2017 for the 1981 and 1982 cohorts, respectively.[10]

[9] We analyze other cohorts, sampled in the same way as described here, to assess the robustness of our results.

[10] For the measures using information from ages 30–35, we drop observations with parents older than 35 in 1980 (i.e., parents ages 37 or older for birth cohort 1981 and 38 or older for birth cohort 1982). This removes 8.10% of the population. However, we do not have to make such restrictions in our main specifications using parents' resources centered around children's ages (e.g., parents' resources when the child was ages 0–4).

One question is whether to measure parents' resources at fixed ages of children to approximate investments during childhood or at fixed ages of parents to ensure that child-parents comparisons are performed at similar ages. For completeness we consider both approaches in the paper.

First it should be noted that while our lifetime measures (ex ante and ex post PDV) are computed at specific age ranges of children or parents, they are based on full life cycle information. We estimate the expected PDV as described in Section 4 and we estimate parents' realized lifetime resources using income in all years until 2019 discounted back to a specific child age (or individual age). We also show in Section 5.2 that expected PDV is relatively stable across age and therefore not sensitive to specific sampling windows. This is not the case for the traditional income measures.

The timing of parents' income measures are as follows:

- *Correlations between parents' resources and children's outcomes*: Parents' resources at child ages 0–4, 5–9, and 10–14, and when parents were ages 30–35 (the latter is presented in Appendix D).
- *IGE estimates by OLS*: Parents' resources at child ages 0–4, 5–9, and 10–14, and when parents were ages 30–35 (Appendix E presents robustness results using different age ranges of parents and children).
- *IV estimates of the effects of parents' resources at specific child ages*: Parents' resources at child ages 0–4, 5–9, 10–14, and 15–19.

Additional Data and Measures

A subset of outcome measures such as exam scores at the end of compulsory schooling are not available for the 1981 and 1982 cohorts. For our analysis of these specific outcomes, we use cohorts born between 1995 and 1997, with the sample defined in the same way as described for the 1981 and 1982 cohorts above (i.e., those native Danes for whom we can establish a link to parents, whose parents did not migrate, and who did not themselves migrate). We have an initial sample of 209,603 child-parent pairs of native Danes (reflecting that birth cohorts from the 1980s were smaller than those from the 1990s). Our selection rules result in a final sample of 185,710 individuals.

We supplement our main data in three ways. First, we use information on the adult population (age 25–85) from 1980 to 2019 to construct synthetic cohort data as described in Section 4. For each individual in each year, we have information on total personal income, disposable income, and imputed consumption (see below), as well as information on education, cohabitation, number of children, homeownership, and employment.

Second, we use information from the Danish Household Expenditure Survey, a diary-based survey of expenditures within the household, collected by Statistics Denmark (Browning et al., 2021; Danmarks Statistik, 1999). The survey provides detailed information on various categories of consumption expenditures for a rotating sample of individuals between 1995 and 2012. We link the survey data to the register data using the individual unique identifiers.[11,12]

Third, we link the register data to information on proxies of parents' investments in their children at age 7 of the child using survey data from the Danish Longitudinal Study of Children (the DALSC is representative survey of around 5,000 children born in 1995).

4 Identification and Estimation

In this section we introduce the identification and estimation beyond the standard measures used in the earlier literature.

[11] We use household disposable income and detailed information on assets and liabilities in periods t and $t-1$ to predict household consumption from the expenditure survey. The imputation is conducted using a random forest estimator, which is a nonparametric prediction algorithm (see Ho et al., 1995). We select the number of trees using a 5-fold cross-validation approach. The correlation between predicted and observed consumption using a training set is 0.95. See Appendix B.2 for a full description of our imputation procedure.

[12] While consumption can be imputed based on information on income and net-assets across years (see, e.g., Browning and Leth-Petersen, 2003), this procedure leads to measurement error and thereby attenuation bias due to approximation error. Bruze (2018) uses an alternative strategy by applying instrumental variables to correct for approximation error and Danish Expenditure Survey data to instrument parents' imputed consumption.

4.1 Identifying and Estimating Information Sets

In order to estimate the expected PDV, we extend the nonparametric synthetic cohort strategy approach in Abbott and Gallipoli (2022) who follow Cunha and Heckman (2016); Cunha et al. (2005) and approximate the information set $\mathcal{I}_{i,t}$ by a vector of time-varying and time-invariant individual characteristics. We then take the expectation nonparametrically given the $\mathcal{I}_{i,t}$ using information from different cohorts and weighting the information by proximity to the cohort of individual i (using the Nadaraya-Watson estimator). We evaluate this expectation recursively from the end of the lifecycle at age 85 to age a. We discuss further details about the estimation in Appendix C.1.

We approximate information sets ($\boldsymbol{\mathcal{I}}_{i,t}$) using characteristics that carry information about their future earnings potential. To test the sufficiency of our information sets, we adapt the procedure of Cunha and Heckman (2016). For a vector $\boldsymbol{\mathcal{Z}}_{i,t}$, the idea is to use forecasts of future income based on $\boldsymbol{\mathcal{Z}}_{i,t}$ to test if the forecast error correlates with choices that depend on these forecasts. Components of income not in the information set should not predict future outcomes.

We first test whether consumption at age 30 is associated with the difference between realized future income at age 50 and future expected income at age 50 based on an information set estimated at age 30. If $\boldsymbol{\mathcal{Z}}$ is defined correctly, the residualized incomes at age 50 based on characteristics $\boldsymbol{\mathcal{Z}}$ measured at age 30 or uncorrelated with the consumption at age 30 (see Appendix C.2 for a formal presentation of the test). This is indeed what we find in panel (a) of Table 1. Column (1) shows that the coefficient of a regression of consumption at age 30 and disposable income at age 50 is 0.35. When we include gender and education in the information set in column (2), the estimated coefficient drops substantially. When we further include cohabitation and homeownership status in the information set in column (3), the regression coefficient drops further. When we use the full information set in column (4), the regression coefficient between consumption at age 30 and the residual (unexpected) income at age 50 is even lower and not statistically different from zero (t-statistic of 0.72). Similarly, to assess whether there is any relationship between any mismeasurement of the information set and child's outcomes, panel (b) of Table 1 considers associations between parents' disposable income at age 50 and child outcomes. These associations are strongly significant. Once we residualize parental income using the full information set we see no significant relationship.

Our final information set, which passes specification tests, is based on gender, education level (primary school, high school, college, and university), employment status, cohabitation, number of children, quartiles for mean income level, quartiles for mean consumption level, quartiles for mean consumption growth, quartiles for standard deviation of consumption, and homeownership status. Our nonparametric approach for forming expected values allows for all interactions among these factors. In Section 5.2, we show how education, and life-cycle profiles of family formation and income change across generations. By including these characteristics in the information set, cohort effects related to changes in them are explicitly taken into account. We interpret the results from Table 1 as evidence that our information set is correctly specified. Moreover, as parents' residualized income based on our preferred information set is not associated with child outcomes, any minor misspecification would likely attenuate the estimated role of parents' lifetime resources on child outcomes.[13]

4.2 Identification and Estimation When Using Instruments

The combination of policy instruments and lifetime resources holds the implicit assumption of expected policy stationarity in the future. In addition, the identifying assumptions follow the standard IV assumptions. First, the instruments have to predict the endogenous variable of interest. Table G.1 presents the first stage regression results and show that this is indeed the case. Second, instruments should be independent of unobserved characteristics affecting child outcomes. Fig. 1 presents the correlations between families' expected PDV and the policy innovations on the one hand, and fathers' wage income and education

[13]Note that the stronger predictive power of parents' expected lifetime measures is not a mechanical consequence of lower measurement error from the information set; while classical measurement error attenuates regression coefficients, we also find that *correlations* between parents' resources and children's outcomes are stronger for parents' expected lifetime resources (see Sections 5.3 and 6.3). Moreover, the finding that parents' residualized income is not significantly related to children's later outcomes partly resembles the discussion of instruments and potential bias in IGE estimation from e.g., Solon (1992).

Table 1: Specification Tests ($\mathcal{Z}^j$ Is the Candidate Proxy for Information Set)

		(1)	(2)	(3)	(4)
		y_{50}	$y_{50} - \mathbb{E}(y_{50} \mid \mathcal{Z}^1_{30})$	$y_{50} - \mathbb{E}(y_{50} \mid \mathcal{Z}^2_{30})$	$y_{50} - \mathbb{E}(y_{50} \mid \mathcal{Z}^3_{30})$
(a) Full Population					
Consumption (Age 30)	β_{OLS}	0.35	0.25	0.23	0.03
	T-stat	(37.50)	(4.88)	(4.55)	(0.72)
(b) Main Sample, Child Outcomes					
		y_{30}	$y_{30} - \mathbb{E}(y_{30} \mid \mathcal{Z}^1_{29})$	$y_{30} - \mathbb{E}(y_{30} \mid \mathcal{Z}^2_{29})$	$y_{30} - \mathbb{E}(y_{30} \mid \mathcal{Z}^3_{29})$
Disposable Income (Age 30)	β_{OLS}	0.10	0.07	0.05	-0.00
	T-stat	(14.75)	(10.89)	(8.84)	(-0.12)
Wage Income (Age 30)	β_{OLS}	0.18	0.10	0.07	0.01
	T-stat	(31.49)	(19.10)	(13.60)	(1.57)
College Attainment	β_{OLS}	0.32	0.15	0.06	-0.04
	T-stat	(11.91)	(5.53)	(2.27)	(-0.80)
Years of Schooling	β_{OLS}	2.04	1.23	0.49	-0.09
	T-stat	(15.28)	(9.02)	(3.60)	(-0.39)

Notes: The table reports sufficiency tests using the tests described above from Cunha et al. (2005). Panel A shows the regression associations between disposable income at age 50 with own consumption at age 30 (for all individuals born in 1951), and Panel B reports regression associations between parental income at age 30 with various child outcomes (disposable income, wage income, college attainment, and years of schooling). Column (1) reports the associations using disposable income. Columns (2)–(4) report the associations using disposable income residualized with respect to different information sets ($\mathcal{Z}^k_{30}$). $\mathcal{Z}^1_{30}$ includes information on gender and educational attainment, $\mathcal{Z}^2_{30}$ adds cohabitation and homeownership status to the information set, and $\mathcal{Z}^3_{30}$ is our final information set, which includes information on gender, education level (primary school, high school, college, and university), employment status, cohabitation, number of children, quartiles for mean income level, quartiles for mean consumption level, quartiles for mean consumption growth, quartiles for standard deviation of consumption, and homeownership status. We report t-statistics for the null hypothesis that the OLS coefficient is zero in parenthesis.

level measured in 1981 on the other hand. Not surprisingly, families' expected PDV strongly correlates with fathers' characteristics measured in 1981. However, the figure also shows that the correlations between the policy innovations and fathers' characteristics are either zero or very close to zero irrespective of whether we consider policy innovations at ages 0–4, 5–9, 10–14, or 15–19 of the child. Our identifying assumptions are, thus, satisfied.

Nevertheless, in Appendix G, we present an alternative identification strategy based on an income dynamic model (in spirit of Friedman and Kuznets (1945) Morgan (1990), Lillard and Willis 1978, Hause 1980, and Lochner and Park 2022) where income innovations affect parents' expected PDV and they are used as instruments for parental income. The estimated IGEs are largely similar to those based on our main specification.

We use standard GMM to serve estimates. We describe this in detail in Appendix C.3. The objective function for the IV-GMM model can be written as

$$\tilde{Q}(\beta) = \left(\frac{1}{n}\sum_{i=1}^{n}\mathbf{Z}_i'(y_i - \mathbf{X}_i\beta)\right)' W \left(\frac{1}{n}\sum_{i=1}^{n}\mathbf{Z}_i'(y_i - \mathbf{X}_i\beta)\right)$$

In our setting, $\mathbf{X}_i = \log(Y^p_{a_1,a_2})$, $\mathbf{z}_i = [\Delta_{a_1-J}, \Delta_{a_1-J+1}, \Delta_{a_1-J+2}, \ldots, \Delta_{a_1-1}, Y_{a_1-1}]'$, where $Y^p_{a_1-1}$ denotes parental income measure (expected PDV) at child age $a_1 - 1$, $Y^p_{a_1,a_2}$ denotes averaged parental income measure between child age a_1 and a_2, Δ_t denotes the parental policy innovation from equation (5), J denotes the number of policy instruments, and y_i denotes the child's outcome of interest. The optimal weighting matrix ($W = M^{-1}$) uses the inverse of covariance matrix of the moment conditions to produce the most efficient estimator (Hansen, 1982). To obtain a consistent estimator of M we use residuals derived from 2SLS.

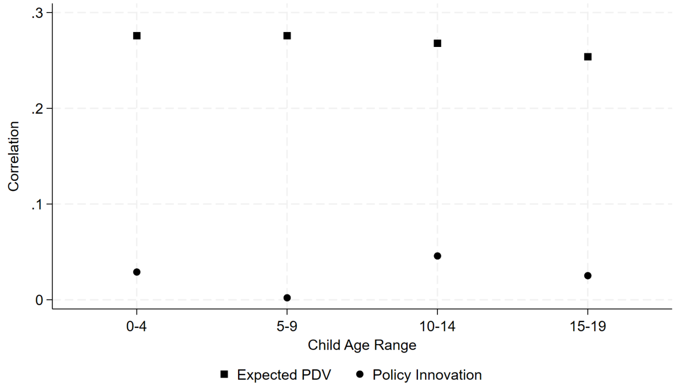
5 Lifetime Income Measures and Lifecycle Outcomes

The literature on intergenerational income mobility largely focuses on the association between children's and parents' realized income in fixed age intervals without clear consensus on whether to measure income as earnings, including public transfers, or factoring in tax payments. For completeness, we therefore consider a variety of different income definitions measures over fixed age ranges of parents and children along with our lifetime measures. Table 2 provides an

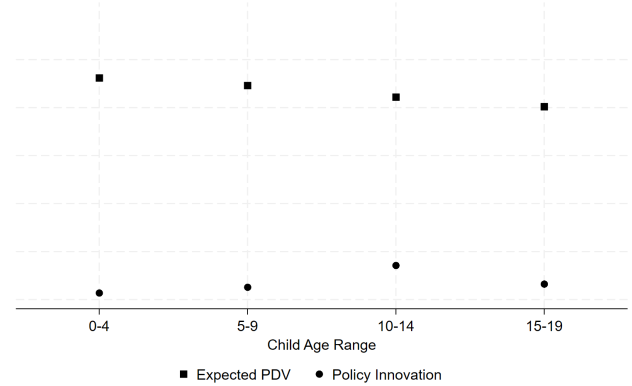
Figure 1: Correlation Between Father's Wage Income and Education Level, and Expected PDV and Policy Innovations

Correlation Between Father's Wage Income in 1981 and:

(a) Expected PDV and Policy Innovations, Fathers

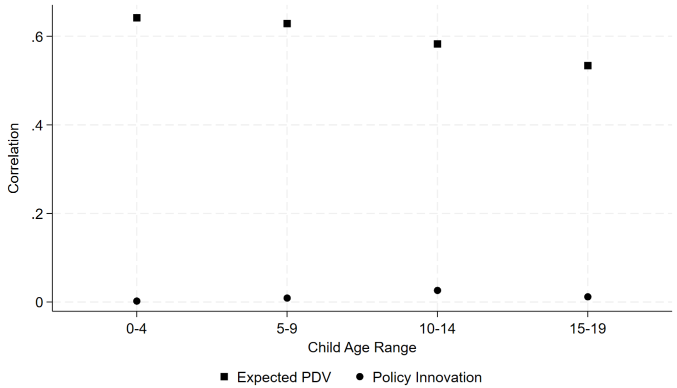


(b) Expected PDV and Policy Innovations, Parents Jointly

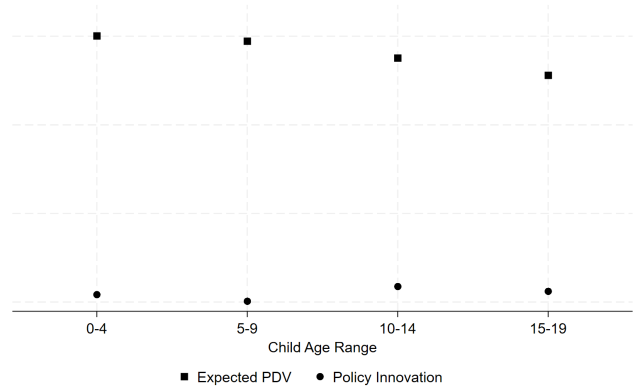


Correlation Between Father's Education Level in 1981 and:

(c) Expected PDV and Policy Innovations, Fathers



(d) Expected PDV and Policy Innovations, Parents Jointly



Notes: This figure shows correlations between father's wage income / education in 1981, and father's / parents' expected PDV and policy innovations at child ages 0–4, 5–9, 10–14 and 15–19.

overview of the measures we compare in this paper.

Below, we argue for the importance of using income measures that explicitly take into account lifetime dynamics. We analyze the relationship between different measures of resources and provide evidence that snapshot measures are neither accurate proxies of individuals' realized lifetime resources nor of individuals' expected lifetime resources. We motivate the importance of lifetime measures by showing how household fertility and cohabitation decisions and educational attainment have changed significantly between the two cohorts in our study, leading to very different income profiles. Lifetime measures, rather than snapshot measures, are needed to correctly account for such effects when estimating the intergenerational mobility. We then compare the associations between important child outcomes, and our *ex ante* lifetime measures of income and the traditional *ex post* measures of income. We also compare the performance of realized lifetime income in predicting important child outcomes with the performance of our *ex ante* lifetime measure. We find that *ex ante* measure to be more strongly correlated with life outcomes of the child. Moreover, while the correlations between child outcomes and parental resources focus on the relative position in the distribution, we also show in Section 7.4 that misalignment of income trajectories across generations affects estimated absolute mobility levels.

5.1 Comparing Alternative Measures of Resources

To illustrate how expected PDV differs from the traditional measures of resources and the realized PDV, Table 3 shows correlations between the measures of resources for fathers of the 1981 and 1982 cohorts at child ages 0–4.[14] Expected PDV correlates most strongly with wage income, income without transfers, and income with transfers (correlations ranging from 0.29 to 0.43). Realized PDV is more weakly correlated (0.24) with its expected value counterparts. Most surrogate measures of lifetime resources widely used previously are only weakly correlated with their decision-relevant counterparts. Similarly, consumption is only weakly correlated with expected PDV, while a large body of applied litera-

[14]Tables D.1, D.2, and D.3 present the corresponding correlations at child ages 0–5 and 10–14, and fathers' age 30–35, respectively. Tables D.4 and D.5 present the corresponding correlations for parents' and children's resources, respectively.

Table 2: Definitions of Income Indicators Used in this Paper

Group		Variable	Definition
Traditional Snapshot Measures	(1)	Wage Income	Taxable wage earnings and fringes, labor portion of business income, non-taxable earnings, severance pay, and stock options.
	(2)	Income with Transfers	Total personal income (excluding rental value of own home). Total personal income is equal to the sum of wage income, business and self-employment income, capital income, public transfer income, property income, and other non-classifiable income that can be attributed directly to the individual person.
	(3)	Income without Transfers	Total personal income (as specified in item (2) above) minus public transfer income. The main items of public transfer income include: social assistance cash benefits, unemployment insurance benefits including leave, sickness benefits, pensions including disability pension and early retirement pay, housing allowance, and child allowance.
	(4)	Disposable Income	Total personal income including public transfers (as specified in item (2) above) and rental value of own home (for owner-occupied individuals) minus taxes, interest expenses, and child support.
	(5)	Survey Imputed Consumption	Total household expenditures, imputed from the relationship between the Danish Expenditure Survey and the Danish register.
Lifetime Measures	(6)	Expected Present Discounted Value	The expected present discounted value of future total income, using a deterministic discount factor (β): $$\mathrm{PDV}_{i,t} = \mathbb{E}_{i,t}\left[\sum_{\tau=1}^{T-1} \beta^{\tau} y_{i,t+\tau} \mid \mathcal{I}_{i,t}\right],$$ where $y_{i,t}$ is the total income including interest on assets, public transfers, the estimated rental value of own home for owner-occupied individuals, and unrealized capital gains from housing stock for individuals who are homeowners, minus taxes and interest expenses at age t. β is a common discount factor, and $\mathcal{I}_{i,t}$ is agent i's information set.
	(7)	Realized Present Discounted Value	Same as (6) with realized lifetime measures for parents.

ture has assumed otherwise.

As a further illustration of the differences between the various measures, Fig. 2 shows correlation between our various measures of parental resources at age 5–9 and proxies of investments in children at age 7. The correlation between the traditional measures of parents' resources and the investment proxies are only 40-80% of corresponding correlations for parents' expected PDV.

Table 3: Correlations of Measures of Resources at Child Ages 0–4

	Wage Income	Income w/o Transfers	Income w. Transfers	Disposable Income	Household Cons.	Realized PDV
Income w/o Transfers	0.51					
Income w. Transfers	0.47	0.99				
Disposable Income	0.53	0.59	0.61			
Household Cons.	0.46	0.51	0.49	0.37		
Realized PDV	0.45	0.46	0.46	0.71	0.35	
Expected PDV	0.43	0.32	0.29	0.29	0.45	0.24

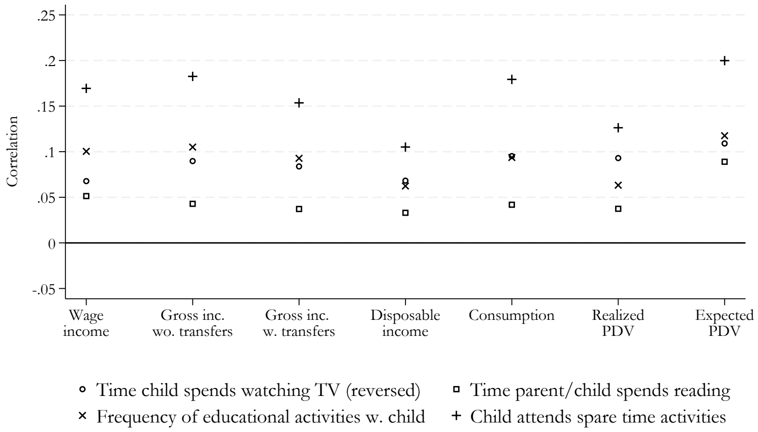
Notes: The table shows correlations between various measures of resources at child ages 0–4 for fathers of the 1981–1982 cohorts.

5.2 Nonstationarity across Cohorts

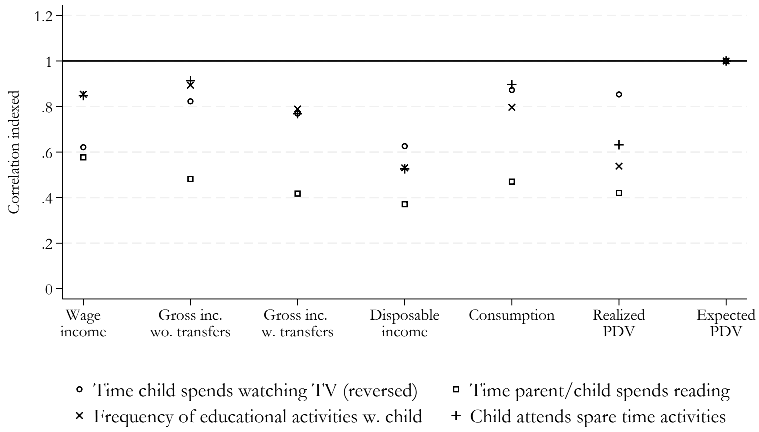
Figs. 3(a) and (b) show the dramatic change in educational attainment across the cohorts we analyze. Educational attainment for both females and males has increased substantially. The majority of parents completed at most 10 years of schooling. In contrast, for children, most females have completed a college or master's degree (15 years or higher), while most males hold either a vocational high school degree (13 years) or a college degree (15 years). Individuals in successive generations have very different life-cycle trajectories; the timing of key life events differs substantially. Figs. 3(c) and (d) illustrate the delay of marriage from the 1955 to the 1975 cohorts for female and males, respectively. The remaining plots in Fig. 3 focus on the 1981–1982 cohorts and shows the distributions of age at birth of first child and age at completion of highest degree for children and their parents. The timing of family formation is delayed by 5–7 years on average for the most recent cohort. Most parents finished schooling in their late teens, while most children graduated with their final degree in their mid- to late-20s. While parents' and children's education and fertility behavior are associated,

Figure 2: Correlation between parents' resources and child investments at age 7

(a) Correlation



(b) Correlation, Indexed to Expected PDV



Notes: The figure shows the correlations between measures of parents' resources at age 5–9 and proxies of investments in children's development: time spent reading with the child, time child spends watching TV (reversed), frequency of activities (reading with, helping with homework, and excursions), and whether child attends spare time activities (e.g., music lessons or sports). The figure is based on mothers' survey responses in the DALSC (1995 cohort).

a simple parallel shift in timing across the two generations does not characterize cohort shifts (the delay is most pronounced among college-educated, see Fig. D.2). The correlation coefficients between fathers' and sons' ages at birth of first child and ages at completion of highest degree are 0.14 and 0.23, respectively. Similarly, the correlations for mothers and daughters are 0.25 and 0.18, respectively. Income measured over any fixed age range will inherently be an inaccurate proxy of an individual's permanent income.

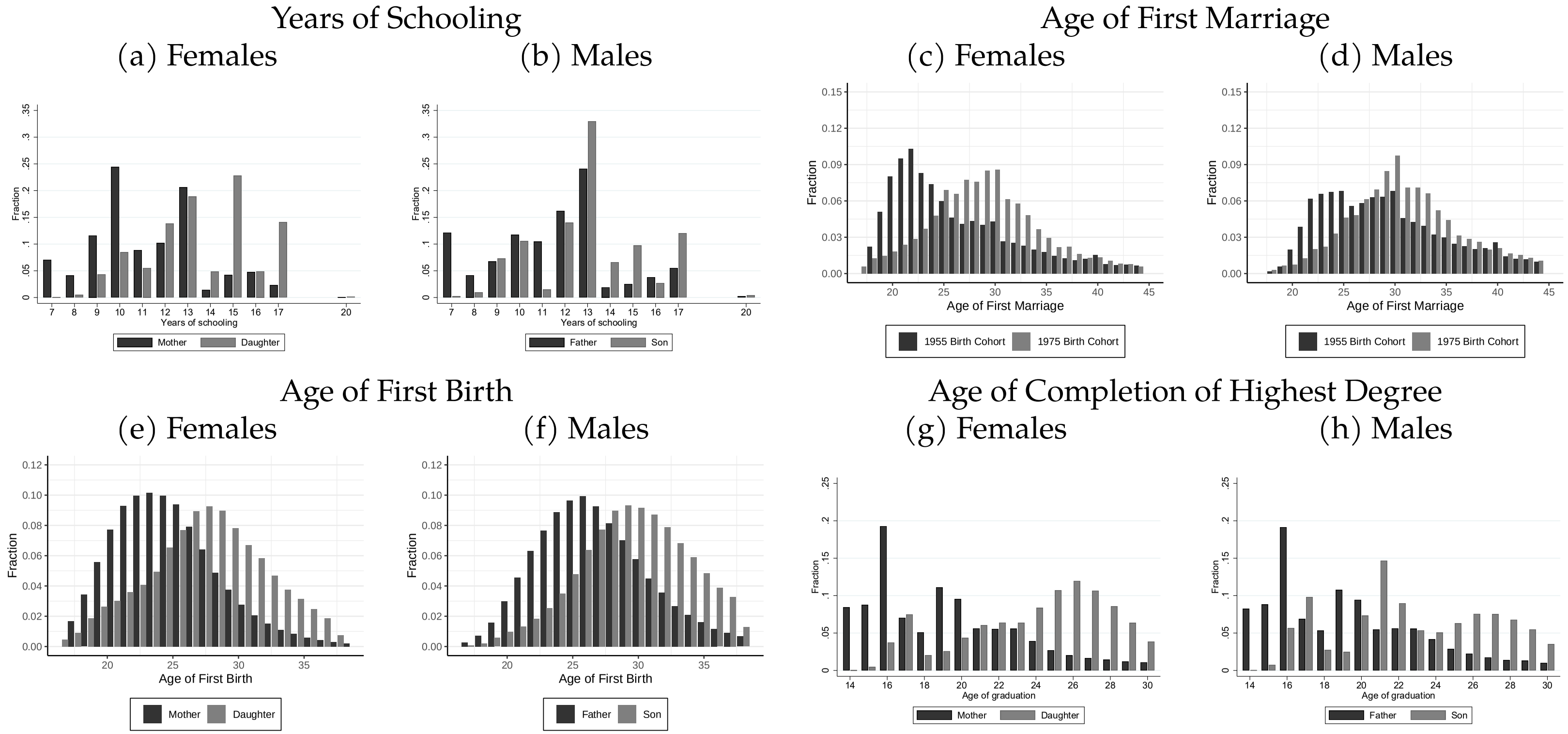
Not only has the life cycle timing of key life events changed over cohorts, but so have levels of income and uncertainty, which Fig. 4 illustrates. The figure shows average disposable income (a–b) and estimated expected PDV (c–d) by age and college education for the 1945–1946, 1965–1966, and 1980–1981 cohorts, respectively. Disposable income has increased and income profiles have become steeper—particularly for the college educated. These differences in levels at a given age and profiles across education levels and cohorts underline the problems of finding suitable age ranges to measure resources. Figs. 4(c) and (d) show how the expected PDV mitigates this: Variation across ages is minimal because expectations are based on the full life cycle (with a slight downward slope from age 40 onward), and level differences across education levels are accounted for throughout while also capturing differences between generations. College educated individuals' expected PDV is consistently more than 50% higher than the expected PDV for individuals without a college degree.

Moreover, expected lifetime resources have increased substantially across time. The increase is most prominent when comparing the cohort of 1945 with those born in 1965 (i.e., between those entering the labor market around 1970 and around 1990, respectively). The figure also suggests a further increase in expected lifetime resources when comparing the cohort of 1965 with those born in 1980 and 1981, but this is mainly for college educated individuals.

The figure thereby captures the large changes in economic conditions in Denmark over the period in question. During the late 1970s, 1980s, and early 1990s, Denmark was characterized by a high level of structural unemployment, an inflexible labor market with low productivity growth, high interest rates, and general uncertainty about the viability of the level of public expenses. Today, virtually all these features have been reversed: Unemployment rates are low with a more flexible labor structure following a series of reforms during the 1990s and 2000s, credit markets have been liberalized, prodivtivity has increased substantially, and the several welfare reforms have ensured the long-run viability of the current level of public expenditures.[15]

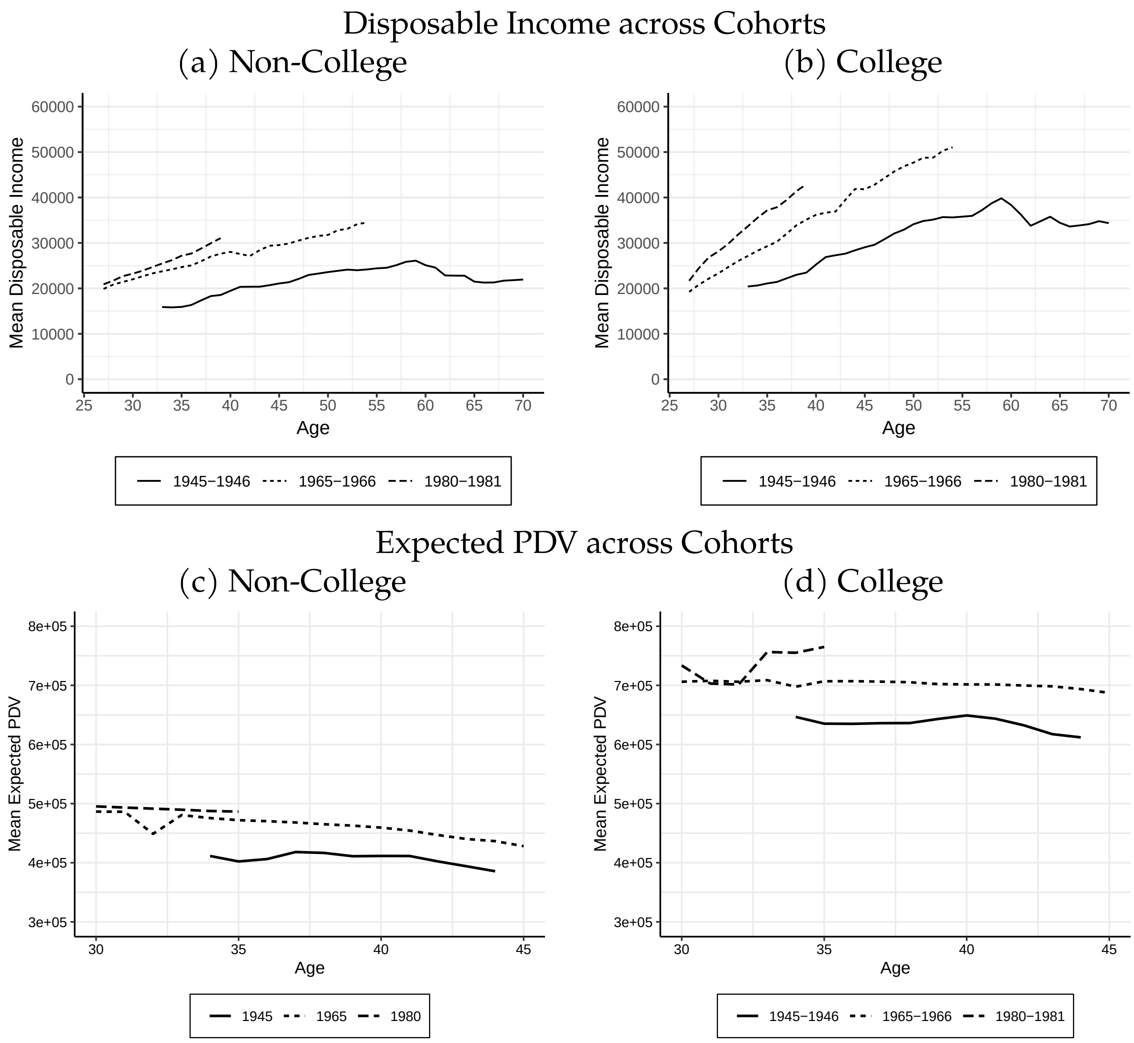
[15] See descriptions of policy reforms and challenges in Andersen and Svarer

Figure 3: Timing of Key Life Events across Generations



Notes: Figs. (a)–(b) show distributions of years of schooling for males and females born in 1981–1982 and their parents. Figs. (c)–(d) show the distribution of the age at which individuals get married for the first time for the 1955 and 1975 birth cohorts respectively, for males and females separately. Figs. (e)–(f) show the distribution of the age at birth of first child for the 1981–1982 cohorts and their parents. Figs. (g)–(h) show the distribution of the age ofcompletion of highest degree for the 1981–1982 birth cohorts and their parents.

Figure 4: Income and Expected PDV across Cohorts



Notes: Figs. (a) and (b) show disposable income for the 1945, 1965, and 1981 birth cohorts respectively, by college and non-college educated individuals. The expected PDV are measured in 2010 USD. Figs. (c) and (d) show the expected PDV for the 1945–46, 1965–66, and 1981–82 birth cohorts respectively, for college and non-college educated individuals.

(2007); De Økonomiske Råd [The Economic Council] (2021); Kreiner and Svarer (2022); Ministry of Industry, Business, and Financial Affairs (2013); Statistics Denmark (2001).

5.3 Parental Resources and Child Outcomes

We compare parental expected PDV measured how with their realized counterparts and traditional measures in the literature, with respect to their predictive power over important child outcomes. Fig. 5 displays the correlations between different measures of parental resources, children's test scores, and educational attainment when parental resources are measured at different ages of the children. Comparing first the correlations across measures of parental resources within each figure, Fig. 5 shows that there are much stronger correlations for the parents' expected PDV than for the other measures. The correlations between test scores and educational attainment on the one hand and parents' expected lifetime resources on the other hand range between 0.28 and 0.39, while the corresponding correlations for the traditional measures of income are around 50% lower ranging from 0.12–0.25. Fig. D.3 presents the corresponding results for children's crime and having a child by age 20. Again, the expected PDV is more predictive of child outcomes than the traditional measures of parental resources.

Comparing next the predictive power of parental resources across children's ages, Fig. 5 shows some variation for the traditional measures of resources with no apparent clear pattern. In contrast, the predictive power lifetime resources is more stable across the time of measurement.[16] Moreover, the figure shows that—while the realized ex-post lifetime PDV has a stronger predictive power than the traditional snapshot measures (consistent with Deutscher and Mazumder, 2023; Mazumder, 2005; Solon, 1992)—the realized lifetime resources display a weaker predictive power than the predicted ex-ante counterparts. In sum, these results show that traditional measures of realized family income understate the importance of family resources in predicting a variety of dimensions of child lives. The findings in this section motivate our choice of the expected PDV, which manifest a much tighter link between parents and children than the snapshot measures of income that are currently used in the literature on intergenerational income mobility to measure intergenerational transmission or realized life-cycle incomes.[17]

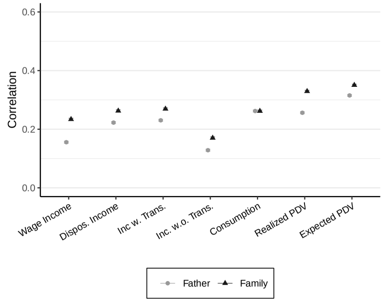
[16] Note that even though snapshot disposable income is highly correlated with realized PDV, it is not equally predictive of child outcomes.

[17] This is true even when we analyze the relationship between the resources of

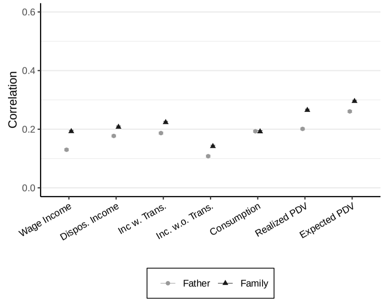
Figure 5: Parental Resources and Child Outcomes

Parents' Resources Measured at Child age 0–4

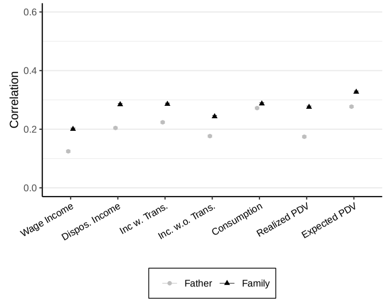
(a) Math test scores



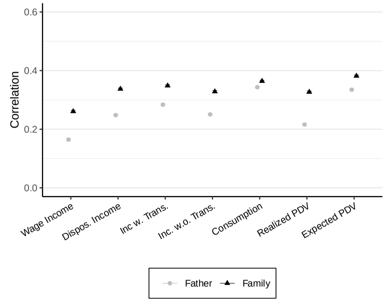
(b) Danish test scores



(c) College attainment

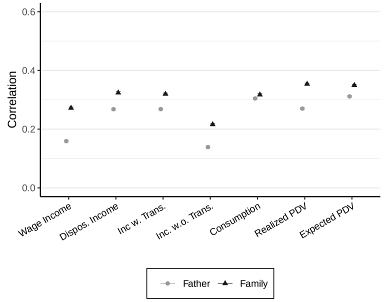


(d) Years of school.

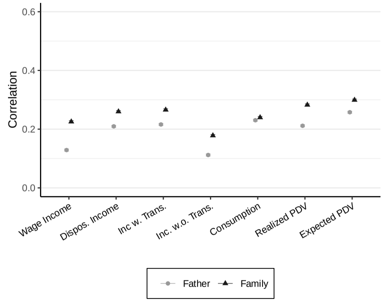


Parents' Resources Measured at Child age 5–9

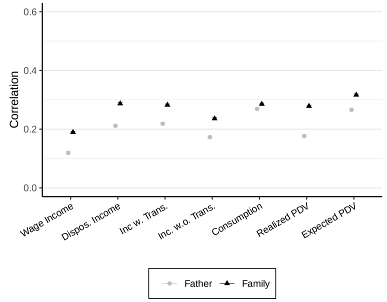
(e) Math test scores



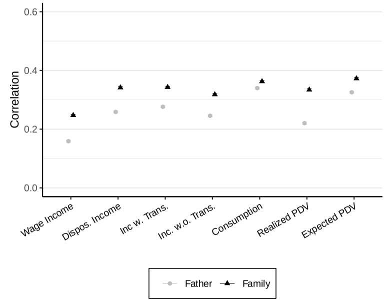
(f) Danish test scores



(g) College attainment

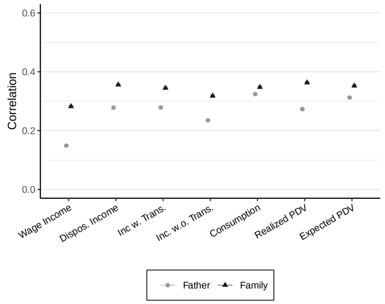


(h) Years of school.

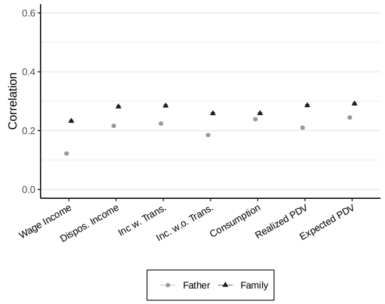


Parents' Resources Measured at Child age 10–14

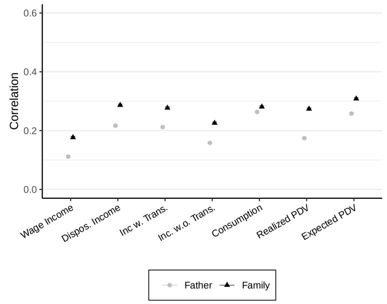
(i) Math test scores



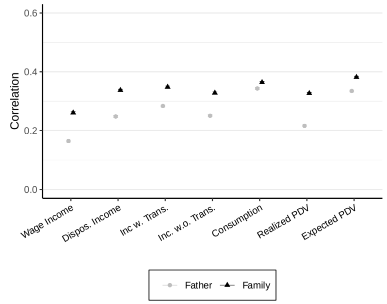
(j) Danish test scores



(k) College attainment



(l) Years of school.



Notes: The figure shows correlations between child outcomes and parents' resources at child ages 0–4, 5–9, 10–14.

6 Estimates of Intergenerational Mobility

This section presents our estimates of intergenerational income mobility in three steps. First, we document the differences in estimated income mobility for the traditional income measures, realized lifetime resources, and expected lifetime resources in Section 6.1. Here, we also discuss robustness results. Next, in Section 6.2, we present the IV estimates by child age and compare these with the corresponding OLS estimates. While the first subsection documents the importance of the resource measures used when estimating the association between parents and children, Section 6.2 breaks new ground and control for endogeneity bias in constructing the IGE and discusses potential avenues for future research based on our IV strategy. Finally, Section 6.3 investigates the role of differences in inequality across generations for estimated mobility.

6.1 Intergenerational Elasticities for Lifetime Measures by OLS

Fig. 6 shows IGE estimates for father-child pairs and parents-child pairs with resources measured at different age ranges of children in 6(a)-(c) and when parents were 30-35 years old in 6(d). The figure shows that in all specifications, the IGE estimates based on expected PDV are substantially higher than those based on standard measures of realized income measured over fixed age intervals, the traditional measures of lifetime resources. The estimated father-son IGEs for the traditional measures range from around 0.1 for disposable income to around 0.25 for gross income excluding transfers.[18] The estimates for the expected PDV are substantially higher with an estimated IGE between fathers' and children's expected PDV close to 0.40. The IGE for consumption lies in the middle of the two, with father-child IGE estimates around 0.30. We observe a similar pattern when studying parents-child IGEs, where the IGE based on expected PDV is close to 0.50, which is substantially higher than the counterparts based on parents' realized PDV where estimates range from 0.25–0.35. Across measures, IGEs summing over both parents' resources are larger than individual-based IGEs reflecting that both parents' resources matter for children.

grandparents and child's academic achievement (see Figs. D.5 and D.6).

[18] Landersø and Heckman (2017) show that IGE estimates increase when excluding redistribution through taxes and transfers from measured income.

One possible reason why estimates based on lifetime measures (ex ante and ex post) differ from estimates based on traditional income measures is that lifetime measures average out measurement error to a greater extend. We find that the traditional income IGEs increase in value when we move from measuring individuals at a single age (for example, 30 or 35, see Fig. E.2) to measuring them with the average taken over ages 30–35 (as documented in e.g., Mazumder, 2005; Solon, 1992), or if we move from measuring parental resources over ages 30–35 to measuring them over a 40-year average of realized values. Yet, Fig. 6 shows that even when we average over long ranges (as we do in the realized lifetime measures—we use children's expected PDV as outcome), we still find that the expected PDV provides a significantly better prediction of children's outcomes.

A common alternative to the IGE is rank-rank regression. The estimator avoids problems with zero earnings (see, e.g., Dahl and DeLeire, 2008). Fig. E.1 shows results from regressions of children's rank (in their cohort) on the parents' rank. As with the IGE, rank-rank associations are significantly higher for expected PDV than for the traditional measures of income. The figure also presents rank-rank estimates for both *ex ante* and *ex post* measures of lifetime resources. The results show that the rank-rank association is significantly higher for *ex ante* lifetime measures than for their *ex post* counterpart.

We demonstrate in Figs. E.2, E.3, and E.4 that the patterns documented in Fig. 6 and Table 5 remain once we change the age of measurement.[19,20] We re-estimate the IGEs for different measures of resources computed at different child and parental ages.[21] Fig. E.5 presents results seperately by child birth order.

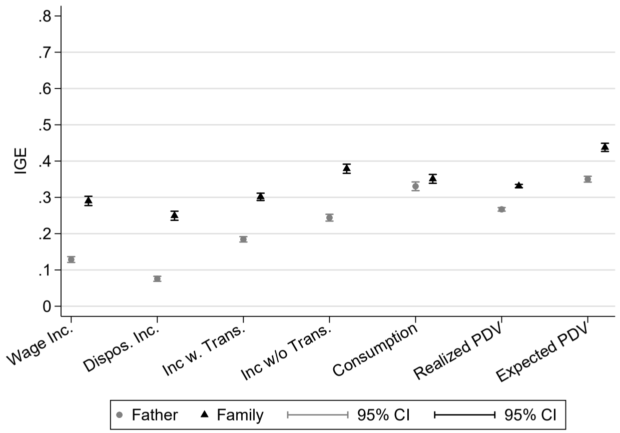
[19] Studies discussing a positive association between earnings IGE estimates and age of child at observation include, for example, Behrman and Taubman (1985); Chadwick and Solon (2002); Couch and Dunn (1997); Grawe (2006); Nilsen et al. (2012); Reville (1995); Solon (1999, 2002).

[20] The other source of bias is the impact of measurement error and transitory fluctuations in measured earnings (Atkinson, 1980; Solon, 1989).

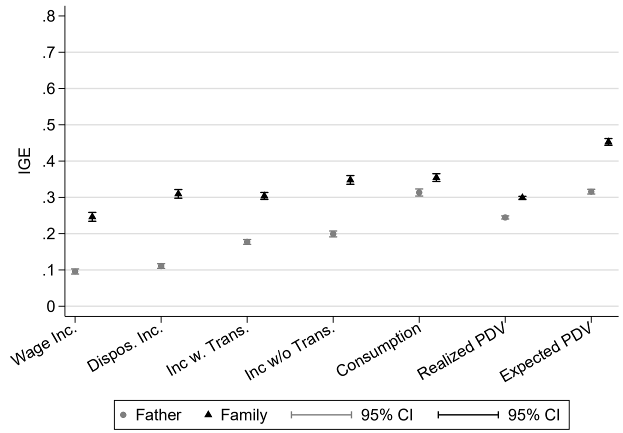
[21] In doing so, we rely on children from older birth cohorts, since we only observe income up to 2019. In Fig. E.4, we compare IGEs when parents' resources are measured at ages 25–30, 30–35, and 35–40 for cohorts born in 1976 and 1977. In Fig. E.4, we compare the IGE estimates with lifetime measures over different six-year intervals from ages 55–60 (for the 1956–1957 birth cohort) to ages 30–35 (for the 1981–1982 birth cohort).

Figure 6: Log-Log IGE Estimates

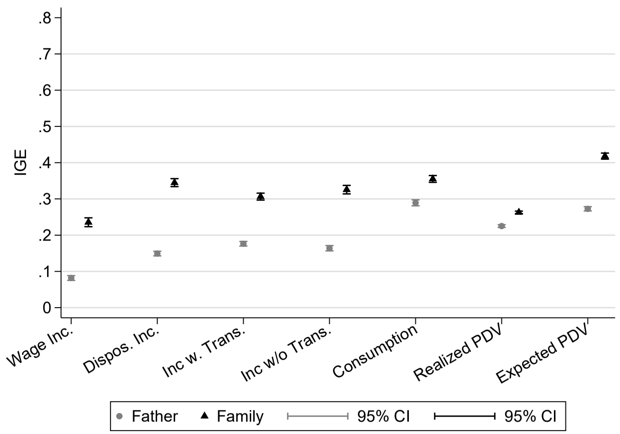
(a) Parents' Resources Measured at Child Age 0–4



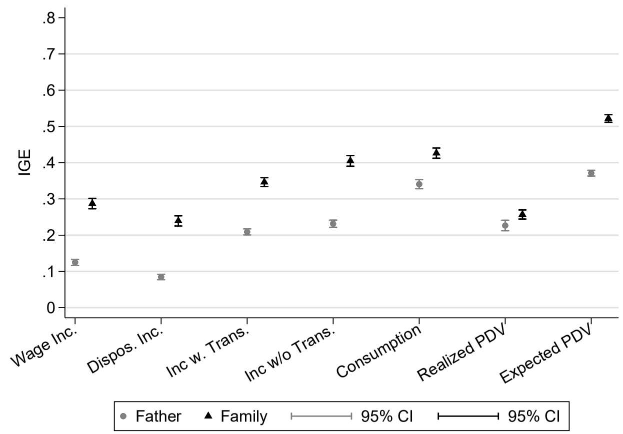
Parents' Resources Measured at Child Age 5–9



(c) Parents' Resources Measured at Child Age 10–14



(d) Parents' Resources Measured at Parents' age 30-35



Notes: The figure shows IGE estimates for different measures of resources. (a), (b), and (c) show the estimates when parental resources are measured when the children were 0–4, 5–9, and 10–14 years old, respectively. (d) shows the estimates when parental resources are measured at age 30–35 of the parents.

Across all ages and cohorts, the IGE estimates using expected PDV are larger than those using the realized PDV or the traditional income measures. This emphasizes that our main findings are not driven by our choice of measuring resources at specific ages or focussing on the 1981–1982 cohorts.

6.2 IV Estimation Results

We next present the estimated effects of parental expected lifetime resources on children's outcomes based on our policy instruments, and we compare the results to the corresponding OLS estimates presented earlier in the paper. Appendix F.1 shows results when we allow for behavioral responses to reforms (such as anticipation effects) in the IV strategy,[22] Appendix F.2 relaxes the IV strategy to take interdependence of the policies into account,[23] and Appendix F.3 shows the estimation strategy based on 2SLS instead of GMM as in the main text.

Table 4 presents the estimates from the IV-GMM approach on children's expected PDV. We present both IV-GMM estimates and the corresponding OLS estimates for comparison for parental resources measured at different ages of the child, and we present estimates based on fathers' and parents' resources.

Focusing first on the effects of parents' expected PDV on children's expected PDV (i.e., the IGE), columns (3) and (4) show that the IV-GMM estimates are around 25% lower than the OLS estimates (we also presented these OLS estimates in Fig. 6 earlier in the paper) with declining effects as children age. At child age 0–4, the IGE identified through exogenous shocks to parents' resources

[22]For policy changes (Δ terms), individuals' incomes in year $t+1$ might be partly impacted by behavioral responses to the policy changes in t if, for example, there was a lag between the announcement of the policy and its implementation or due to the ongoing debates in the parliament. We obviate this concern by using a higher order lag when we compute our instrument by comparing policies in t vs $t+2$ (as opposed to t vs $t+1$).

[23]In the main specification we define $\Delta_t = log(Y_t + \Delta_t^T + \Delta_t^r + \Delta_t^S) - log(Y_t)$, which ignores any interdependence of the income shocks due to different policy innovations taking place simultaneously. In our robustness check, we take into account the interdependencies by imbedding the transfer and interest changes into the TAXSIM program (Jakobsen and Søgaard, 2022) and compute the updates to the tax policy component as $\Delta_t^T = (Y_t|P_{t+1}) - (Y_t|P_t)$, where P_t denotes all relevant policies at time t capturing all policy-induced variation jointly.

is 0.42 while estimates at ages 5–9, 10–14, and 15–19 are 0.40, 0.38, and 0.31, respectively. The results for fathers' expected PDV on children's expected PDV follow the same pattern, although the estimates are lower than for resources measured jointly for both parents (as found throughout the paper). Thus, while the correlational results overstate the actual effects of parental resources, the effects of parent' expected PDV estimated through exogenous shocks are still larger than earlier IGE estimates based on the conventional income measures using Danish data (see e.g., Landersø and Heckman, 2017). Family resources available in childhood are a key causal determinant of inequality of opportunity.

Table 4: OLS and IV-GMM IGE Estimates, Children's Expected PDV

	Father		Parents	
	(1)	(2)	(3)	(4)
Variables	IV-GMM	OLS	IV-GMM	OLS
E(PDV^p), child age 0–4	0.329***	0.378***	0.417***	0.512***
	(0.008)	(0.005)	(0.011)	(0.007)
IV: innovations. child age 0–4				
E(PDV^p), child age 5–9	0.342***	0.396***	0.397***	0.531***
	(0.010)	(0.005)	(0.013)	(0.006)
IV: innovations, child age 0–4				
E(PDV^p), child age 10–14	0.325***	0.356***	0.380***	0.481***
	(0.006)	(0.004)	(0.009)	(0.005)
IV: innovations, child age 5–9				
E(PDV^p), child age 15–19	0.260***	0.305***	0.310***	0.431***
	(0.006)	(0.004)	(0.008)	(0.005)
IV: innovations, child age 10–14				

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows OLS and IV estimates of fathers' (col. 1-2) and parents' (col. 3-4) expected PDV at different child-ages on children's exptected PDV.

This is a major step forward for a literature that has mainly focussed on documenting associations between parents' and children's resources. Yet, several questions and potential extensions beyond the scope of this paper remain. For example, while our IV strategy eliminates endogeneity concerns in transmission due to genetics, preferences, etc. and appeals to Caucutt and Lochner (2020) and related studies of investment in children, a natural extension of this paper introduces a closer focus on the effects of specific types of policies for child investments and equality of opportunity. Also, an extension of the expected PDV is to explicitly estimate value functions, which would also imply integrating the estimation of subjective discount factors into the IV framework.

6.3 Correlations and Cross-Sectional Inequality

Estimated IGEs depend on the correlation between parents' and children's resources, and the ratio of the standard deviations ($\hat{\beta} = \rho_{\text{child,father}} \frac{sd(\text{child})}{sd(\text{father})}$). Any differences in the IGE estimates (e.g., Fig. 6) must reflect differences in correlations between children's and parents' resources or differences in cross-sectional inequality. Table 5 decomposes the IGE estimates presented in Fig. 6(a) (child ages 0–4). Tables E.1, E.2, and E.3 present the corresponding decompositions for the IGEs computed over child ages 5–9 and 10–14, and parents' age 30-35.

The table shows that children's resources correlate more strongly with pooled parents' resources jointly than with fathers' resources alone, but some of the difference between IGE estimates at the parents'-child level and those at the father-child level also relate to differences in cross-sectional inequality. By averaging the income of the two parents, we reduce the variance of parental resources, which in turn increases the IGE. However, the table also shows that the intergenerational correlation for expected PDV is higher than for traditional measures of income. If anything, the gaps between the two sets of measures are greater for correlations than for the IGEs. At the family level, for example, correlations are between 0.12 and 0.19 for the traditional measures and 0.30 for our *ex ante* lifetime measure. Moreover, the correlation based on realized lifetime income is lower than the correlations for several other measures.[24]

The final row of Table 5 decomposes the IV estimates from Table 4. It shows

[24] Another line of studies considers whether the role of the family has been underestimated by including information on the extended family. For example, Adermon et al. (2021) use data on the entire Swedish population and estimate long-run intergenerational persistence using information on outcomes for the extended family. They find that traditional parent-child estimates for the persistence in years of schooling, log income, and social stratification to be 0.36–46, which is substantially lower than the counterpart estimates when they consider the extended family tree (i.e., dynasty), which is in the range of 0.52–0.60.

that the correlation between child expected PDV and parental expected PDV after correcting for selection (i.e., the value which is predicted by our instruments in the first stage) is lower than the corresponding correlation before we correct for selection (0.21 vs 0.30).

Table 5: IGE Estimates (Parents' Resources Measured at Child Ages 0-4)

	Father-Child IGE $\hat{\beta} = \rho_{\textbf{child,father}} \frac{sd(\textbf{child})}{sd(\textbf{father})}$	**Parents-Child IGE** $\hat{\beta} = \rho_{\textbf{child,family}} \frac{sd(\textbf{child})}{sd(\textbf{family})}$
Traditional Measures, OLS		
Wage Income	$0.105^{***} = 0.089\frac{1.132}{0.966}$	$0.170^{***} = 0.123\frac{1.136}{0.821}$
Disposable Income	$0.074^{***} = 0.069\frac{0.456}{0.430}$	$0.163^{***} = 0.107\frac{0.458}{0.299}$
Income with Transfers	$0.186^{***} = 0.156\frac{0.510}{0.428}$	$0.299^{***} = 0.194\frac{0.511}{0.332}$
Income without Transfers	$0.096^{***} = 0.111\frac{1.075}{1.237}$	$0.243^{***} = 0.172\frac{1.086}{0.767}$
Household Consumption	$0.233^{***} = 0.135\frac{0.306}{0.177}$	$0.244^{***} = 0.146\frac{0.306}{0.183}$
Lifetime Measures		
Realized PDV	$0.128^{***} = 0.214\frac{0.286}{0.478}$	$0.255^{***} = 0.293\frac{0.286}{0.328}$
Expected PDV	$0.378^{***} = 0.265\frac{0.282}{0.198}$	$0.512^{***} = 0.300\frac{0.271}{0.159}$
Expected PDV IV	$0.329^{***} = 0.205\frac{0.258}{0.161}$	$0.417^{***} = 0.212\frac{0.250}{0.127}$

Notes: The table decomposes estimates from Fig. 6(a) and Table 4 into its components. We obtain decompositions of expected PDV IV using the first-stage predicted values from our IV approach (i.e., we use expected PDV of parents after correcting for selection).
* $p < .1$, ** $p < .05$, *** $p < .01$.

7 Extensions

This section extends the preciding analysis by considering the influence of parents' resources on children's education, non-linearities, differences across family income and child gender, and the implications for absolute mobility.

7.1 Effects of Parents' Resources on Education

In Section E.2 we decompose our estimated IGEs by OLS using linear approximations to explain income dynamics with two key results: First, around 60%

of the father-son IGE estimates based in the traditional measures of resources is unexplained. In contrast, for expected lifetime resources only 10-20% of the IGE estimates is unexplained. Second, the lion's share of the covariance between father's and their sons' expected lifetime resources can be explained by education underscoring the importance of accounting for educational transmission and varying graduation ages when estimating intergenerational mobility.

Having shown that the greater predictive power of parents' expected lifetime resources is closely related to educational attainment, we next explicitely investigate the effects of parents' resources on children's years of schooling.

Table 6 presents OLS and IV estimates focusing on children's educational attainment. Just as found earlier, the OLS estimates are substantially larger than their IV counterparts. Moreover, both associations and causal estimates are largest for parental resources in early childhood. For example, a one percent increase in parents' resources when the children were 0–4 years old leads to an increase in children's completed schooling by 27%, while the corresponding increase in parents' resources when the children were 15–19 only leads to 18% more completed schooling, likely reflecting that many differences in skill formation and education tracks are set in place by late adolescence.

7.2 Differences Across Parents' Level of Resources

Landersø and Heckman (2017) show that IGEs in Denmark, based on realized incomes, are highly nonlinear. Fig. 7 shows estimated non-linear IGEs using local-linear regressions for children's and parents' disposable income and expected PDV. Measured by disposable income, there is near full mobility (locally) for children from low-income families with estimates of IGEs close to zero, while there is a much greater intergenerational persistence for children from affluent families. However, intergenerational mobility in expected PDV is much closer to linear with local IGE estimates around 0.5 across parental levels of expected PDV. If anything, mobility is now lowest for children from disadvantaged backgrounds, with local IGEs close to 0.6, and highest for children from affluent backgrounds, with local IGEs close to 0.4.

Of course, Fig. 7 only presents associations. Table 7 compares estimated IGEs from OLS and IV regressions focusing on resources measured for parents at

Table 6: OLS and IV-GMM IGE Estimates, Children's Completed Schooling

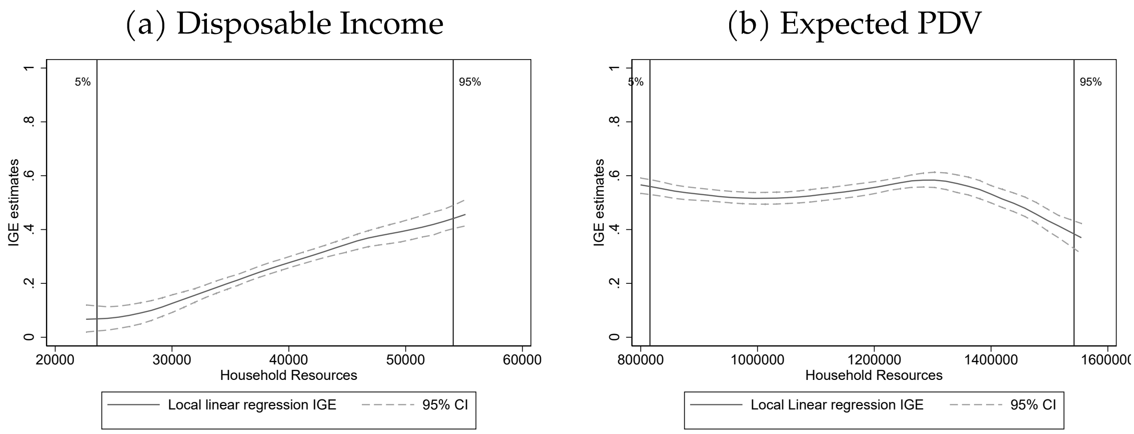
	Father		Parents	
	(1)	(2)	(3)	(4))
Variables	IV-GMM	OLS	IV-GMM	OLS
E(PDV^p), child age 0–4	0.211***	0.263***	0.270***	0.358***
	(0.005)	(0.003)	(0.007)	(0.004)
IV: innovations. child age 0–4				
E(PDV^p), child age 5–9	0.215***	0.268***	0.248***	0.365***
	(0.006)	(0.003)	(0.007)	(0.004)
IV: innovations, child age 0–4				
E(PDV^p), child age 10–14	0.207***	0.237***	0.240***	0.324***
	(0.004)	(0.002)	(0.005)	(0.003)
IV: innovations, child age 5–9				
E(PDV^p), child age 15–19	0.153***	0.201***	0.182***	0.286***
	(0.004)	(0.002)	(0.005)	(0.003)
IV: innovations, child age 10–14				

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows OLS and IV estimates of fathers' (col. 1-2) and parents' (col. 3-4) expected PDV at different child-ages on children's log-years of completed schooling.

different child ages. Panel (a) presents results for children's log-expected PDV and panel (b) presents results for children's log-years of schooling. The OLS estimates confirm the patterns from Fig. 7 with estimates either being slightly higher for children from low-income families than for children from high-income families or at par. However, when we turn to the IV-estimates this pattern is reversed. Table 7(a) shows that at all ages except at ages 5–9, the effect of parents' expected PDV on children's expected PDV is higher for children from high-income families with IV-GMM estimates between 0.4 and 0.5. In comparison, IV-estimates for children from low-income families range from approximately 0.3–0.4. These results emphasize three points: First, while there is extensive redistribution at the individual level through taxes and transfers, between local areas through spatial redistribution, and tuition-free education, parental resources still play a crucial role for children from low-income families. Second, the results speak to a large intergenerational persistence among affluent families

Figure 7: Non-Linear IGEs for Lifetime Measures



Notes: The figure shows estimated non-linear IGEs of disposable income and expected PDV (measures averaged over ages 30–35 of children and parents). The non-linear IGEs are estimated using local linear regression slopes as formulated in Landersø and Heckman (2017). Vertical lines represent the 95% confidence interval from 60 bootstraps. The vertical lines indicate the 5th and 95th percentiles in the parental resource distributions.

even when we adjust for endogeneity through our IV-strategy with children's expected lifetime resources increasing by 0.4-0.5% for every percent parental expected lifetime resources increase. Third, the IV estimates' age profiles differ across parental resources. For children from high-income families, IV estimates are declining as children age. In contrast, among children from low-income families, the effect of parent's expected PDV is largest during age 5–9.

The results for children's educational attainment in panel (b) of Table 7 follow those presented in panel (a) and speak to the importance of education as a mediator in the effects of parental resources on children's lives. The table shows that IV estimates are largest for children from high-income families. Moreover, the estimated effects of parents' resources on children's educational attainment also follow the same age profiles as the estimated effects on children's expected PDV with declining estimates as children age in high-income families and largest estimates in early school age for children from low-income families, which suggests that early school-age is a particularly sensitive age-window for children from disadvantaged backgrounds.

Table 7: OLS and IV-GMM IGE Estimates, Children's Expected PDV and Completed Schooling, Low- and High-Income Families

	(a) Outcome: log(E(PDV))				(b) Outcome: log(months of completed school.)			
	Below Median		Above Median		Below Median		Above Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	IV-GMM	OLS	IV-GMM	OLS	IV-GMM	OLS	IV-GMM	OLS
E(PDV^p), child age 0–4	0.307***	0.557***	0.501***	0.527***	0.194***	0.422***	0.357***	0.400***
	(0.0362)	(0.020)	(0.012)	(0.010)	(0.02)	(0.013)	(0.007)	(0.006)
IV: innovations. child age 0–4								
E(PDV^p), child age 5–9	0.507***	0.665***	0.518***	0.561***	0.329***	0.476***	0.366***	0.419***
	(0.031)	(0.016)	(0.012)	(0.010)	(0.020)	(0.011)	(0.007)	(0.006)
IV: innovations, child age 0–4								
E(PDV^p), child age 10–14	0.300***	0.558***	0.491***	0.556***	0.192***	0.402***	0.340***	0.400***
	(0.022)	(0.015)	(0.012)	(0.010)	(0.014)	(0.010)	(0.006)	(0.006)
IV: innovations, child age 5–9								
E(PDV^p), child age 15–19	0.377***	0.492***	0.441***	0.526***	0.250***	0.358***	0.289***	0.376***
	(0.016)	(0.011)	(0.012)	(0.009)	(0.010)	(0.007)	(0.007)	(0.005)
IV: innovations, child age 10–14								

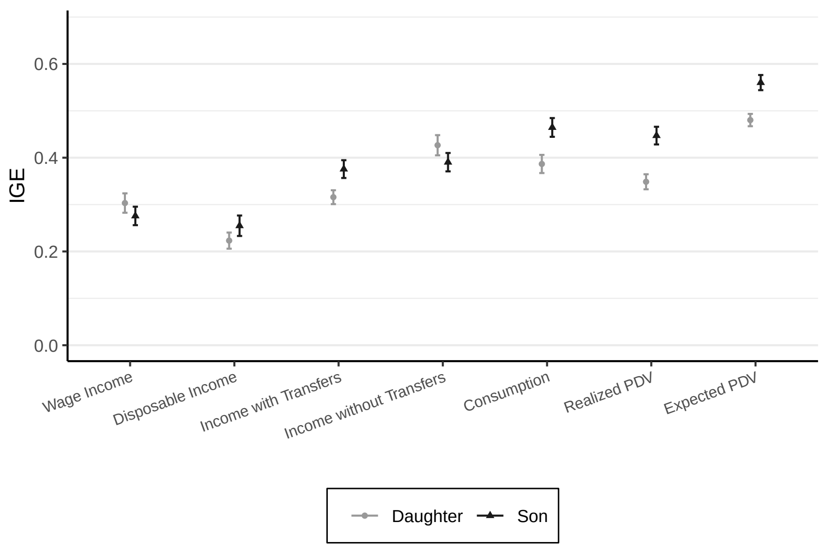
*** p<0.01, ** p<0.05, * p<0.1

Notes: The table shows OLS and IV estimates of parents' expected PDV at different child-ages on children's expected PDV and log-years of completed schooling (col. 1-4 and 5-8, respectively) separately for children from families with below median income in year $t-1$ (col. 1-2, 5-6) and children from families with above median income in year $t-1$ (col. 3-4, 7-8) .

7.3 Differences in Mobility by Child's Gender

In Fig. 8, we break down the family influence by child's gender. The figure shows that the overall pattern presented earlier remains with IGEs being largest for expected PDV for both males and females. Furthermore, focusing on the traditional measures of income, there is no clear pattern as to whether intergenerational mobility is highest for sons or daughters. Yet, once we focus on estimated IGEs for consumption (which is a proxy for lifetime resources), realized PDV, and expected PDV, estimates are substantially larger for sons.

Figure 8: Log-Log IGE Estimates Separately by Child Gender



Notes: The figure shows IGE estimates for different measures of resources separately by child's gender based on the children's individual resources. Parental resources are measured at age 30–35 of the parents.

Having presented the associations between parents' and children's resources by child gender, a natural next step is the effects identified through exogenous variation in parents' resources. Table 8 presents the corresponding IV results. Just as for the OLS estimates, the IV estimates suggest a stronger relationship between child's expected PDV and parents' expected PDV for sons than for daughters, which is consistent with findings in previous studies of the relationship between parents' and children's income in the US (Chadwick and Solon, 2002), Sweden (Hirvonen, 2008), and Canada (Chen et al., 2017).

Table 8: OLS and IV-GMM IGE Estimates, Children's Expected PDV and Completed Schooling, by child gender

	(a) Outcome: log(E(PDV))				(b) Outcome: log(years of completed school.)			
	Daughters		Sons		Daughters		Sons	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	IV-GMM	OLS	IV-GMM	OLS	IV-GMM	OLS	IV-GMM	OLS
E(PDV^p), child age 0–4	0.424***	0.487***	0.482***	0.534***	0.303***	0.361***	0.293***	0.357***
	(0.0107)	(0.00849)	(0.0132)	(0.0105)	(0.00683)	(0.00567)	(0.00728)	(0.00592)
IV: innovations. child age 0–4								
E(PDV^p), child age 5–9	0.424***	0.508***	0.487***	0.567***	0.296***	0.373***	0.288***	0.371***
	(0.0106)	(0.00812)	(0.0132)	(0.0101)	(0.00693)	(0.00548)	(0.00736)	(0.00571)
IV: innovations, child age 0–4								
E(PDV^p), child age 10–14	0.369***	0.444***	0.424***	0.509***	0.256***	0.322***	0.257***	0.324***
	(0.00847)	(0.00732)	(0.0105)	(0.00911)	(0.00541)	(0.00494)	(0.00576)	(0.00514)
IV: innovations, child age 5–9								
E(PDV^p), child age 15–19	0.317***	0.402***	0.374***	0.457***	0.210***	0.288***	0.207***	0.286***
	(0.00798)	(0.00646)	(0.00977)	(0.00797)	(0.00530)	(0.00437)	(0.00552)	(0.00453)
IV: innovations, child age 10–14								

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table shows OLS and IV estimates of parents' expected PDV at different child-ages on children's expected PDV and log-years of completed schooling (col. 1-4 and 5-8, respectively) separately for sons (col. 1-2, 5-6) and daughters (col. 3-4, 7-8) .

However, when we focus on the impact of parents' expected PDV on children's years of schooling, we do not observe significant differences in estimates across child gender. While gender differences in the importance of early environments have been examined in previous studies (see García et al., 2018, for an example and a review of related literature), the contrast between effects on education vs. economic resources suggests that gender differences in educational attainment and returns to education also influence how resources are transmitted across generations. Despite a female advantage in higher education among recent generations (as shown in Fig. 3(a) and found in most OECD countries in Borgonovi et al., 2018), gender differences in the labor market (see e.g., Nikolka, 2016) may influence how the transmission of family influence manifests.[25]

7.4 Absolute Mobility

We have thus far discussed relative mobility. Absolute mobility is another important dimension of social mobility. One measure of it is the percentage of children who have better outcomes than their parents (Berman, 2018; Chetty et al., 2017; Manduca et al., 2020). For ease of comparison we compare fathers to their sons in Figs. 9(a) and (b), and mothers to their daughters in Figs. 9(c) and (d). For each measure of resources we estimate the percentage of children (of the 1981—1982 birth cohort) whose resources are greater than those of their parents where we measure resources over ages 30–35.

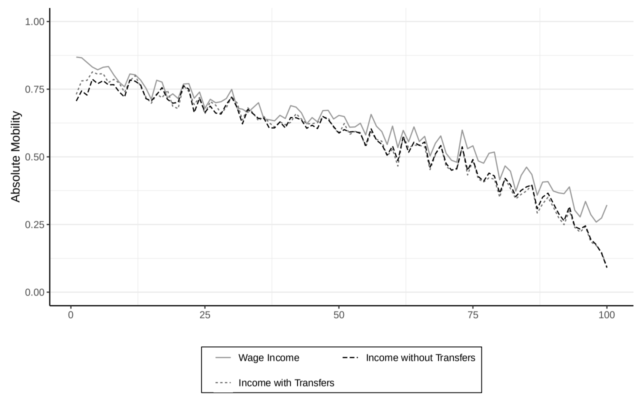
Fig. 9 plots the estimates by parents' wage income percentile (to keep a fixed axis in the comparison). Figs. 9(a) and (c) present the results for wage income, and gross income in- and excluding transfers, and Figs. 9(b) and (d) present the results for disposable income, consumption, and expected PDV. Focussing first on 9(a) and (c), the steep gradients for wage income, gross income excluding transfers, and gross income including transfers suggest substantial mean reversion across generations for both father/sons and mother/daughters. However, once redistribution via taxes is factored in as done for disposable income and consumption, the gradient is much smaller.

[25] There are also non-pecuniary benefits to education, for example in the marriage market which might benefit women the most (Caucutt et al., 2002). Also, non-pecuniary schooling costs may differ across gender (Fahle and Reardon, 2018).

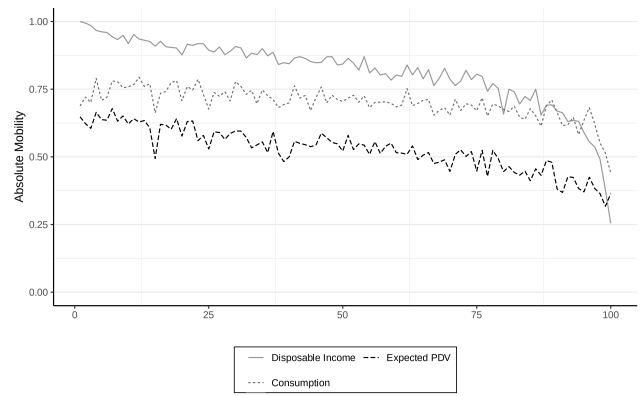
Figure 9: Absolute Mobility

Fathers and sons

(a) Traditional Measures

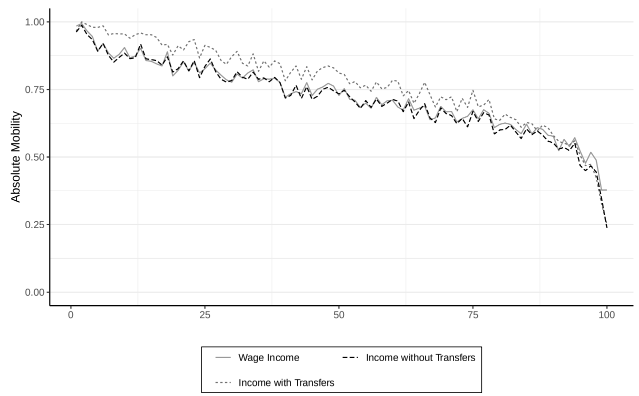


(b) Lifetime Measures

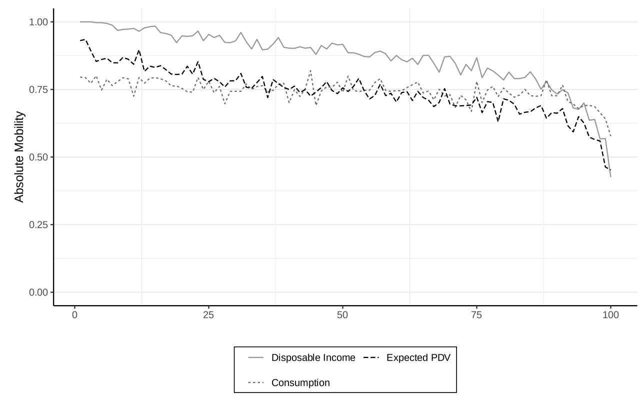


Mothers and daughters

(a) Traditional Measures



(b) Lifetime Measures



Notes: The figure shows the percentage of children (of the 1981–1982 cohort) whose measured resources are greater than those of their parents by percentile in the parents' wage income distribution. Resources are averaged over ages 30–35 for both parents and children. Figures (a) and (c) compare the absolute mobility pattern for wage income, gross income without transfers, and gross income with transfers for fathers/sons and mothers/daughters, respectively. Figures (b) and (d) compare the absolute mobility pattern disposable income, consumption, and expected PDV for fathers/sons and mothers/daughters, respectively.

Comparing next results for disposable income, consumption, and expected PDV, the figure shows that absolute mobility is decreasing the closer we approximate the life cycle perspective when we consider fathers/sons in Fig. 9(b) and to some degree for mothers/daughters in 9(d). For disposable income, almost 80% of male children have higher income than their fathers had at a similar age. For consumption, this fraction is around 70%, while for expected PDV around 60% have higher expected lifetime resources than their father. Turning to daughters relative to their mothers, upward absolute mobility is higher, which likely also reflect differences in female labor supply across generations. The percentage with higher disposable income, consumption, and expected PDV than that of their mother is, respectively, 90%, 75%, and 75% on average.

In sum, income measures that do not take into account changes in economic environments mischaracterize gains and losses across generations. The stark differences in absolute mobility presented here illustrate the consequences of not adequately accounting for the changes in income profiles across generations.

8 Conclusion

This paper presents new measures of social mobility based on the expected lifetime resources of parents and children, which allows us to study the role of parents' expected lifetime resources at crucial stages of investment in the lives of children. These measures take into account intergenerational differences in life-cycle family dynamics, earnings uncertainty, and revisions in agent information sets by age. Age-specific expected lifetime measures are better predictors of child human capital outcomes due to the much closer connection to the resources parents use when making decisions to invest in children. In this regard, our expected lifetime measures quantify long-term family influence on children.

We estimate significantly higher intergenerational persistence in expected lifetime measures compared to what is found using traditional measures of income and compared to realized lifetime measures. Our evidence is robust across a variety of specification checks and alternative measures of persistence. Our measures also show the importance of accurately accounting for differences in life cycle profiles when estimating absolute mobility.

We furthermore extend earlier studies of social mobility by combining our measures of expected lifetime resources with innovations to parents' income due to policy changes. While the IGEs identified through exogenous variation in parents' expected lifetime resources at a given age of the child is lower than the corresponding OLS estimates, estimates remain large ranging from 0.42 in early childhood to 0.31 in adolescence.

We utilize the exogenous variation in parents' expected lifetime resources to estimate intergenerational mobility separately for children from low- and high-income families and by child gender. While IGEs are larger for children from high-income families than for children from low-income families, the IGE estimates remain sizable across parents' income distribution nevertheless. We also show that IGE estimates are also larger for males than for females when we focus on children's expected lifetime resources but similar when we consider their educational attainment. These results could point to gender differences in the labor market as a potential mediator in the transmission of family resouces.

Our paper shows how integrating key insights from different economic literatures when studying intergenerational mobility allows for better understanding of the importance of factors such as the role of the family, changes in individual life cycles across generations, and the expectations and trajectories individuals face across their lifetimes. The combination of economic theory and data on individual and family life-cycle dynamics gives a deeper understanding of the mechanisms shaping social mobility.

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