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THE IMPACT OF THE LEVEL AND TIMING OF PARENTAL RESOURCES ON CHILD DEVELOPMENT AND INTERGENERATIONAL MOBILITY

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ABSTRACT

This study explores the relationships between parental resource trajectories and child development, and their implications for intergenerational mobility. By modifying child skill formation technology to incorporate new skills emerging during adolescence, we analyze the importance of the timing of family resources on life outcomes, such as educational attainment and participation in crime. Parental financial resources partially offset deficiencies in nonpecuniary inputs to children's human capital, such as family stability. IGE estimates are less sensitive to parental and child reference ages but are strongly influenced by the choice of lifetime versus snapshot parental income measures.

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1 Introduction

Becker and Tomes (1979, 1986) link the study of intergenerational mobility with the study of child development. In their overlapping generations model under perfect certainty, persons live three periods: as a child; as an altruistic adult investing in children; and as a retiree. Resources in adulthood determine the possibilities for investing in children. Welfare of each generation and entire dynasties are well defined, including parental returns to investment.

Recent research extends their original framework by incorporating multiple stages within each of the three periods in child and adult life cycles. It introduces the notions of critical and sensitive stages for the effectiveness of investments in children. Constraints in the early years of parental adulthood impact child investment. Given what is known about the technology of skill formation, and the presence of lifetime credit constraints, the timing of receipt of resources matters for shaping the skills of the next generation.[1] Hai and Heckman (2019) show that more able and educated people with rising but not easily verifiable wage profiles face age-dependent credit constraints that weaken as parental income and information are realized. Caucutt and Lochner (2020) develop a model that incorporates this feature and explore its consequences for child investment.

Early childhood is often characterized as the most sensitive life cycle period for skill formation and as a period in which there is a potentially strong role for parental credit constraints.[2] However, there is considerable evidence on the emergence of skills in adolescence.[3] Carneiro et al. (2021) present evidence that parental income received in later years of childhood has a more substantial impact on child investment than income received in middle childhood.

This paper contributes to the literature on the importance of timing and measurement of family resources on child development. We analyze the impacts of different measures of family resources at different ages that are most predictive of important child outcomes.

[1] See Caucutt and Lochner (2020); Cunha et al. (2010); Heckman and Mosso (2014).
[2] See e.g., Knudsen et al. (2006); Shonkoff and Phillips (2000).
[3] See Belsky et al., 2020; Crone, 2016; Steinberg, 2014.

The predictive power of parental resources on child outcomes varies greatly across different measures of resources. Those based on anticipated lifetime measures are the best predictors. The parental age at which they are constructed is far less important. There is no best age at which to pair parent and child in the study of social mobility.

We interpret our estimates using the technology of skill formation modified to account for the emergence of new skills in adolescence.[4] Our estimates suggest that resource-sensitive ages for investment vary greatly across child outcomes. Children's language and mathematics test scores are most sensitive to differences in parental resources during early childhood, while completed education and criminal activity depend more strongly on parental resources in early school years and early adolescence, respectively. These findings are consistent with a large body of literature on child skill development that documents the importance of lifetime credit constraints, the evolution of information about the lifetime income flows, and skills that emerge post-puberty when the adolescent brain forms and consolidates new pathways that affect decision making and behavior (see, e.g., Steinberg, 2014 and Moffitt, 2018).

This paper builds on and complements Eshaghnia et al. (2022) who use full population register data from Denmark to develop and estimate measures of age-dependent expected lifetime resources. They show that long-run measures of anticipated income are far more predictive of important child outcomes than conventional measures of income traditionally used in the study of intergenerational mobility.[5] We extend their finding by linking it — both empirically and theoretically — to the literature on childhood investments. We show that the predictive power of expected parental resources depends on the child age ranges used to measure them. This is consistent with the emergence of skills during childhood and adolescence in combination with credit constraints and the absence of complete markets.

[4]See Cunha and Heckman (2007).

[5]Eshaghnia et al. (2022) also show that expected lifetime resources are not more predictive just due to reduced measurement error arising from life cycle averaging. They are more strongly linked to child outcomes than realized measures of family resources (even using very long-run averages). They show that expected lifetime resources account for non-stationarity across generations while traditional income measures do not. In addition, they establish that estimates of both relative and absolute intergenerational mobility differ greatly. They further show nonlinearities in intergenerational dependence measures. Their lifetime wealth measures account for life cycle evolution in credit constraints and the resolution of uncertainty.

This paper builds on and extends Carneiro et al. (2021) who study the impacts of parental resources across childhood and draw on a large literature on early childhood skill formation (Heckman and Mosso, 2014). They analyze the relationship between measures of *realized* parental resources and child outcomes measured over a range of childhood ages from birth to 18. Our paper extends their analysis by computing the age-dependent parental *expected* present value of resources (accounting for differences in parental expectations about future resources as impacted by credit constraints and uncertainty that are updated over the life cycle) at each stage of childhood and relating it to later child outcomes in a model with multiple skills and multiple possible sensitive periods.

This paper also contributes to the literature on intergenerational income mobility. The focus in much of that literature is on measurement error and alignment of ages of parents and children, and their impact on estimates of social mobility (see, e.g., Haider and Solon, 2006; Mazumder, 2005; Solon, 1992). Our results emphasize that there is no single age or range of ages at which conventional measures closely proxy individual lifetime measures contrary to practice in the literature (Nybom and Stuhler, 2017; Stuhler and Nybom, 2022).[6] Intergenerational associations of parental value functions on child outcomes depend on the ages at which they are measured. There is a potential continuum (by age) of intergenerational parameters linking parental incomes and child outcomes. Nonstationarity in life cycle timing across generations further complicates matters.[7] We illuminate these issues by computing social mobility using **maximally predictive measures and ages**. There is no "best" age or set of ages for computing intergenerational mobility when its myriad facets are investigated.

The rest of the paper is organized as follows. Section 2 first characterizes the intergenerational associations we study using an amended version of the technology of skill formation, and then presents our measures of expected lifetime resources. Section 3 describes our data and measures of parental resources and child outcomes. Section 4 presents estimates of the

[6]This age is sometimes motivated by Mincer (1974)'s "overtaking age," which is proposed as a summary of lifetime resources. See Willis (1986). We contribute to the literature by studying the heterogeneity in the Intergenerational Elasticity (IGE) by gender of the child, and educational and cohabitional stability of parents.

[7]See Eshaghnia et al. (2022) and Stuhler and Nybom (2022).

best ages and measures of parental resources for predicting child outcomes. There is no best age. Section 5 presents estimates of intergenerational mobility for the most predictive measures and ages. Section 6 isolates the role of parental background characteristics such as education and stability of cohabitation in shaping income expectations and in direct investment. Section 7 presents estimates of our model of the technology of skill formation. Section 8 concludes.

2 Anticipated Resources Across Childhood and Skill Formation

We first present our framework of analysis. We review the technology of skill formation (Cunha and Heckman, 2007), and amend it by recognizing the emergence of new skills in adolescence as documented in Steinberg (2014) and Belsky et al. (2020). We relate our approach to that of Carneiro et al. (2021) and Eshaghnia et al. (2022).

2.1 Measuring Lifetime Welfare

A large body of literature studies the association between parental resources and child outcomes.[8] Yet, much of the previous literature almost exclusively focuses on snapshot measures of realized income at a given point in time or over limited ranges of ages.[9] This approach does not accurately capture the age-by-age updating of anticipated resources based on the information parents use to make decisions.

To address this issue, Eshaghnia et al. (2022) introduce a theory-based measure of lifetime wealth. Focusing on expected lifetime wealth, we make two main innovations compared to the traditional measures of family resources. First, we explicitly distinguish *ex-ante* (expected) and *ex-post* (realized) measures.[10] *Ex-ante* lifetime measures better predict

[8]See Corak (2013).
[9]For an exception see, Deutscher and Mazumder (2023).
[10]We use the approach of Cunha and Heckman (2007, 2016).

child outcomes because they better proxy the resources parents act on when they make investment decisions. Averages of lifetime income measures also reduce measurement error. *Ex-ante* measures better predict child outcomes compared to measures of realized parental income averaged over 40 years.[11] Previous studies such as Solon (1999) and Deutscher and Mazumder (2023) show that long run averages of realized income or related IV strategies minimize measurement error and are better predictors of child outcomes. This paper's findings are not just a consequence of reductions in measurement error, but also because we approximate resources available to families at the time child investment decisions are made. To estimate them, we approximate the *information set*, $\mathcal{I}_{i,t}$ available to individual i at each age t. Section 3.3 details how we estimate agent information sets.

Our second innovation is to measure wealth using the subjective valuation of future income. In the presence of credit constraints, uncertainty, and decreasing marginal utility of consumption and welfare, investment decisions not only depend on expected lifetime income, but also on uncertainty and access to the future income.

We define an individual's expected lifetime wealth (LW) at period t $(LW_{i,t})$ as

$$\text{LW}_{i,t} = \mathbb{E}_{i,t}\left[\sum_{\tau=1}^{T-t} s_{i,t+\tau} y_{i,t+\tau} \middle| \mathcal{I}_{i,t}\right], \tag{1}$$

where $s_{i,t+1}$ is individual i's stochastic discount factor (SDF) at age t when expectations are taken with respect to the information set of individual i at age t and T is the upper bound on life. The SDF is the expected marginal rate of time preference between future and current consumption:

$$s_{i,t+1} \equiv \mathbb{E}_{i,t}\left[\beta \frac{U_c(c_{i,t+1})}{U_c(c_{i,t})} \mid \mathcal{I}_{i,t}\right],$$

where $c_{i,t}$ and $c_{i,t+1}$ are individual i's consumption at age t and $t+1$, respectively, $U(c_{i,t})$ is utility at t, U_c is the marginal utility of consumption, and β is a fixed discount factor. Using measured consumption to form $s_{i,t+1}$ accounts for age-dependent liquidity constraints. In

[11] See Eshaghnia et al. (2022), who explicitly analyzes expected vs. realized outcomes and show that the former is a better predictor of child outcomes.

addition, we account for uncertainty and the insurance value of social programs such as social assistance and unemployment insurance.[12]

2.2 The Technology of Skill Formation

Equipped with a stage-dependent measure of the resources that parents use to determine investments in their children, we examine the impact of the timing of resources and investment across childhood. We use the technology of skill formation introduced in Cunha and Heckman (2007) and Cunha et al. (2010) to interpret the impact of family resources at different life cycle stages on child outcomes. We assume that agents make investments using a policy function which we approximate.

Skills $\boldsymbol{K}(t)$ evolve via the technology of skill formation:

$$\boldsymbol{K}(t+1) = \boldsymbol{F}_t(\boldsymbol{K}(t), \boldsymbol{I}(t)). \tag{2}$$

where $\boldsymbol{I}(t)$ is investment at age t. A critical period t^* for investment is a period for which $\frac{\partial \boldsymbol{K}(t+1)}{\partial \boldsymbol{I}(t)} > 0$ for $t = t^*$ and $\frac{\partial \boldsymbol{K}(t+1)}{\partial \boldsymbol{I}(t)} = 0$ all $t \neq t^*$. A sensitive period t^{**} is a value of t that lies in a set Ψ, characterized by $\frac{\partial \boldsymbol{K}(t+1)}{\partial \boldsymbol{I}(t)}|_{t\in\Psi} > \frac{\partial \boldsymbol{K}(t+1)}{\partial \boldsymbol{I}(t)}|_{t\notin\Psi}$ for all admissible values of $\boldsymbol{K}(t)$ and t.

Child outcomes $\boldsymbol{Y}(t)$ at age t depend on $\boldsymbol{K}(t)$ and other determinants, such as effort, perseverance, preferences, and parental environments and community, $\boldsymbol{X}(t)$:

$$\boldsymbol{Y(t)} = \Phi_t(\boldsymbol{K(t)}, \boldsymbol{X(t)}). \tag{3}$$

Lagging (2) one period, we obtain:

$$\boldsymbol{K}(t) = \boldsymbol{F}_{t-1}(\boldsymbol{K}(t-1), \boldsymbol{I}(t-1))$$

[12]We follow Eshaghnia et al. (2022) and use a CRRA utility function: $U(c_{i,t}) = \frac{c_{i,t}^{1-\rho}-1}{1-\rho}$, where $c_{i,t}$ denotes the adult-equivalence consumption (to adjust for family size and composition) of individual i at time t. We set the risk aversion parameter at 0.67.

and by recursion, we obtain:

$$\boldsymbol{K}(t+1) = \boldsymbol{F}_t(\boldsymbol{F}_{t-1}(\boldsymbol{K}(t-1), \boldsymbol{I}(t-1)), \boldsymbol{I(t)}). \tag{4}$$

Making repeated substitutions:

$$\boldsymbol{K}(t+1) = \boldsymbol{Q}_t(\boldsymbol{I}(t), \boldsymbol{I}(t-1), \dots, \boldsymbol{I}(0); \boldsymbol{K}(0)). \tag{5}$$

Agents are assumed to maximize life cycle programs as in Del Boca et al. (2014), Caucutt and Lochner (2019), and Agostinelli and Wiswall (2022), among others. Letting $V(t)$ be the value function of the program at age t, the policy function for investment is

$$\boldsymbol{I}(t) = \boldsymbol{G}_t(\boldsymbol{V}(t), \boldsymbol{X}(t)) \tag{6}$$

where $\boldsymbol{X}(t)$ includes other determinants of investment.

Substituting repeatedly,

$$\boldsymbol{Y(t)} = \Phi_t(\boldsymbol{Q}_{t-1}(\boldsymbol{G}_{t-1}(.,.), \boldsymbol{G}_{t-2}(.,.), \dots, \boldsymbol{G}_0(.,.); \boldsymbol{K}(0)), \boldsymbol{X(t)}) \tag{7}$$

2.3 Linking Expected Lifetime Resources to the Technology of Skill Formation

We use age-specific lifetime wealth to approximate value functions and obtain the state equation:

$$\boldsymbol{K}(t+1) \doteq \boldsymbol{Q}_t(LW_t, LW_{t-1}, \dots, LW_0, K(0)).$$

This approach contrasts with that of Carneiro et al. (2021), who approximate Equation (7) using measures of realized family income in each period t to approximate LW, and control for the realized present value of future income. They ignore other factors $\boldsymbol{X}(t)$ and realized initial conditions $\boldsymbol{K}(0)$ by the present value of discounted income over the life of the child evaluated at birth and do not account for information updating.

Define $\boldsymbol{Z_t} = [LW_t, LW_{t-1}, \ldots, LW_0, K(0)]$. Investment at each age produces the stock of skills that govern behavioral Equation (7). Expanding it in a Taylor series without remainder to second order, the outcome equation is:

$$\boldsymbol{Y}(t+1) \doteq \alpha_0(t) + \boldsymbol{\alpha_1'}(t)\boldsymbol{Z_t} + \boldsymbol{Z_t'}\Psi(t)\boldsymbol{Z_t} \tag{8}$$

where $\boldsymbol{\alpha}_1(t)$ is $t \times 1$ vector. $\boldsymbol{\Psi}(t)$ is $(t+1) \times (t+1)$ matrix. Like Carneiro et al. (2021), we use broad age intervals for our lifetime income measures to avoid problems with collinearity. Unlike them, we form intervals on the basis of the correlation patterns of the $\boldsymbol{Z}_t$ and account for the updating of information sets. The coefficients $\boldsymbol{\alpha}_1(t)$ and $\boldsymbol{\Psi(t)}$ give information about critical and sensitive periods because we can form $\frac{\partial \boldsymbol{Y}(t+1)}{\partial \boldsymbol{Z}_t} = \boldsymbol{\alpha}_1' + \boldsymbol{\Psi}(t)\boldsymbol{Z}_t$ for each t.

2.4 Emergent Skills

There are at least two periods of rapid skill and preference development in the life of a child: early childhood and adolescence. Resources available to families in each period of life may play important roles in child development if markets are incomplete so full insurance against all contingencies is ruled out and borrowing constraints apply for some. Hai and Heckman (2019) document that even for able and highly educated people, the timing of income in these sensitive periods may matter.

This helps to explain the U-shaped relationship between child outcomes and parental income through adolescence documented by Carneiro et al. (2021) for which we show partial support. Sensitive periods with binding credit constraints can rationalize their evidence. We amend the Cunha et al. (2010) model to account for the emergence of skills as documented in Steinberg (2014), Crone (2016), and Belsky et al. (2020).

The framework of Section 2.2 follows the recent literature and assumes that the dimension and skill categories of $\boldsymbol{K}(t)$ remain the same over the life cycle. This ignores a large literature on the flourishing of lifetime skills. As children mature, new preferences and behaviors emerge. Steinberg (2014) and Crone (2016) document dual systems of adolescent behavior. The centers of the brain that respond to stimulation and pleasure mature early after the onset of puberty with its corresponding hormonal rush. Centers of the brain associated with self-control and executive functioning (the prefrontal cortex) become active later, creating patterns of behavior (and associated evolution of skills) unique to the adolescent years.

We allow the dimension of $\boldsymbol{K}(t)$ to change as new skills emerge. At age t_e, new skills and possibly new investment strategies, emerge. In a simplified model,

$$\begin{bmatrix} \boldsymbol{K}(t+1) \\ \tilde{\boldsymbol{K}}(t+1) \end{bmatrix} = \boldsymbol{J}_t(\boldsymbol{K}(t), \tilde{\boldsymbol{K}}(t), \boldsymbol{I}(t), \tilde{\boldsymbol{I}}(t))$$

where "$\sim$" denotes the new skills stocks and investment emerging at and after t_e. We define $\tilde{\boldsymbol{I}}(t) = 0$ and $\tilde{\boldsymbol{K}}(t) = 0$ for $t < t_e$.

The distinctions previously made apply here. New forms of complementarity emerge: $\frac{\partial^2 \boldsymbol{J}_t(\boldsymbol{K}(t), \tilde{\boldsymbol{K}}(t), \boldsymbol{I}(t), \tilde{\boldsymbol{I}}(t))}{\partial \boldsymbol{K}(t) \partial \tilde{\boldsymbol{K}}(t)} > 0; t \geq t_e$ and investments of different types may cross-fertilize. Outcomes may depend on $\boldsymbol{K}(t)$ (e.g., IQ) and on "soft skills" $\tilde{\boldsymbol{K}}(t)$. Thus, outcome j (e.g., management skills) may depend on both cognitive ability and personality traits: $\boldsymbol{Y}_j(\boldsymbol{K}(t), \tilde{\boldsymbol{K}}(t))$.

Mandelbrot (1962) characterizes occupations or tasks by bundles of traits.[13] Some skills may have negative marginal product in some occupations, e.g., gregariousness may reduce productivity for an abstract mathematician. Sensitive periods can arise when skills emerge (i.e., after t_e for $\tilde{\boldsymbol{K}}(t)$). Early investment may or may not enhance the productivity of later investment. Some skills may interfere with other skills. We extend the definition of $\boldsymbol{I}(t)$ to also account for investment in emergent skills $\tilde{\boldsymbol{I}}(t)$.

[13] See Heckman and Sedlacek (1985) for an empirical application of his model.

3 Data and Measures of Outcomes and Resources

This paper uses population administrative register data from Denmark for the years 1980 through 2019. The data have unique identifiers of individuals, which enable us to combine information on a wide range of measures across all ages. The data include unique identifiers of parents and spouses, allowing us to link families throughout the entire period. In addition to information on the income measures of children and their parents, we also add information on completed education, household structure and demographic characteristics, and crime.[14]

3.1 Main Samples and Definitions

We base our analysis on the sample of children born in 1981 and 1982 for whom we can establish a link to parents, whose parents did not migrate, and who did not themselves migrate. This results in a sample of around 100,000 children and their families. We observe the birth cohorts of 1981 and 1982 from birth to age 38 and 37, respectively (in 2019). We also have information on their parents in all years between 1980 and 2019.[15]

For our Intergenerational Elasticity (IGE) analysis, we measure child outcomes at ages 30–35, but we report results for alternative age ranges in Appendix C. We measure average years of education as the minimum years it takes to complete the highest obtained degree by age 35. We measure criminality as having received a prison sentence by age 35.

As additional measures of child human capital, we also consider children's language tests at age 11 and math test scores at age 16. For the former, we use the Danish Longitudinal Survey of Children (DALSC), which is a representative survey of children born in 1995. For the latter, we focus on all children born between 1995 and 1997 in Denmark, and we measure

[14] Using the individual identifiers, we link data from registers containing educational attainment (UDDA register), income, assets, transfers (IND register), marital status, and fertility (BEF register) for each individual and his or her spouse and parents. We also include information on criminal convictions from the sentencing register (KRAF).

[15] The results in the main text are based on the full sample irrespective of whether we can track the family across all years. The patterns and main conclusion remain the same for a balanced sample. Appendix H reports the results.

math test scores at the 9th-grade national leaving exam. Precise definitions for the variables in the samples used are given in Appendix A.

3.2 Measures of Parental Resources

Register data on income, assets, and liabilities are based on information from Danish tax authorities. We pool resources of spouses or cohabitees when appropriate. We analyze three measures of parental resources:

1. **Wage income** includes (pre-tax) taxable wage earnings as the main component along with sources of income such as fringes and stock options. Wage income is the main source of personal income for the majority of the population.
2. **Disposable income** is total personal income,[16] which includes public transfers (such as social assistance, unemployment insurance benefits, disability insurance benefits) plus the rental value of own home (for owner-occupiers) minus taxes and interest expenses.
3. **Expected lifetime wealth** (as introduced in Section 2.1) is the subjective present value of lifetime income (measured by disposable income) discounted by SDF at each age t. It captures the expected resources available to a family across childhood. Lifetime wealth is updated at each age of the child through changes to parents' information set (e.g., income shocks) and subjective discounting of future resources (e.g., through changing uncertainty or liquidity constraints).

We define parental income as the sum of the mother's and father's resources, irrespective of their marital status, to proxy the total resources available for investment in the child at each age. Table 1 summarizes the three measures of resources we analyze. Eshaghnia et al. (2022) consider a wider range of measures, including pre-tax total personal income with and without transfers and the expected present discount value of future income (the risk-neutral equivalent of lifetime wealth).

[16] Total personal income is 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 person.

Table 1: Definitions of the Measures of Parental Resources Analyzed

	Variable	Definition
(1)	Wage Income	Taxable family wage earnings and fringes, labor portion of business income, non-taxable earnings, severance pay, and stock options.
(2)	Disposable Income	Total family personal income (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 person) and rental value of own home (for owner-occupiers) minus taxes and interest expenses.
(3)	Expected Lifetime Wealth	The expected present discounted value of future total income (defined as disposable income in (2)) using a subjective stochastic discount factor. The lifetime wealth at time t for individual i is $$\mathrm{LW}_{i,t} \equiv \mathbb{E}_{i,t}\left[\sum_{\tau=1}^{T-t} s_{i,t+\tau} y_{i,t+\tau} \mid \mathcal{I}_{i,t}\right], \text{ where } s_{i,t+1} \equiv \mathbb{E}_{i,t}\left[\beta \frac{U'(c_{i,t+1})}{U'(c_{i,t})} \mid \mathcal{I}_{i,t}\right]$$ where $y_{i,t+\tau}$ is the future total income (where income is defined as in (2)) at age $t+\tau$. β is a common discount factor, and $\mathcal{I}_{i,t}$ is agent i's information set. We set β to 0.96, following Ogaki and Reinhart (1998). The information set is being updated over ages (see Section 3.3). See Eshaghnia et al. (2022) for details on the estimation procedure.

3.3 Information Set $\mathcal{I}_{i,t}$

We estimate agent information for parents and children using the procedure of Cunha and Heckman (2016). For each age, we estimate a vector $\mathcal{Z}_{i,t}$ that forecasts agent future income where the forecast error is uncorrelated with choices that depend on these forecasts. For example, consumption at age 30 should not be associated with the difference between actual income at age 50 and the expected income at age 50 (measured at age 30).

Our choice of information set is based on variables that approximate future income levels and uncertainty, such as education, gender, relationship status, and homeownership. However, information sets based on these characteristics alone do not pass our tests. Eshaghnia et al. (2022) show that a much richer set of variables is required. Our preferred set is gender of the individual,[17] their education level (primary school, high school, college, and university), employment status, cohabitation status, number of children, quartiles for mean income

[17] Family incomes are the sum of the mother's and father's forecast incomes.

level, quartiles for mean consumption level, quartiles for mean consumption growth, quartiles for standard deviation of consumption, and homeownership status, and interactions among these factors.[18] This estimated information set satisfies the condition that components of income not in the information set do not predict future outcomes (Cunha and Heckman, 2016).

Note that forecast income is disposable income adjusted for unrealized capital gains from housing stocks (i.e., 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).

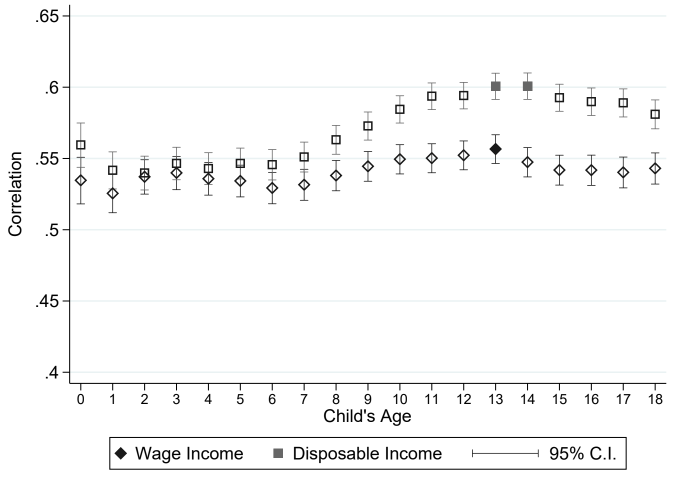
A separate question is whether child outcomes depend on key parental characteristics such as education operating through other channels besides expected future wealth. We explore this in Sections 6.1 and 6.2.

3.4 Relationships Among Different Resource Measures

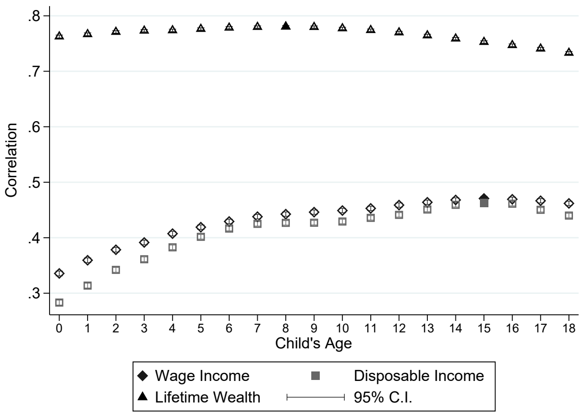
Figure 1 shows the correlation between our measures of parental resources and parental background characteristics at different ages of the child. Panel (a) of Figure 1 shows that the association between parents' expected lifetime wealth and disposable income is stronger at all ages of the child compared to the association between parents' expected lifetime wealth and their wage income. Moreover, the figure also shows that the correlations between expected lifetime wealth and the two other measures of resources differ across child age, particularly for disposable income. Here, the weakest association to parents' expected lifetime is in the preschool years (correlation of 0.54 at around age 4), while the strongest association is in adolescence (correlation of 0.60 at age 14).

[18] Quartiles are based on the average over the past two years (computed across parents' distribution).

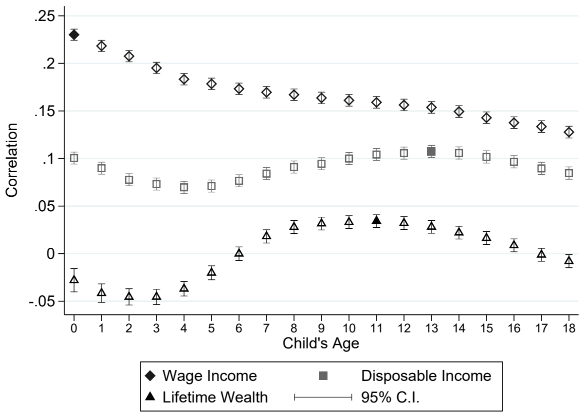
Figure 1: Correlations between Measures of Parental Resources and Parental Background Characteristics by Child's Age



(a) Correlations of expected lifetime wealth with wage income and disposable income



(b) Correlation Between Parental Resources and Parents' Average Years of Education



(c) Correlation Between Parental Resources and Parents' Marital Status

Notes: Panel (a) shows the correlations of parents' expected lifetime wealth with parents' wage income and disposable income, separately, at each age of the child. Panels (b) and (c) show the correlation between the three measures of parental resources and parents' years of completed education and marital status, respectively. For each measure of resources, we use a t-test to evaluate whether the correlation at each age is significantly different from the maximum correlation (at the 5% level). We depict the estimate with solid (filled) symbols if it is not significantly different from the max.

Panel (b) of Figure 1 shows the correlation between the three measures of parental resources and their average years of education. The figure shows a strong correlation between parents' expected lifetime wealth and education. In contrast, the correlations between parents' years of education, and wage income and disposable income, respectively, are more modest; correlation coefficients are initially around 0.35 and increase in child age to around 0.45 at age 18. Panel (c) shows that the expected lifetime wealth is the measure least correlated with parents' marital status at childbirth.

4 Child Outcomes and Parental Resources over the Life Cycle

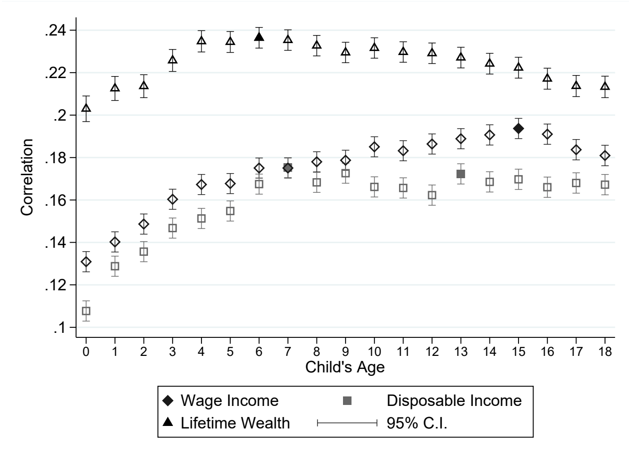
The following sections present evidence on parental transmission of influence. In this section, we present the associations between child outcomes and parental resources measured at different ages of the child. Section 5 shows how estimated intergenerational income elasticities vary according to when parental resources are measured. Section 6 explores heterogeneity across family types along with the role of parental background characteristics such as education for child outcomes. Section 7 connects the different findings by estimating the skill formation model previously introduced.

Figure 2 presents correlations between parental income measures at different child ages from zero to 18 and child outcomes. Each panel of Figure 2 focuses on a specific outcome measure and plots the correlations by age between parental resources (wage income, disposable income, and the expected lifetime wealth) and the child's outcome of interest.[19] For each measure of resources, we use t-tests to evaluate whether the correlation at each age is significantly different from the maximum correlation.[20] We report estimates with solid (filled) symbols if they are not significantly different from the maximum value (given the income measure).

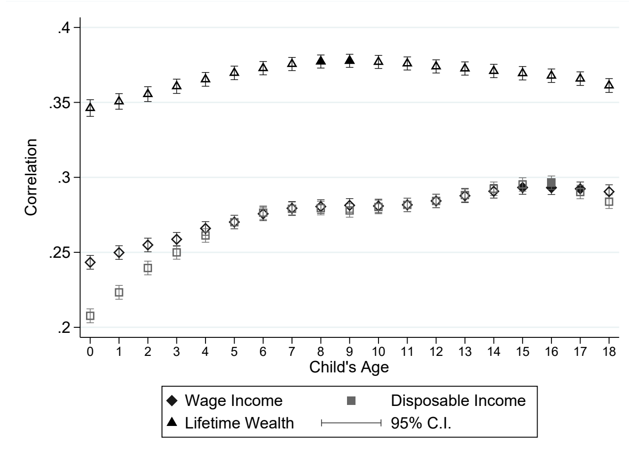
[19]To reduce the impact of measurement errors when measuring parental resources, we use a 5-year rolling average of parental resources centered around the corresponding child's age.

[20]See Appendix B.

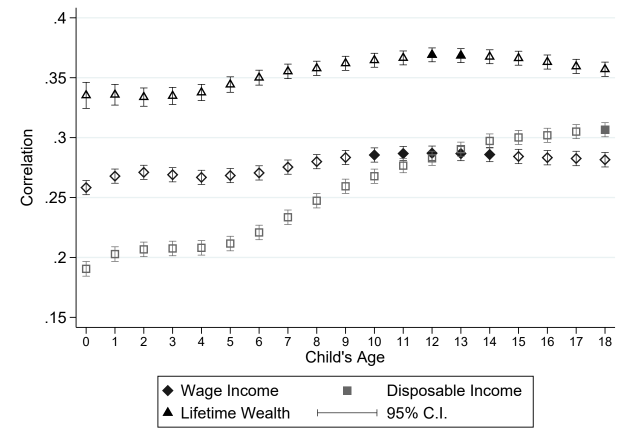
Figure 2: Correlations between Measures of Parental Resources and Various Child Human Capital Outcomes- by Child's Age



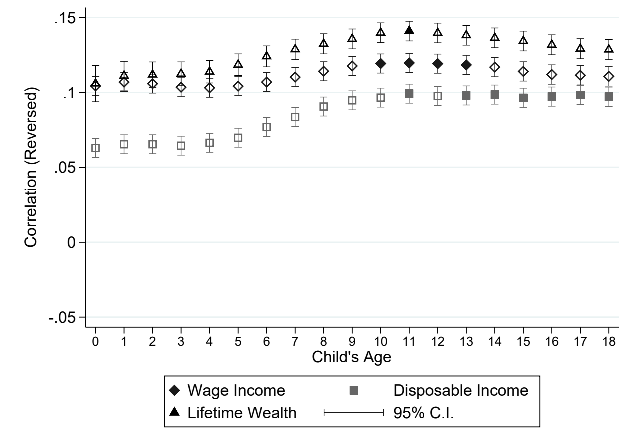
(a) Child's Language Test Score at age 11



(b) Math. National Leaving Exam Grade at age 16



(c) Years of Education by age 35



(d) Participation in Crime (Incarcerated) by age 35

Notes: Panels (a), (b), and (c) plot the correlations between the different parental income measures measured at the different child ages and the child's language test score at age 11, the child's national math test score at age 16, and the child's years of completed schooling by age 35, respectively. Figure (d) plots the inverted correlation between the child's receiving a prison sentence by age 35 and their parental resources. For each measure of resources, we use a t-test to evaluate whether the correlation at each age is significantly different from the maximum correlation (at the 5% level). We depict the estimate with solid (filled) symbols if it is not significantly different from the max.

Panel (a) shows correlations between the child's language test score at age 11 and parental measures of resources at child ages between zero and 18. Panels (b), (c), and (d) present the relationship between parental resources in childhood and the child's national math test score at age 16 (panel (b)), the child's years of completed formal schooling by age 35 (panel (c)), and the child's incarceration by age 35 (panel (d)). The patterns are, in general, similar when we disaggregate the sample by family structure. However, the levels of the correlations change as noted in Section 6.[21]

In accord with Eshaghnia et al. (2022), Figure 2 shows that across all ages of childhood, our lifetime measures of parental resources (expected lifetime wealth) outperform the traditional snapshot measures of parental resources in forecasting child outcomes. In addition, the figure presents three novel findings:

First, while the predictive power of traditional snapshot measures varies strongly across the age of measurement, the associations between expected lifetime wealth and child outcomes are much more stable.

Second, traditional snapshot measures of parental resources reach their highest predictive power in middle childhood and sometimes even after the realization of the child's outcome of interest. For example, while the correlation between the child's language test score at age 11 and the expected lifetime wealth of parents peaks in early childhood (at around age 6), the correlation with parental wage income or disposable income peaks much later in childhood (around ages 13–15), several years after the realization of the outcome in question. The only exception is the child's participation in crime (incarceration), where all measures of parental resources manifest very similar patterns over the child's age and the correlations peak at around ages 10–18 for all measures of parental resources. The measures of parental resources differ significantly in their predictive power. Our lifetime measure outperforms other measures in predicting a child's incarceration by age 35. Additional results for crime when measured by ages 20, 25 and 30 show the same pattern (see Appendix D.1).

[21] Appendix G shows that the child's outcome measures such as education and participation in crime are important in predicting child's earnings in adulthood.

Third, the most predictive ages vary across outcomes. Higher levels of parental expected lifetime wealth during early childhood (age 6) are associated with higher academic achievement and the development of language, while parental income during adolescent years (ages 10–18) is more tightly linked to children's participation in crime. Again, the patterns are generally similar when we break down the samples by family structure or by the education of parents.[22]

Table 2 summarizes the main results from Figure 2. We list the combination of the child's age at measurement and the measure of parental resources with the highest correlation for each of the child outcomes presented in Figure 2. We refer to this combination of child's age at measurement and measure of parental resources as the "best predictor." Column (1) lists the child outcome. We report the corresponding "best predictor" in columns (2) and (3). The "best predictor" is a measure of parental resources (column 2) and child age at measurement (column 3), that has the highest correlation with the child outcome studied. Column (4) presents the corresponding R^2 resulting from a linear regression of the child outcome in column (1) on the measure of parental resources in column (2), i.e., its best predictor, where parental resources are measured at the child's ages listed in column (3). We discuss the results for IGEs in the last two columns (5–6) of Table 2 in Section 5.

Panel (a) of Table 2 presents the results when we compare all measures of parental resources. The lifetime measure of parental resources (age-dependent expected lifetime wealth) outperforms all other income measures. Panel (b) of Table 2 lists the "best predictor" among the traditional income measures, i.e., where we exclude our lifetime measure of parental resources from the analysis. The only measure of child outcome for which the most predictive ranges of the traditional income measures overlap with those of the lifetime measure is participation in crime (incarceration).

We benchmark estimates at each age against the age with the max correlation, separately for each income measure and child outcome measure. We run pairwise t-tests to see whether

[22] See Section 6.1.

each estimate is significantly different from that of the age with the max correlation.[23]

The peak age ranges are very similar for crime, but they are different for test scores. The peak ages for years of schooling overlap across measures of parental resources for some ages. The estimated dependence of child outcomes on family income depends on the outcome measure of interest.

The results presented in this section have two important implications. First, a large literature focuses on the importance of aligning child and parental ages when estimating intergenerational persistence in income (Grawe, 2006; Mazumder, 2005; Nybom and Stuhler, 2017; Solon, 1992). Different ages of measurement not only potentially lead to life cycle and attenuation bias—it also changes the channels studied for the transmission from parental income to child's income, and therefore leads to different interpretations of the IGE. We find that when using lifetime measures for many outcomes *there is no unique range of child ages at which parental income is most predictive*.

Second, our correlational evidence that the channel through which parental resources affect child outcomes depends on the outcome in question and the age of the child at which parental resources are measured, suggests that there are differences in sensitive periods in child development (as documented in e.g., Belsky et al., 2020; Knudsen et al., 2006; Steinberg, 2014). A high level of family income during early childhood may support the development of language, while during adolescence, higher levels of family income may prevent children from committing crimes given development of the prefrontal cortex in adolescence (see, e.g., Crone, 2016; Steinberg, 2014). This finding is supported by long-standing evidence from the child development literature, showing that children develop different faculties at different stages of childhood (Belsky et al., 2020; Murasko, 2007; Nelson et al., 2014).

[23] See Appendix B for details. We account for joint dependence between the measures studied and the maximum correlation.

Table 2: Summary: 'Best Predictor' across Child Outcomes and Corresponding Explanatory Power and IGEs

	Best Predictor			IGE Estimates	
Child's Outcome Measure	**Measure**	**Child's Ages**	R^2	**Corresponding IGE**	**IGE-R^2**
(1)	(2)	(3)	(4)	(5)	(6)
Panel a: Among All Measures of Parental Resources					
Child's Language Test Score at age 11	Expected Lifetime Wealth	6	0.053	0.40 [0.392,0.409]	0.101
Math. Leaving Exam at Age 16	Expected Lifetime Wealth	8-9	0.140	0.39 [0.386,0.401]	0.109
Years of Education by Age 35	Expected Lifetime Wealth	12-13	0.136	0.38 [0.369,0.384]	0.115
Participation in Crime (Incarcerated) by Age 35	Expected Lifetime Wealth	11	0.020	0.38 [0.375,0.390]	0.111
Panel b: Among Traditional Measures of Parental Resources					
Child's Language Test Score at age 11	Wage Income	15	0.034	0.15 [0.142,0.161]	0.017
Math. Leaving Exam at Age 16	Disposable Income	16	0.089	0.30 [0.280,0.308]	0.042
Years of Education by Age 35	Disposable Income	18	0.094	0.29 [0.275,0.308]	0.044
Participation in Crime (Incarcerated) by Age 35	Wage Income	10-13	0.014	0.15 [0.142,0.161]	0.017

Notes: This table presents the parental measure (column 2) and age of measurement (column 3), resulting in the highest correlation ('best predictor') with each child outcome (column 1). Column (4) reports the R-squared of the linear regression of the child outcome in column (1) on the measure of parental resources in column (2). Panel (a) includes all measures of parental resources. Panel (b) restricts the analysis to the traditional snapshot measures of parental resources by excluding the expected lifetime wealth from the analysis. Column (5) presents the corresponding IGE estimate for each of the different 'best predictors', where individuals are measured over ages 30–35. The 95% confidence intervals are shown in brackets. To compute the IGE, we regress the child's lifetime well-being measure, listed in column (2) and measured at ages 30-35, on the parental lifetime well-being measured by the 'best predictor.' Column (6) reports the R-squared of the IGE regression. To compute the IGE in Panel (b), we regress the child's traditional well-being measure, listed in column (2) and measured at ages 30-35, on the parental traditional well-being measured by the 'best traditional predictor.'

5 Estimates of Intergenerational Mobility

We now turn to the relationship between child's lifetime resources and parental lifetime resources, which is the predominant focus in the literature on intergenerational mobility. Here, the most common measure is the intergenerational elasticity (IGE): a measure of the dependence of well-being across generations. Estimates of the IGE, β, are obtained by estimating the following regression:

$$\log(LW_{i,c}) = \alpha + \beta_k \log(LW_{i,k}) + \epsilon_i, \tag{9}$$

where $LW_{i,c}$ denotes a measure of child expected lifetime resources in adulthood for family i, and $LW_{i,k}$ denotes the expected resources of the family (the father and mother) when the child was k years old, and ϵ_i is the error term.[24] Estimating Equation (9) separately for different values of k (children age when parental resources are measured), we obtain a range of IGE estimates, β_k (where $k \in \{0, \ldots, 18\}$), for a given measure of individual's resources.[25]

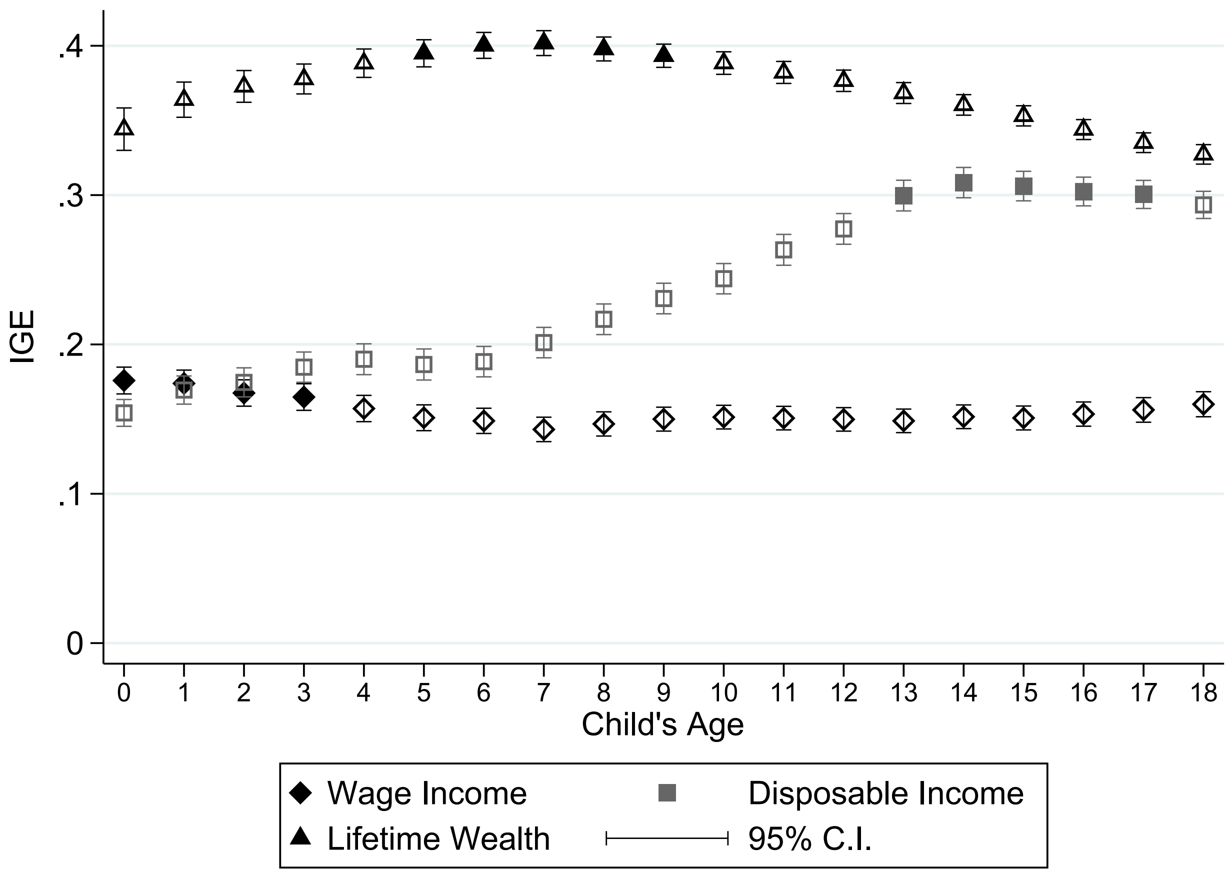
We report the IGE estimates for our traditional measures and lifetime measure in Figure 3. Notably, the IGE for the expected lifetime wealth is at least 0.34, while the IGE in wage income does not exceed 0.18 and the IGE using disposable income peaks at around 0.3.[26] The figure shows that the IGE estimate at a given age increases by at least 0.16 when using expected lifetime wealth to measure the IGE, rather than wage income. Appendix C presents the results using alternative age ranges to measure children's resources.

[24]To mitigate concerns about measurement errors, we use a five-year moving average centered around k, i.e., we use the average of family resources over the child's ages $k-2, k-1, k, k+1, k+2$.

[25]To measure a child's resources in adulthood, we always use the average of child's resources over ages 30–35. Appendix Section C presents the robustness of our results with respect to different age ranges for measuring child outcomes.

[26]The corresponding IGE estimates in Eshaghnia et al. (2022), when both parents and children are measured at ages 30-35, are 0.48, 0.28, and 0.24 for the expected lifetime wealth, wage income, and disposable income, respectively.

Figure 3: IGE Estimates over Age of Child When Parental Resources Measured: Estimates with Solid (Filled) Symbol Are Not Significantly Different from the Maximum IGE Estimate



Notes: This figure plots the IGE for selected income variables. The child's income is measured at ages 30-35, and the parental income is measured at the household level at different child ages. We include children from the 1981-1982 cohorts in Denmark and their parents. The vertical lines around the point estimates represent the 95% confidence intervals. For each income measure, we use a t-test to evaluate whether the estimate at each age is significantly different from the maximum IGE estimate (at the 5% level) where we account for dependence across the estimates.

Table 3: IGE Estimates when Measuring Parental Resources over Different Childhood Ages

Measure of Resources (1)	**Maximum IGE** (2)	**Max-IGE Age** (3)	**Minimum IGE** (4)	**Min-IGE Age** (5)
Disposable Income	0.30 [0.30,0.31]	13-17	0.18 [0.15,0.19]	0-6
Expected Lifetime Wealth	0.40 [0.39,0.41]	5-9	0.34 [0.33,0.35]	18
Wage Income	0.18 [0.17,0.19]	0–3	0.14 [0.13,0.15]	5-17

Notes: For each measure of resources (Column 1), this table presents the maximum (column 2) and minimum IGE (column 4) when we measure parental resources at different ages of children between 0 and 18 (five-year moving average), along ages of children corresponding to the maximum (column 3) and minimum (column 5) IGEs. We measure the child's resources between ages 30-35. The 95% confidence intervals for the IGE estimates are shown in brackets.

We summarize our findings in Table 3. Comparing IGEs for our lifetime measures with those for disposable income, we find that the choice of measure has much larger effects on the estimated IGE than the choice of age intervals.

Section 4 established that our lifetime measure, especially when taken during early childhood and adolescent years, has a much stronger connection to the outcomes of children. In this section, we compute IGEs using measures of parental resources and ages of child that are most relevant to the transmission of family influence. Columns (5)-(6) of Table 2 in display the estimated IGEs using the age ranges with the strongest association between children's human capital outcomes and parental resources.

We reach the following conclusions: First, the IGE measured at the most predictive ages is high, ranging from 0.38–0.40 (see Panel (a) of Table 2). Second, there is no clear, consistent "correct age" or "correct measure." The measures and ages leading to the maximum correlation vary across child outcomes. That said, among measures of family resources, the "best predictor" is always the lifetime measure of expected parental income. Large differences are driven by the choice of income measure, rather than the age range used to measure parental resources. See Panel (b) of Table 2, which shows that the "best predictors" of IGEs using traditional income measures vary from 0.15 to 0.30.

Moreover, choosing the correct age range to measure the IGE based on its predictive power for a specific child outcome can be interpreted as an approximation to the channel of transmission of income from parents to children. Note, however, this is only suggestive of causality. In the presence of imperfect capital markets and the revelation of life cycle information, the timing of parental income can matter. Our correlations and age-by-age IGEs do not necessarily speak to the causal impact of the timing of income as presented by Carneiro et al. (2021), since we don't hold income at other ages constant. A model of skill formation linked to expected lifetime resources addresses this concern. We present such estimates in Section 7.

6 Family Influence Beyond Financial Resources

The intergenerational transmission of family influence arises not only through financial resources but also through family environments, such as the education of parents and the stability of the family unit (Cunha and Heckman, 2007). A large literature documents such associations (McLanahan and Sandefur, 1994). Establishing their importance is helpful in devising policies to promote intergenerational mobility. Is pure income redistribution enough to equalize opportunities, or are there other aspects of family life besides income and wealth that shape mobility? The current emphasis on IGEs focuses attention on financial resources while other factors might also be important.

This section of the paper and the associated appendices explore these influences in several ways. First, we examine how the intergenerational correlations studied in the previous section differ depending on family characteristics apart from income. Second, we examine the extent to which family and environment variables weaken or eliminate the influence of parental financial resources on the child's financial resources.

6.1 Family Characteristics as Mediators

This subsection examines how the estimates reported in Section 5 vary with respect to parental education levels and marital status of parents. Appendix Sections D.3 and E present additional heterogeneity, such as considering child criminality (Appendix D.3) or results by child gender (Appendix E).[27]

Panels (a) and (b) of Figure 4 plot correlations between the child's mathematics test scores at age 16 and parental resources at different ages of children for two different groups of families: college parents where both parents are college or university graduates (Panel a) and parents where none of the parents are college or university graduates (Panel b).[28]

Panels (c) and (d) of Figure 4 plot the correlations between the child's years of education by age 35 and parental resources at different child's ages, separately for the same parental types. Finally, panels (e) and (f) of Figure 4 plot the correlation between the child's participation in crime by age 35 (defined as the absence of any incarceration) and parental resources at different child's ages, separately for the different groups of parental educational background.[29]

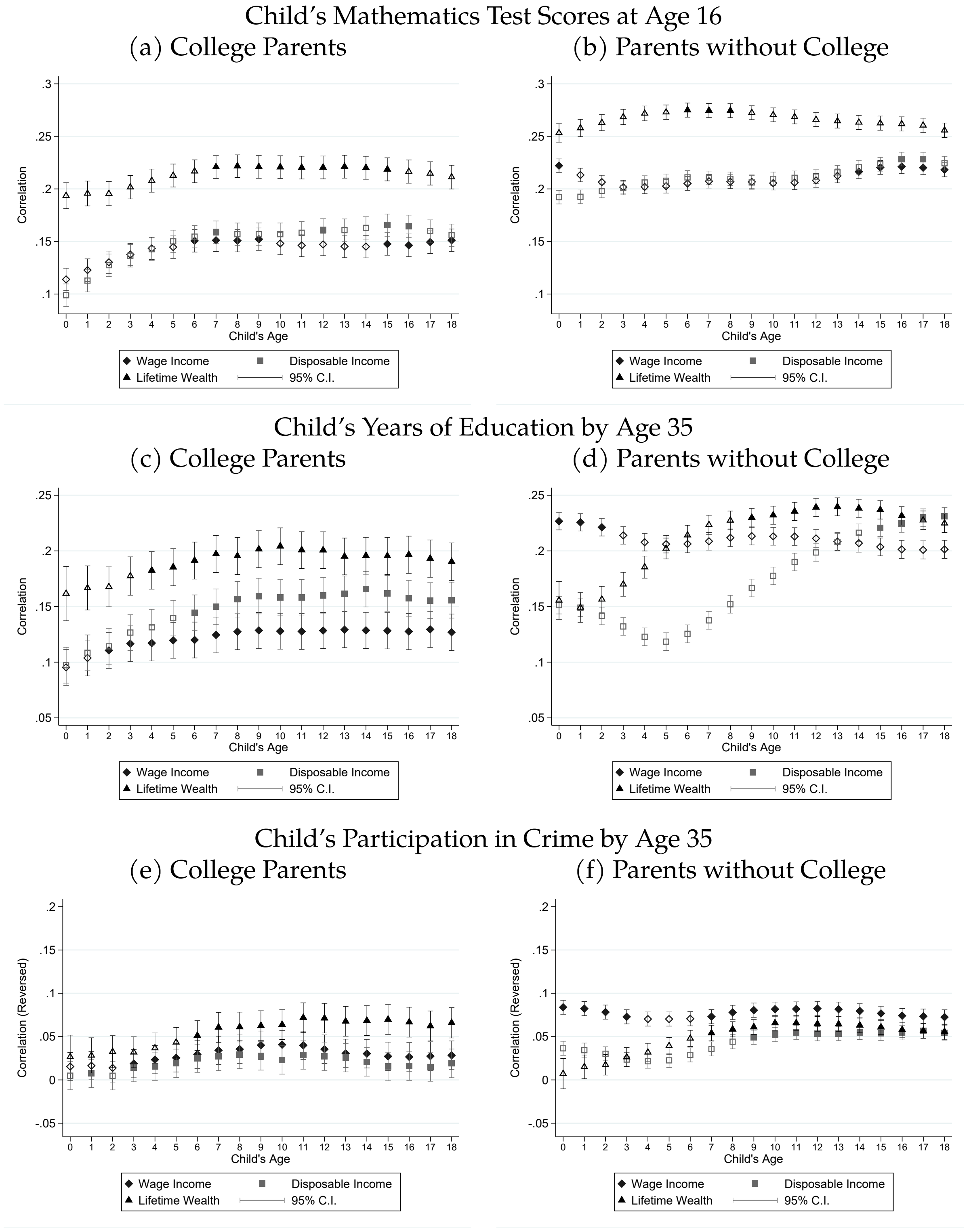
The intergenerational correlation patterns are, in general, similar across different groups of parental educational backgrounds. However, intergenerational correlations tend to be significantly *lower* for the sample of highly educated parents compared to the sample of no-college parents. For example, the correlations between children's math test scores and parental wage income and the expected lifetime wealth are about 0.15 and 0.22, respectively, for the sample of college parents in Panel (a), lower than 0.23 and 0.27 for the sample of less educated parents shown in Panel (b). Parental resources play a more important role in predicting child outcomes for less-educated parents, compared to educated parents.

[27] Unlike our other child outcome measures, the language development at age 11 is obtained from a survey. The intergenerational estimates are less precisely estimated than other outcome measures due to the small sample size, especially when we break down the sample by family types. Hence, we do not present the results for language test scores here.

[28] Appendix E.1 presents the results for other groups, e.g., for parents where only the father or the mother is a college or university graduate

[29] Appendix Figure E.4 presents the corresponding IGE estimate by parental education background when we measure parental resources at different child profile ages from zero to 18.

Figure 4: Correlations of Parental Resources with Child Outcomes by Parental Education Level



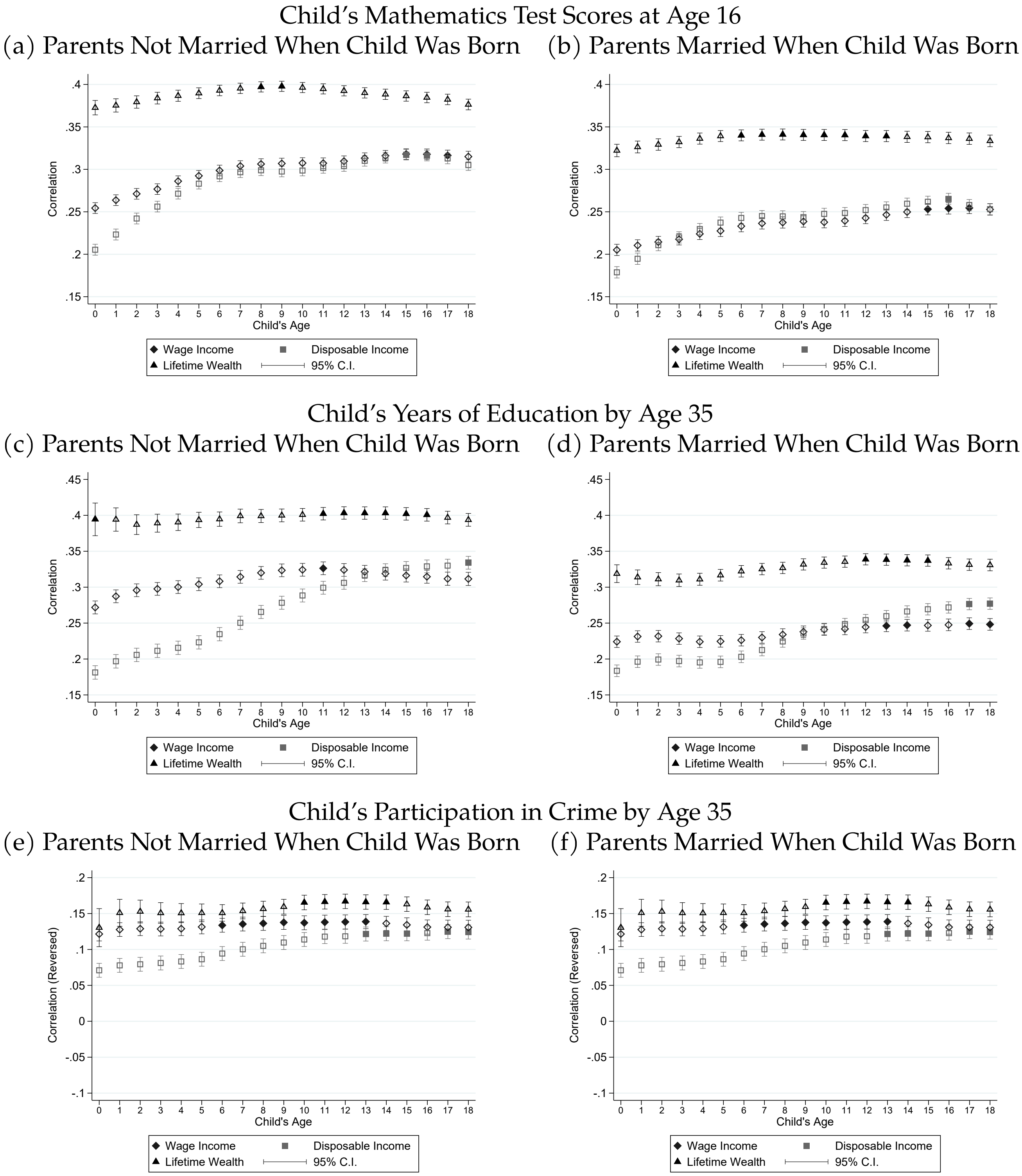
Notes: This figure plots the correlation between various child outcomes and parental income variables measured at the household level at different child's ages, separately by parents' education levels. Panels (a) and (b) present the results for the child's mathematics test score (at around age 16) in national leaving examinations (for cohorts born in 1995-1997). Panels (c) and (d) present the results for the child's years of education (for cohorts born in 1981-1982). Panels (e) and (f) present the results for the child's participation in crime (for cohorts born in 1981-1982). For each outcome (mathematics test score, years of education, and participation in crime), we present the results separately for the sample of college parents (where both parents are college –or university– graduates) and for the sample of parents where none of the parents are college –or university– graduates.

Figure 5 plots the correlation between the child outcomes — mathematics test scores at age 16, years of education, and criminality — and parental resources measured at the household level at different child's ages, separately for married and non-married parents. For each child, we consider the family as married if the mother and the father were registered as married when the child was born.[30]

Three findings emerge. First, the ranking of predictive power across measures of parental resources remains as previously discussed. The most predictive measure, by far, is expected lifetime wealth. Second, in contrast to the case when considering heterogeneity by parental education, separating children by marital status of parents does not substantially attenuate the correlation between family resources and child outcomes. Third, the associations between parental resources and child outcomes are stronger for non-married parents than for married parents. The advantages of a two-parent family (Kearney, 2023) are at least partially compensated by family resources.

[30] Appendix Section E.3 shows the corresponding results by gender. Appendix Section E.4 presents the results when we estimate heterogeneity by the intactness of the family where we consider a family as intact if the mother and the father were living together over the whole childhood stage (from age zero to 18 of the child). The patterns are very similar to those presented below based on the marital status of parents at the birth of children.

Figure 5: Correlations of Parental Resources with Child Outcomes by Parental Marital Status at Birth of the Child



Notes: This figure plots the correlation between various child outcomes and parental income variables measured at the household level at different child's ages, separately by whether parents were married at the time of the child's birth. Panels (a) and (b) present the results for the child's mathematics test score (at around age 16) in national leaving examinations (for cohorts born in 1995-1997). Panels (c) and (d) present the results for child's years of education (for cohorts born in 1981-1982). Panels (e) and (f) present the results for the child's participation in crime (for cohorts born in 1981-1982). For each outcome (mathematics test score, years of education, and participation in crime), we present the results separately for married and non-married parents. For each child, we consider the family as married if the mother and the father were registered as married when the child was born.

6.2 The Direct Role of Parental Characteristics on Child Outcomes

The weaker correlations between child outcomes and parental resources obtained after conditioning on parents' education and marital status, displayed in Figure 5, suggest that parental characteristics predict unconditional child outcomes through other channels besides family financial resources. Cunha et al. (2007) amend the Becker-Tomes model to account for this influence.[31]

Figure 6 plots the regression coefficient of parents' education (average of mother's and father's years of education) and marital status at childbirth, on child outcomes (mathematics test scores, years of education, and criminality).[32] The circles show the unadjusted estimates, and the diamonds show the estimates controlling for parental resources (either wage income, disposable income, or expected lifetime wealth) from age 0-18 of the child. The squares show the estimates when, in addition to parental resources from age 0-18 of the child, we also control for other parental background characteristics such as the average age of parents at arrival of the child.[33]

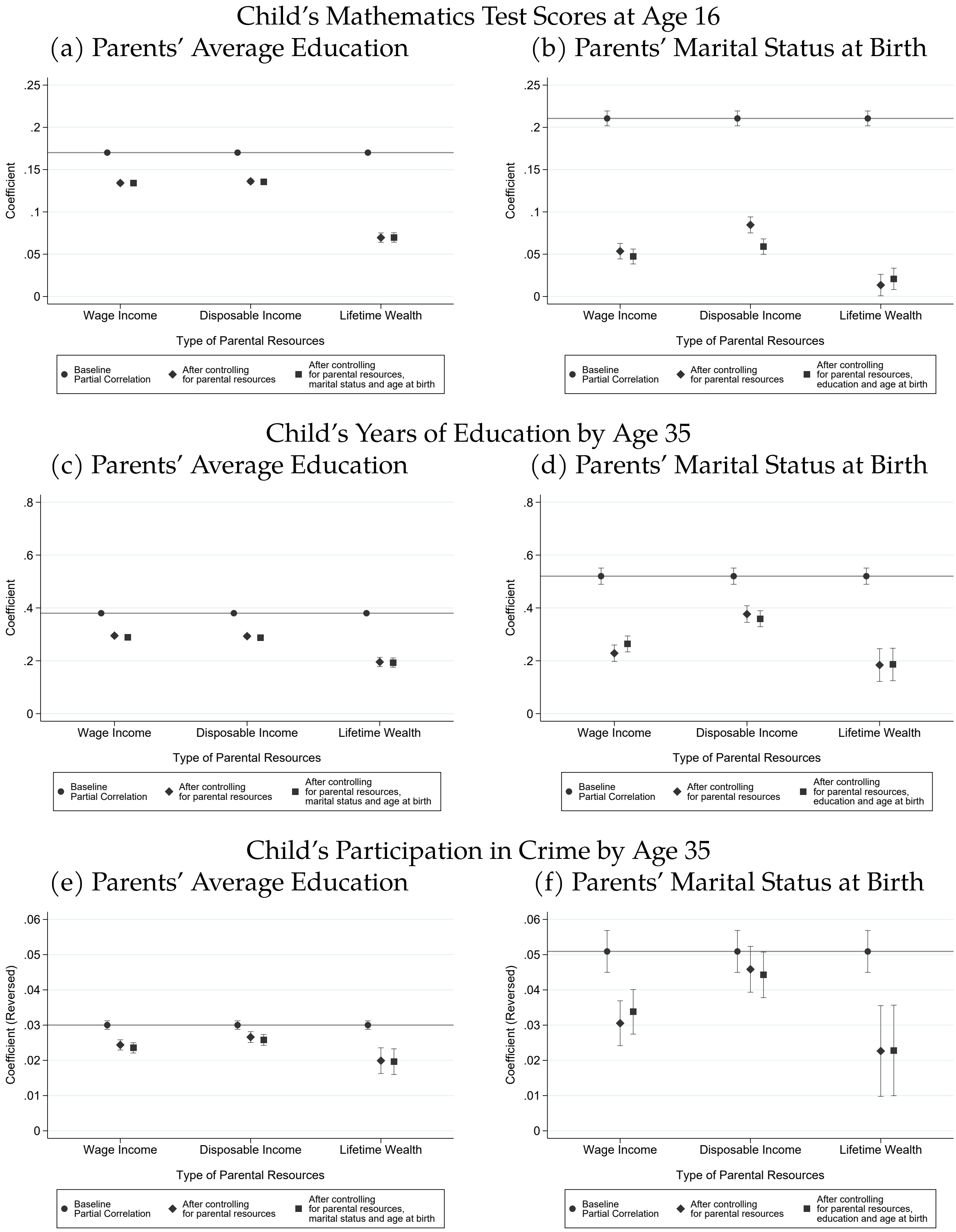
Expected lifetime wealth explains a larger fraction of the association between parents' characteristics and child outcomes compared to the two traditional income measures. For child mathematics test scores and years of education (Figures 6a and c), the estimates for parents' education drop by 50-60% once we control for the expected lifetime wealth of parents. For children's criminality (Figure 6e), there is a 35% reduction in the association between parents' characteristics and the child's participation in crime once we control for the lifetime wealth of parents. Turning to parents' marital status, estimates drop to almost zero once we control for parents' lifetime wealth when we consider children's mathematics test scores and years of education as outcomes (Figures 6b and d), while the estimated association between children's criminality and parents' marital status drops by more than 50% when we condition on parents' lifetime resources (Figure 6f).

[31] Becker et al. (2018) use the Cunha et al. (2007) insight to explain the Gatsby curve.

[32] We conduct a similar analysis for parental age at the arrival of children. We report the results in Appendix F.

[33] See Eshaghnia (2023) for the role of parents' ages at childbirth on the development of their children.

Figure 6: Associations of Parental Education (Marital Status) with Child Outcomes before and after Adjusting for Parental Resources



Notes: This figure plots the association between various child outcomes and parental characteristics (years of education of parents and marital status of parents at the time of the child's birth) both before and after adjusting for the impact of parental resources during childhood stage between ages of zero and 18 of the child and other characteristics of parents. Unadjusted coefficients are obtained by regressing the corresponding child's outcome on parental characteristics (years of schooling of parents or their marital status). Adjusted coefficients report the estimate of the effect of parental characteristics of interest (in the caption of each panel) after we add regressors to control for parental resources in different childhood ages from zero to 18 and other parental characteristics. Panels (a) and (b) present the results for child's mathematics test score (for cohorts born in 1995-1997). Panels (c) and (d) present the results for child's years of education (for cohorts born in 1981-1982). Panels (e) and (f) consider the child's participation in crime (for cohorts born in 1981-1982).

Thus, while parents' education and expected lifetime resources are highly correlated (see Figure 1b), Figure 6 shows that parents' education likely plays a role in child outcomes through channels other than pecuniary resources. In contrast, parental expected lifetime resources appear to fully capture the link between family structure and child outcomes such as test scores and years of education, even though the correlation between parents' marital status and expected lifetime wealth is lower than for wage income and disposable income (see Figure 1c).[34] We next evaluate the role of parental lifetime wealth at different childhood stages while holding parental education, marital status, and age constant.

7 Estimating the Technology of Skill Formation

This section reports estimates of a quadratic approximation to the technology of skill formation (Equation (8)) for three different child outcomes realized at different ages. Table 4 documents how we define the periods used for each outcome and at what age each child outcome is realized. $\boldsymbol{Z}_t$ values are very similar within the selected intervals. Table I.1 of Appendix I shows the correlations between parents' expected lifetime wealth across different age intervals. Table I.2 shows that the correlations of these variables within these intervals are very high. Finer partitions of resources by age lead to severe problems with multicollinearity. Hence, we use the coarse approximations reported here.[35,36]

We regress child outcomes on parental expected lifetime wealth in each interval as well

[34]We also conduct a simple decomposition exercise (Hertz, 2008) where we decompose the correlation between parental lifetime wealth and child outcomes (such as test scores and years of education) to the within-group vs. between-group components where we use parental education levels to define the groups (i.e., four groups of parents: both parents are college or university graduates, none of them is a college or university graduate, only the father is a college or university graduate, and only the mother is a college or university graduate). Our results suggest that the between-group effect accounts for about 50% of the overall correlations between parental lifetime wealth and the child's test scores. The between-group share is about 30% (40%) of the overall correlations between parental wage income (disposable income) and the child's test scores. The between-group shares are slightly higher when analyzing the correlations between parental resources and the child's years of education by age 35.

[35]Appendix Table I.2 presents the correlations across all children's ages from zero to 18.

[36]Also, Appendix Figure I.1 presents the eigenvalues from principal components analyses of parents' expected lifetime wealth over the child's age intervals of $[0, 5]$, $[6, 11]$, $[12, 17]$, $[18, 23]$, and $[24, 29]$. Except for the first eigenvalue, other eigenvalues are close to zero.

Table 4: Age Ranges Studied for Indicated Child Outcomes

Outcome	Child's age intervals	Num. of periods
Math Problem Solving at Age 16	[0,5], [6,11], [12,17]	3
Has Experienced Incarceration by 35	[0,5], [6,11], [12,17],[18,23], [24,29]	5
Years of Education by Age 35	[0,5], [6,11], [12,17],[18,23], [24,29]	5

Notes: This table presents the specific periods used for each outcome as well as the number of periods (until the realization of the outcome) to run the model in Equation (8).

as interactions among the expected lifetime wealth measures across different periods while controlling for parental characteristics (average years of schooling, marital status at childbirth, the average age at childbirth) and their interactions with parental lifetime wealth in different intervals.[37] We use two different specifications of the ranges of periods studied:

1. Birth until realization of the outcome: All periods starting at birth up to and including the period during which the outcome studied is realized.
2. Birth until age 17: All periods starting at birth up to and including the terminal period of childhood (at age 17).

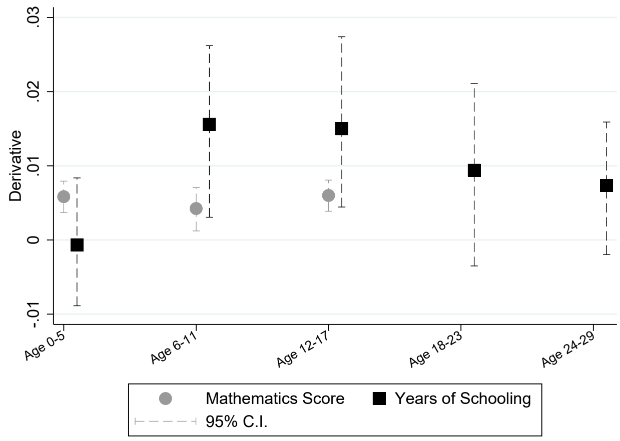
Controlling for the expected lifetime wealth at different ages when investments are made, accounts for updating of family resources and constraints at different ages. This extends the approach of Carneiro et al. (2021) by introducing sequential updating of expected family resources.

Tables I.5–I.8 of Appendix I report the coefficients obtained from these two specifications of the model. In what follows, we focus on the estimates for the first specification. The results for the second specification, presented in Appendix I, show similar patterns.

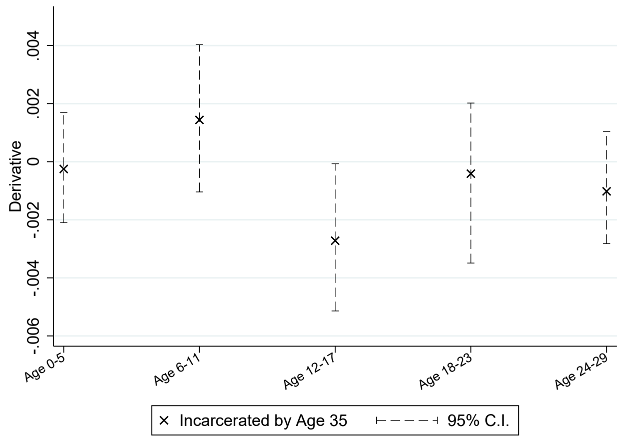
[37] Appendix I discusses the details.

Figure 7: Derivative of Child Outcomes with respect to Parental Lifetime Wealth at Different Childhood Age Intervals, Evaluated at the Mean (First Specification)

(a) Mathematics Test Scores (Age 16) and Years of Education (Age 35)



(b) Participation in Crime (Experienced Incarceration) by Age 35



Notes: This figure depicts the value of the derivative of each of the child outcomes (mathematics test scores at age 16, years of education by age 35, and crime measured by ever experienced incarceration by age 35) with respect to the parental lifetime wealth in each interval (in 10,000 USD in 2010 values), evaluated at the mean. Table I.4 reports the values. We estimate Equation (8), assuming that the coefficients $\alpha_0(t)$, $\boldsymbol{\alpha}'_{1,i}(t)$, and $\boldsymbol{\Psi}_{i,j}(t)$ are constant within the selected intervals. The full set of estimation results, including the constant and the coefficients on the interaction terms, are reported in Tables I.5-I.8 of Appendix I.

Figure 7 plots the derivatives of child outcomes with respect to our lifetime wealth proxies for child investment in different childhood intervals.[38] A consistent regularity across the outcomes studied is that we *do not* reproduce the U-shaped profile reported by Carneiro et al. (2021).

Our measures of investment show stronger effects on education in the elementary school years than in the preschool years, tapering off later. For mathematics skills, the early years are sensitive periods. For participation in crime, the adolescent-young adult years are more potent–consistent with the research of Steinberg (2014) and Crone (2016) on the onset of puberty and the maturation of the prefrontal cortex and emergence of self-control. The derivatives of child outcomes with respect to parental lifetime wealth in different childhood stages are up to 50% lower compared to the specification where we do not take into account the direct impacts of parental characteristics (years of schooling, marital status at childbirth, age at childbirth) on child outcomes, apart from their impacts through the lifetime wealth of parents.[39]

From Equation (6), $\frac{\partial^2 \boldsymbol{G}_t}{\partial \boldsymbol{Z}_t \partial \boldsymbol{Z}'_{t+j}}$ is a measure of complementarity or substitutability because $\boldsymbol{Z}_t$ proxies $\boldsymbol{I}_t$. The concept of dynamic complementarity is extended for skills not in play at early ages. It is meaningful only for ages where emergent skills are relevant (have non-zero partials). Table 5 shows that dynamic complementarity operates across many stages of investment in producing adult education. Yet not all cross-partials are statistically significant, and some are negative.[40] The evidence for dynamic complementarity for other outcomes is more mixed. See Tables I.5-I.8 in the appendix.

[38] Table I.4 presents the point estimates.

[39] The derivatives of child's years of schooling and participation in crime with respect to parental lifetime wealth in adolescence is about 50% lower when we account for parental characteristics in our specification. For mathematics test scores, the derivative with respect to parental lifetime wealth in early childhood (ages 0–5) drops by about 40%, but the derivatives with respect to parental lifetime wealth in later childhood stages (ages 6–11 and 12–17) remain unchanged. Appendix I.3 presents the full set of results for both specifications.

[40] Cross effects may be negative. Thus, for example, extraversion may well be a negative aspect of the productivity of a professional mathematician but not for a salesperson.

Table 5: Dynamic Complementarity for Educational Attainment by Age 35 (First Specification; Birth–Realization of Outcome)

Child's Age	$[0,5]$	$[6,11]$	$[12,17]$	$[18,23]$
$[6,11]$	0.00138 (0.00327)			
$[12,17]$	-0.00340 (0.00337)	0.00761* (0.00413)		
$[18,23]$	0.00265 (0.00336)	-0.00814* (0.00428)	0.0114*** (0.00427)	
$[24,29]$	-0.00139 (0.00236)	0.00367 (0.00305)	-0.00439 (0.00309)	0.000652 (0.00304)

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the dynamic complementarity for educational attainment by age 35. We estimate Equation (8), taking coefficients $\alpha_0(t)$, $\boldsymbol{\alpha}'_{1,i}(t)$, and $\boldsymbol{\Psi}_{i,j}(t)$ to be constant within the selected intervals. The full set of estimation results are reported in Table I.8 of Appendix I.

8 Conclusion

This paper connects the literature on intergenerational mobility to the recent literature on child development and suggests a procedure for examining the impact of family resources by age on the development of children. We present estimates of the impacts of age-specific intergenerational expected life cycle resources instead of measures of current income over narrow intervals as used in many studies of social mobility.

We introduce a new approach for selecting measures of expected lifetime income, and the age ranges for measuring it, when computing IGEs. Instead of choosing income measures to align ages across generations or to eliminate measurement errors, we estimate IGEs on the basis of how well they predict child academic achievement, criminal behavior, and educational attainment.

This approach provides an interpretative guide for linking measures of family influence across generations. The predictive power of parental income on measures of child outcomes guides our choice of ages of measurement. We select the combination of measures and age ranges that best predict important human capital outcomes of children such as academic performance, educational attainment, and participation in crime. This approach accounts for non-stationarity across cohorts documented in Stuhler and Nybom (2022) and Eshaghnia et al. (2022).

The predictive power of parental resources on child human capital measures crucially depends not only on when parental resources are measured (over the life cycles of children), but also on which measures of parental resources are considered. The choice of resource measure makes more of a difference to estimated IGEs than the choice of age intervals for parental income measurement. The traditional approach, based on income flows in narrow intervals, substantially overestimates intergenerational mobility and underestimates the persistence of advantage across generations.

Our analyses suggest that parental resources are significantly more important in predicting child outcomes for disadvantaged families, compared to more educated and stable families. Financial resources compensate in part for disadvantages in terms of parental characteristics. We extend Carneiro et al. (2021) by allowing for sequential updating of agent information sets in estimating relevant lifetime resources. We do not reproduce their U-shaped impact of income timing patterns by age. For math and language skills, early investment has the biggest impact. For years of schooling, impacts are greatest in the middle school years of children. For crime, investment in the adolescent and young adult years is more impactful. This is consistent with the analysis of Cunha et al. (2010) who show that noncognitive skills become more important later in life and the studies of Steinberg (2014), Crone (2016), and Belsky et al. (2020) about the emergence of these skills in adolescence. We present evidence of both dynamic complementarity and dynamic substitutability of investment over the life cycle, especially for educational outcomes. The evidence for other outcomes is more mixed. We amend the technology of skill formation to account for new skills emerging in adolescence. This enables us to account for the appearance of sensitive periods in adolescence and helps to rationalize our evidence and that of Carneiro et al. (2021).

Our analysis is a beginning for a research program that uses economics to interpret the statistics on social mobility. We challenge many of the conventions that have become standard in the literature. There is no "best" age for comparing the status of parents and children. Measures of permanent income do not approximate theory-derived measures of lifetime wealth that account for credit constraints and uncertainty.

Much remains to be done. The causal status of our estimates remain to be determined. Our use of long-run averages attenuates classical measurement error, and forecasting future incomes using data on others introduces exogeneity into the construction of lifetime wealth. Nonetheless, there may remain individual components of heterogeneity transmitted across generations. In a companion paper, Eshaghnia et al. (2022), we use policy variation in income to surmount these difficulties.

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