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Abstract

How do education, skills, investments of parental time and school quality, and family circumstances during childhood contribute to the persistence of earnings across generations? Building on a classic literature in sociology and a more recent literature in economics, our model allows each of the above variables to affect lifetime earnings directly, as well as through their contribution to human capital formation. The model allows us to decompose the intergenerational elasticity of earnings (IGE) into its drivers. Using data from a representative British cohort followed from birth to age 55, we show the above variables explain most of the IGE. A key driver is the increased levels of parental investments received by children of high income parents early in their lives, and the resulting cognitive development.

Keywords: Parental Investments, Cognitive Skills, Intergenerational Elasticity of Earnings

JEL codes: I24, J24, C38

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1 Introduction

Income across generations is persistent - those who grew up in richer families tend to become richer themselves. Many differences between those from rich and poor families may be driving such persistence, including differences in educational attainment, skills, parental investments received during childhood, as well as parental education and family size.[1] How much do these differences contribute to the earnings persistence we observe? And how do they relate to each other? This paper brings together approaches from a classic literature in sociology and a more recent literature in economics to answer these questions.

Using the National Child Development Study (NCDS), which follows a British cohort from birth to age 55, we show that differences in educational attainment, skills, parental investments in time and school quality, and family background account for 55% of the intergenerational elasticity of earnings (IGE) for males, and 68% for females. Parental investments are a crucial driver of the link between parents' income and children's earnings via their impact on the cognitive development of children.

We estimate a flexible multi-stage model of child development, educational attainment, and lifetime earnings. We use the model to conduct counterfactuals which allow us to quantify not only the contribution of different variables to earnings persistence, but also to understand the mechanisms by which these variables operate.[2] For example, children from richer families tend to attain more education, which leads to higher earnings. They also have higher cognitive skills, which leads to higher educational attainment and thus earnings. Our framework allows us to quantify how much of the contribution of education to the IGE is explained by differences in skills between those from richer and poorer families. Likewise, it allows us to quantify how much of the contribution of cognitive skill to the IGE is, in turn, explained by differences in parental time and school quality investments.

Similar to Heckman et al. (2018), we do not explicitly model agents' preferences, but instead we approximate their decision rules. Other than restrictions arising from the lifecycle timing of human capital development, we impose few assumptions regarding which variables affect the production of other variables. Thus, within a flexible model of human capital development, we let the data speak to the importance of each variable in the formation of intergenerational persistence.

We model four distinct mechanisms that can generate persistence in earnings across generations. The first mechanism is the higher educational attainment of children from richer families which explains a

[1]See Blau and Duncan (1967) and Sewell and Hauser (1972) for early work in sociology and the papers collected in Taubman (1977) for early work in economics on determinants of intergenerational mobility. See Solon (1992), Dearden et al. (1997), Mazumder (2005) and Chetty et al. (2014) for evidence on the intergenerational elasticity of earnings. The importance of time investments in children for their later life earnings has been extensively studied (Cunha and Heckman (2008), Daruich (2018), Lee and Seshadri (2019)) and it has been well documented that richer parents invest more time in their children (Guryan et al. (2008)). Aizer and Cunha (2012) and Del Boca et al. (2014) show that richer parents have fewer children, allowing them to invest more time in each child.

[2]See Klein and Goldberger (1955) and Theil (1958) for early applications of mediation analysis in economics, and Blanden et al. (2007), Heckman et al. (2013), Conti et al. (2016), Mogstad et al. (2021) for recent relevant applications.

significant share of the IGE.

The second mechanism comprises cognitive and non-cognitive skills. Richer parents have children with greater cognitive skills, which increases earnings. Additionally, higher cognitive skills increase educational attainment which, in turn, increases earnings. In fact, the education differences between those from rich and poor families can entirely be explained by differences in cognitive skills. Differences in cognitive skills by parental income, therefore, are crucial for intergenerational persistence - they directly contribute to earnings differences and are also the main driver of differences in educational outcomes.

The third mechanism driving the IGE is differences in investments made by parents with different incomes. Richer families invest more time in their children and also send their children to better quality schools. These investments explain 28% (24%) of the IGE for males (females) once we allow investments to subsequently affect the development of skills and educational attainment. Investments impact later-life earnings through their effect on cognitive skills and educational attainment. We find little evidence that these investments are important for earnings over and above their impact via cognitive skills. This is an interesting finding, as it is typically *assumed* in economics that investments impact later-life outcomes only through their impact on observable skills. However, this assumption is rarely tested (see Heckman et al. (2013) for an example that does test this assumption). We fail to reject this key assumption.

The fourth mechanism is family background, specifically maternal education, paternal education, and family size. By increasing skills directly and via increased investments, these explain 23% (37%) of the IGE for males (females). Differences in family background partially explain the differences in investments which we discussed immediately above. However, they do not fully explain them: even accounting for the differences by family background, differences in investments between high and low income parents play an important role. The parental income gradient in investments still explains 20% (12%) of the IGE when accounting for family background (compared to the 28% (24%) when not accounting for family background). Combined with our finding that the higher educational attainment of children of high income parents is fully explained by their higher cognitive skills, these results are consistent with the view that if financial constraints are important for understanding the persistence in income across generations, it is because they constrain early-in-life investments, not educational attainment.

This paper provides a bridge between two important literatures studying intergenerational persistence. An older literature in sociology analyzed intergenerational persistence using dynamic models, emphasizing the analysis of multiple channels such as educational attainment and family background, imposing few restrictions as to how they operate. A more recent literature in economics uses improvements in data and methodology to quantify the impact of family background and early life parental time and school quality investments on skill development (Cunha et al. (2010), Attanasio et al. (2020)). The economics literature also studies the link between early adulthood human capital and later life earnings (Keane and Wolpin (1997)). However, none of these papers in economics evaluate whether early life factors such as family background and parental investments have an impact on lifetime earnings above and beyond skill development, as the sociology literature suggests. This is exactly what we do: we jointly evaluate these major drivers of the IGE and test, rather than impose, the restrictions of human capital theory.

Our contribution is to evaluate the importance of a variety of channels in explaining the intergenerational elasticity of earnings using a framework that a) admits the broader channels considered in a now dormant literature in quantitative sociology, and b) nests a human capital model of the type that is now dominant in economics. We do this using data on a single cohort throughout our analysis, which enables us to measure inputs and outputs for the same people, and also to test whether early-life investments (e.g., parental time) have independent effects on later-life outcomes, over and above their effects on intermediate outcomes (e.g., cognitive skill). Our analysis accounts for complementarities in the returns to various child investments and builds on recent advances in latent factor methods, carefully taking into account measurement error. The latter turns out to be important - ignoring measurement error attenuates the fraction of the IGE explained by parental investment by over half.

The rest of this paper proceeds as follows. Section 2 relates our work to previous literature. Section 3 describes the data and documents descriptive statistics on education, skills, investments, and family background. Section 4 outlines our decomposition and Section 5 provides results and robustness checks. Section 6 concludes.

2 Literature

This paper focuses on modelling how intergenerational persistence in earnings arises via different mechanisms. In particular, we explore how parents' income relates to children's income throughout the lifecycle. Doing so is hardly new. Mid-20th century sociologists applied "path-analysis" developed by Wright (1921) to study factors leading to social stratification. Blau and Duncan (1967) trace an individual's lifecycle from educational attainment to occupational choice, thus modelling several drivers of intergenerational persistence in earnings. They impose few restrictions on how these factors operate. For example, they allow paternal education and occupation to directly affect education and occupational attainment. Building on this, Sewell et al. (1969) and Sewell and Hauser (1972) developed the "Wisconsin Model", where family background (including parental income) and cognitive skills influence academic performance, parental and teacher encouragement, aspirations, and thus subsequent educational and occupational attainment, and finally earnings. Their findings revealed that parental earnings still had significant predictive power for children's earnings, over and above a rich set of other variables, with parental earnings viewed as a proxy for parental connections, other aspects of socioeconomic status, and possibly genetics (Bowles and Gintis, 1976, 2002; Taubman, 1976). By decomposing the IGE using a similar set of channels as this earlier literature, we test for the existence of a residual direct effect of parental income and find that it indeed has significant predictive power, even after controlling for parental investments, skills, and education.

The data used in the Wisconsin Model and similar structural equation models[3] typically began tracking individuals during high school and later, thereby excluding the crucial period of early child development. Although a concurrent literature studying the production of cognitive skills developed (Bowles, 1970; Hanushek, 1979), progress in this area was hampered by the lack of data on early childhood circumstances. As Griliches and Mason (1972) lamented, the lack of data on childhood circumstances limited researchers' ability to quantify the impact of early life investments on cognitive skills and education. Our NCDS data allow us to build a child skill production phase into a structural equation model. By including a child development phase, our model largely nests the Wisconsin Model and allows us to quantify the importance of childhood investments for intergenerational persistence. To do this, we use methodology from a recent literature in economics which applies a latent variable framework to many mismeasured variables in order to estimate non-linear skill production functions (e.g., Cunha et al. (2010), Attanasio et al. (2020), Agostinelli and Wiswall (2024)). Whilst the older literature in sociology (e.g., Duncan and Featherman (1972), Winship and Mare (1984), Hauser and Sewell (1986)) and economics (Chamberlain and Griliches (1975)) was also careful to account for measurement error, it relied on linear equations. By allowing for non-linearities, our approach allows for dynamic complementarity between current and past investments. These methodological advancements, in combination with the unique NCDS data, which measures childhood investments, intermediate outcomes, and lifecycle earnings, enable us to simultaneously quantify the importance of multiple channels contributing to intergenerational earnings persistence.

At around the same time as the sociology literature was flourishing, Becker and Tomes (1979) developed an economic human capital theory of the intergenerational persistence of earnings. Subsequent research documented significant parental income gradients in the determinants of human capital: parental time with children,[4] the cognitive skills of those children,[5] as well as the quality and length of their school-

[3]The combination of path analysis with latent factor modeling to capture structural relationships between (potentially unobserved) variables is often called a structural equations model (Goldberger (1972) and Bielby and Hauser (1977)). Note that such structural equations do not account for behavioral responses, which structural models in economics would typically allow for.

[4]See, for example, Guryan et al. (2008).

[5]Papers exploiting plausibly exogenous variation in income (e.g Milligan and Stabile (2011), Dahl and Lochner (2012) and Agostinelli and Sorrenti (2018)) find that increases in parental income have a positive effect on children's test scores, though their effects on earnings are usually estimated to be smaller than for cognitive skill.

ing.[6] Differences in family structure[7] and parental education[8] by parental income are also evident. The fact that each of these factors relate to parents' income and that each matters for the earnings of their children mean that they contribute to intergenerational earnings persistence.[9] Much of this literature, summarized by Black et al. (2011), has focused on exploiting plausibly exogenous variation to estimate the role of individual channels that contribute to intergenerational persistence. As recently noted by Cholli and Durlauf (2022), understanding the determinants of social mobility using these channels *jointly* took a backseat, though Bowles and Gintis (2002) and Blanden et al. (2007) are notable exceptions. Recently estimated dynastic lifecycle models have allowed further insights into how these channels operate together (see e.g., Gayle et al. (2018), Daruich (2018), Caucutt and Lochner (2020), Lee and Seshadri (2019)). However, such models require many assumptions about which channels matter for the IGE and how they affect each other. For instance, they assume that time investments made in childhood do not have any further impact on earnings. Is this the case? Our framework complements those models by exploring multiple channels and how they affect each other, in the spirit of early quantitative sociological studies, but using recently developed estimation methods.

3 Data

Our data come from the National Child Development Study (NCDS).[10] The survey started with almost the entire population of children born in Britain in one particular week of March 1958 and continues to follow them to this day. Due to its longevity, the NCDS is a globally-unrivalled resource for social scientists in its combination of information about investments in early childhood with information on skills, educational outcomes, and earnings throughout adulthood.[11]

The initial survey at birth has been followed by subsequent surveys at ages: 7, 11, 16, 23, 33, 42, 46, 50 and 55.[12] The data from childhood includes information on several measures of cognitive and non-cognitive skill, parental investments, number of siblings, parental education, and parental income. Later waves of the study record educational outcomes, demographic characteristics, earnings, and hours

[6]The literature on schooling finds that children of richer parents attain more years in education, partly due to greater parental resources (Lochner and Monge-Naranjo (2012), Lee and Seshadri (2019), Caucutt and Lochner (2020)) and greater cognitive skills which keep them in school for longer (Keane and Wolpin (1997), Carneiro and Heckman (2002)). A smaller literature studies the role of school quality (e.g., Altonji and Dunn (1996) and Dearden et al. (2002)).

[7]See Black et al. (2005), Angrist et al. (2010), Bhalotra and Clarke (2020).

[8]See Meghir and Palme (2005), Nybom and Stuhler (2014).

[9]Whilst the importance of most of these characteristics for the earnings of children has been long known, the formative role of parental investments has been more recently demonstrated (by e.g., Cunha and Heckman (2008), Cunha et al. (2010), Attanasio et al. (2020)).

[10]The NCDS is provided by the Centre for Longitudinal Studies (2017) at the Institute of Education, University College London.

[11]While more recent surveys such as the NLSYC and PSID also contain measures of early life investments, their more limited time horizon means that they are less suited for measuring lifetime earnings.

[12]The age-46 survey is not used in any of the subsequent analysis as it was a more limited telephone interview only.

of work. Details about variable construction, sample selection, and additional descriptives are given in Appendix A.

Because the data set includes multiple measures of cohort members' skills and investments received at different ages during childhood, we can posit the existence of underlying latent factors and extract signals from noisy measures rather than proxying for skills and investments using specific measures.

In the rest of this section, we first describe how we construct the measures of parental income and child earnings that we use. We then document inequalities in family background, investments, and outcomes by parental income over the lifecycle in the NCDS data.

Parental income When NCDS cohort members were aged 16, comprehensive data on parental income was collected. Our measure of parental income sums across father's earnings, mother's earnings, and other income, all net of taxes. The first row of Table 1 reports annual parental income, which ranges from £12,200 (in 2014 prices) in the bottom parental income tertile to £26,400 in the top tertile.

Children's earnings Using cohort members' gross earnings at ages 23, 33, 42, 50, and 55, we construct average undiscounted gross annual earnings (setting earnings of non-workers to 0) over all ages 23-55. The second row of Table 1 shows the positive gradient of earnings with respect to parents' income – average annual earnings of NCDS cohort members rises from £15,600 for those with parents in the bottom income tertile, to £20,900 for those whose parents are in the top income tertile.

Educational attainment The age at which an individual left school is constructed using the highest educational qualification recorded by the time cohort members reach age 33.[13] The second panel of Table 1 shows that children with parents in the bottom income tertile spend 0.8 years (9.6 months) less in school than children with parents in the highest income tertile.

Cognitive skill As part of the survey, cohort members took part in standardized tests to measure their cognitive skills. The third panel of Table 1 summarizes math and reading test scores at age 16 by parental income tertile. As one might expect, children from richer households develop greater cognitive skills; at age 16, average reading and math scores were, respectively, 44% and 46% of a standard deviation higher for children with parents in the highest income tertile compared to children with parents in the lowest tertile. Similar patterns can be found for our other cognitive skill measures.

[13] School leaving age is coded such that the lowest levels of education (no qualification or Certificate of Secondary Education 2-5) are coded as leaving school at the minimum school leaving age of 16; completing a higher qualification than this up to A-levels is coded as leaving school at age 18; having a qualification higher than A-levels is coded as leaving education at age 21. This approach is similar to the preferred approach in Antonovics and Goldberger (2005).

Table 1: Descriptive statistics by parental income tertile

	avg	sd	bottom	middle	top	F-test
Income variables						
Parents' household income at 16	18,900	6,800	12,200	18,100	26,400	0.00
Children's average annual earnings	17,800	14,600	15,600	17,000	20,900	0.00
Education						
Age left education	18.4	1.8	18.1	18.3	18.9	0.0
Cognitive skills						
Reading at age 7	0.00	1.00	-0.09	-0.03	0.13	0.00
Reading at age 11	0.00	1.00	-0.20	-0.04	0.24	0.00
Reading at age 16	0.00	1.00	-0.20	-0.04	0.24	0.00
Maths at age 7	0.00	1.00	-0.09	-0.06	0.15	0.00
Maths at age 11	0.00	1.00	-0.20	-0.06	0.26	0.00
Maths at age 16	0.00	1.00	-0.21	-0.05	0.25	0.00
Non-cognitive skills						
% Hostile to children 7	12.5	33.0	11.8	12.7	12.9	0.70
% Hostile to children 11	12.7	33.3	12.7	12.9	12.6	0.98
% Fights with others 16	5.9	23.7	6.2	6.2	5.5	0.69
% Depressed 7	38.2	48.6	39.4	37.3	37.8	0.55
% Depressed 11	40.2	49.0	42.2	39.4	39.1	0.28
% Depressed 16	9.8	29.7	10.5	10.4	8.5	0.20
Time investment						
% Mothers reading to child every week 7	51.8	50.0	50.0	49.7	55.8	0.01
% Fathers reading to child every week 7	38.5	48.7	37.2	36.6	41.7	0.04
% Mothers going on outings w child most weeks 11	56.0	49.6	52.9	57.8	57.2	0.05
% Fathers going on outings w child most weeks 11	53.8	49.9	49.0	55.2	56.8	0.00
% Mothers very interested in child's education 16	43.0	49.5	34.7	41.5	52.4	0.00
% Fathers very interested in child's education 16	40.6	49.1	31.1	37.9	51.9	0.00
School quality						
% Whose PTA holds meetings at age 7	60.3	48.9	56.5	59.7	64.7	0.00
Student-teacher ratio at age 11	24.2	9.4	25.1	24.2	23.3	0.00
% From child's class suitable for GCEs at age 11	26.5	16.5	23.6	24.6	31.3	0.00
Student-teacher ratio at age 16	17.0	1.9	17.2	17.1	16.8	0.00
% From child's class studying for GCEs at age 16	52.2	32.8	46.1	49.2	61.2	0.00
% From child's school who complete school	60.6	26.9	55.6	57.8	68.5	0.00
Family background						
Number of siblings	1.9	1.4	2.0	1.9	1.8	0.00
Father's age left school	15.5	1.9	14.9	15.2	16.3	0.00
Mother's age left school	15.5	1.5	15.1	15.3	16.0	0.00

Note: This table presents descriptive statistics and means by parental income tertile for parental income, child earnings, and several measures of the mediators in our analysis (educational attainment, skills, time investments, school quality, family background). The relevant sample consists of 3,308 individuals. Income and earnings variables are reported as annual values, deflated to 2014 prices. The final column reports *p-values* from the *F-tests* testing the null hypothesis of equality of means across income tertiles.

Non-cognitive skill The NCDS also has detailed measures of non-cognitive skills reported by teachers at ages 7, 11, 16. In contrast to cognitive skills, we do not find parental income gradients in non-cognitive skills. Differences in non-cognitive skills between those from the top versus bottom tertile are modest and are not statistically significant.

Parental investments The NCDS has detailed measures of the parental investments received by cohort members during childhood. The full set of parental time and school quality measures as well as skill measures are listed in Table 2 and are described in detail in Table 7 in the appendix. These measures come from different sources – some are from surveys of parents, others from surveys of school teachers and principals.

The fifth panel of Table 1 documents income gradients in how often parents read to the cohort member, measured during the age 7 wave; how often parents take the cohort member on outings, measured during the age 11 wave; and how interested parents are in the cohort member's education, as reported by the school teacher at age 16.[14] The differences by parental income are evident at all ages for both parents. For example, in the age 7 survey, 50% of mothers in the bottom tertile read to their child every week, compared to 56% of mothers at the top. Similarly, in the age 11 survey, 49% of fathers from the bottom income tertile very often go on outings with their child compared to 57% of fathers from the top income tertile. Table 7 in the Appendix shows that a qualitatively similar gradient between parental income and time investments is evident for our other measures of time investment.

Table 2: List of skill and investment measures

Cognitive Skills	
Age 7	Math score, Copying-Design score, Draw-a-Man score
Age 11	Reading score, Math score, Copying-Design score
Age 16	Reading score, Math score, Teacher-assessed Math and English ability
Non-cognitive skills	
Age 7	Teacher reported Bristol Social Adjustment Guide: Inconsequential, hostile to children, hostile to adults, writes off adult standards, depressed
Age 11	Teacher reported Bristol Social Adjustment Guide: Inconsequential, hostile to children, hostile to adults, writes off adult standards, depressed
Age 16	Teacher reported: Unconcentrated, fights with others, disobedient, irritable, depressed
Time Investments	
Age 0-7	Teacher's assessment of father's interest in child's education, teacher's assessment of mother's interest in child's education, how often father takes child on outings, how often mother takes child on outings, how often father reads to child, how often mother reads to child
Age 7-11	Teacher's assessment of father's interest in child's education, teacher's assessment of mother's interest in child's education, how often father takes child on outings, how often mother takes child on outings, father's role in upbringing of child
Age 11-16	Teacher's assessment of father's interest in child's education, teacher's assessment of mother's interest in child's education, parents' ambitions regarding child's educational attainment
School Quality Investments	
Age 0-7	Whether school has a parent-teacher association (PTA), whether PTA conducts educational meetings, social class of fathers in the child's class, fraction of parents in child's class that meet with teacher
Age 7-11	Class size, student-teacher ratio, type of school, proportion of children in class suitable for GCEs, teacher's inititative to discuss child progress, fraction of experienced teachers
Age 11-16	Student-teacher ratio, type of school, proportion of children in child's school who: complete school / move on to full-time degrees / pass 2+ A-levels / are studying for GCEs

Note: Data collected at ages 7, 11, and 16 for children includes measures of ability, non-cognitive skills, parental time investments, family circumstances, and parental income. Note, all investment measures are retrospective, so age 0-7 investments are measured at age 7, age 7-11 investments are measured at age 11, and age 11-16 investments are measured at age 16.

The sixth panel of Table 1 presents some measures of school quality at different ages. Children of high-income parents are more likely to go to schools where: parents attend educational meetings at age

[14] Most of the investment variables we use are categorical. For exposition, Table 1 converts some of the categorical variables into binary ones. For example, the variable capturing reading to the child takes values 1:"never", 2: "sometimes", 3: "each week" which for exposition we convert into a dummy.

7, student-teacher ratios are low at age 11, a high fraction of students are doing GCEs (an optional exam for progressing to further education) at age 16 and completing secondary education. Again, we observe significant gradients by parental income for all these variables as well as for all of the other school quality variables we use.

Family background We use three family background variables: the number of siblings as well as mother's and father's years of education. The seventh and final panel in Table 1 shows the well-known fact that richer families tend to be smaller. NCDS cohort members from households in the highest income tertile grew up with fewer siblings on average than those in the lowest tertile. Parental education also differs significantly by parental income - fathers (mothers) in the highest tertile spent on average 17 (11) more months in school than those in the lowest tertile.

The next section shows how we use this rich data set to understand how the parental income gradients described here map onto the gradient of lifetime earnings.

4 A Model of Intergenerational Earnings Persistence

The intergenerational elasticity of earnings We decompose the intergenerational elasticity of earnings (IGE). To do this, we first estimate it by regressing log lifetime earnings of the NCDS cohort members, $\ln Y$, on log lifetime income of their parents, $\ln Y_P$:[15]

$$\ln Y = \rho_0 + \rho \ln Y_P + u \tag{1}$$

We next describe the model that we use to estimate the importance of different mechanisms driving earnings persistence across generations.

Earnings Following the literature in economics, we allow lifetime earnings to depend on the education, cognitive skills, and non-cognitive skills of an individual. Following the literature in sociology, we also allow lifetime earnings to depend on family background, investments, and parental income (Bowles and Nelson (1974), Sewell and Hauser (1972)). These variables are usually excluded from earnings equations in economics, as their effect is (implicitly) assumed to be captured by their impact on skills and education. However, there is a long tradition in quantitative sociology that considers the effect of these variables beyond skill formation and education choices. For example, they might enhance an individual's earnings by improving their network or might be correlated with an unmeasured heritable trait. Whilst we remain

[15] Eshaghnia et al. (2022) show that measures of (expected) lifetime resources better predict many childhood outcomes than point in time measures.

agnostic about the precise interpretation of these channels (and leave this for further research), we test whether family background, childhood investments, and parental income affect an individual's earnings beyond their effect through other measured characteristics.

We assume that lifetime earnings are given by the following constant elasticity of substitution (CES) process:

$$Y = [\alpha_0 ed^{\phi} + \alpha_1 \theta_C^{\phi} + \alpha_2 \theta_N^{\phi} + \alpha_3 \mathbf{I}^{\phi} + \alpha_4 ed_m^{\phi} + \alpha_5 ed_f^{\phi}]^{\frac{\nu}{\phi}} \cdot A, \tag{2}$$
$$A = \exp(\alpha_6 + \alpha_7 sib + \alpha_8 \ln Y_P + u^Y)$$

where $u^Y \perp \{ed, \theta_C, \theta_N, \mathbf{I}, ed_m, ed_f, sib, \ln Y_P\}$, ed is educational attainment, and θ_C and θ_N are the individual's cognitive and non-cognitive skills, respectively, measured at age 16. $\boldsymbol{I} = [ti_7, ti_{11}, ti_{16}, sq_7, sq_{11}, sq_{16}]$ is a vector of all investments (time investments and school quality) at ages 7, 11, and 16. The variables ed_m, ed_f represent mother's and father's education, and sib is the number of siblings. The CES functional form allows for complementarities between inputs. Furthermore, we allow for a free returns-to-scale parameter (ν) which is greater than 1 if there are increasing returns to scale and less than 1 if there are decreasing returns to scale.

Education We follow the literature on human capital formation and model reduced form choice equations (Cunha et al. (2010), Attanasio et al. (2020), Agostinelli and Wiswall (2024)). Educational attainment depends on final (age 16) skills, investments, family background, and family income:

$$ed = \gamma_{0,ed} + \gamma_{1,ed} \ln \theta_C + \gamma_{2,ed} \ln \theta_{NC} + \gamma_{3,ed} \ln \mathbf{I} + \gamma_{4,ed} ed_m + \gamma_{5,ed} ed_f + \gamma_{6,ed} sib + \gamma_{7,ed} \ln Y_P + u^{ed} \tag{3}$$

and we assume that $E[u^{ed} | \ln \theta_C, \ln \theta_{NC}, \ln \mathbf{I}, ed_m, ed_f, sib, \ln Y_P] = 0$. Skills are included as they may affect the potential returns to education; family background and family income are included as they could affect both preferences and the budget constraint. Finally, investments are included as they might affect unmeasured skills such as an individual's academic motivation, thus having an effect beyond their impact on measured skills.

Skills We follow Cunha et al. (2010) and Attanasio et al. (2020) by specifying skills to be formed according to a CES technology. Each of cognitive and non-cognitive skills is affected by lagged values of both types of skills, as well as investments, parental education, and a TFP term $A_{k,t+1}$. The TFP term depends on the number of siblings, parental income, and an unobserved shock. We include family background characteristics and parental income to capture, for example, differences in productivity of parents in producing child ability. We also allow for a free returns-to-scale parameter in the equation below, thus avoiding restrictive assumptions which can lead to biases when variables (such as skills) do not have a natural scale as described by Freyberger (2021):[16]

$$\begin{aligned}
\theta_{k,t+1} &= [\gamma_{1,k,t}\theta_{C,t}^{\phi_{t,k}} + \gamma_{2,k,t}\theta_{N,t}^{\phi_{t,k}} + \gamma_{3,k,t}ti_t^{\phi_{t,k}} + \gamma_{4,k,t}sq_t^{\phi_{t,k}} + \gamma_{5,k,t}ed_m^{\phi_{t,k}} + \gamma_{6,k,t}ed_f^{\phi_{t,k}}]^{\frac{\nu_{t,k}}{\phi_{t,k}}} \cdot A_{k,t+1}, \quad (4) \\
A_{k,t+1} &= \exp(\gamma_{7,k,t} + \gamma_{8,k,t}sib + \gamma_{9,k,t}\ln Y_P + u_{t+1}^k)
\end{aligned}$$

where $k \in \{C, N\}$ indexes the type of skill (cognitive or non-cognitive respectively). Furthermore, we assume that: $u_{t+1}^k \perp \{\theta_{C,t}, \theta_{N,t}, ti_t, sq_t, ed_m, ed_f, sib, \ln Y_P\}$. As this is a strong assumption, in Section 6.5, we evaluate the robustness of our results to allowing for unobserved heterogeneity following Cunha et al. (2010).

Time investments and school quality We allow time and school quality investments to depend on the lagged skills of the child since parents may base their investment decisions on the skills that they observe in their children. They also depend on family background and parental income since these affect time and budget constraints and could also reflect preferences. We estimate the equations:

$$\begin{aligned}
\ln ti_t &= \gamma_{0,ti,t} + \gamma_{1,ti,t}\ln\theta_{C,t-1} \\
&+ \gamma_{2,ti,t}\ln\theta_{NC,t-1} + \gamma_{3,ti,t}ed_m + \gamma_{4,ti,t}ed_f + \gamma_{5,ti,t}sib + \gamma_{6,ti,t}\ln Y_P + u_t^{ti} \quad (5) \\
\ln sq_t &= \gamma_{0,sq,t} + \gamma_{1,sq,t}\ln\theta_{C,t-1} \\
&+ \gamma_{2,sq,t}\ln\theta_{NC,t-1} + \gamma_{3,sq,t}ed_m + \gamma_{4,sq,t}ed_f + \gamma_{5,sq,t}sib + \gamma_{6,sq,t}\ln Y_P + u_t^{sq} \quad (6)
\end{aligned}$$

where $E[u_t^{ti}|\ln\theta_{C,t-1}, \ln\theta_{NC,t-1}, ed_m, ed_f, sib, \ln Y_P] = E[u_t^{sq}|\ln\theta_{C,t-1}, \ln\theta_{NC,t-1}, ed_m, ed_f, sib, \ln Y_P] = 0$.

Family background Finally, we allow for family background and parental income to be correlated, since high-income parents tend to be more highly educated and have fewer children.

5 Estimation Methods

Our goal is to estimate the lifetime earnings equation, education equation, skill production functions, and parental investment equations. We observe only noisy measures of parental income, skills, and investments, rather than directly observing the underlying variables of interest themselves. The fact

[16] Note that the scale of latent skills in period $t+1$, $\theta_{k,t+1}$, is not separately identified from the returns-to-scale parameter, $\nu_{t,k}$. Changes in the normalization of skills will translate into changes in $\nu_{t,k}$. Note, however, that if $\nu_{t,k}$ was forced to be 1, then changes in the normalization of $\theta_{k,t+1}$ would be absorbed by the other parameters, leading to bias.

that we do not directly observe variables of interest, combined with the non-linearity of the equations, complicates estimation.

To address these issues, we adapt a method proposed by Attanasio et al. (2020). First, we estimate the parameters of a measurement system that links our latent factors (i.e., investments, skills, and parental income) to the observed measures. Second, we predict these latent factors. Because these predicted latent factors contain measurement error, we estimate the joint distribution of the measurement error-free data by i) estimating the joint distribution of the observed data and ii) exploiting the estimated variance of measurement error. Third, we generate a synthetic measurement error-free data set on which we estimate the parameters of our model using non-linear least squares and OLS.

5.1 The Measurement System

We assume that skills and investments are unobserved variables for which we observe multiple noisy measures. Following Cunha and Heckman (2008) and Agostinelli and Wiswall (2016), we assume a log-linear relationship between measures (Z) and underlying unobserved variables $\omega \in \{\ln\theta_C, \ln\theta_{NC}, \ln ti, \ln sq\}$:

$$Z_{\omega,i,t,j} = \mu_{\omega,t,j} + \lambda_{\omega,t,j}\omega_{i,t} + \epsilon_{\omega,i,t,j} \tag{7}$$

Here, $Z_{\omega,i,t,j}$ denotes measure j of latent variable $\omega_{i,t}$ (e.g., a math score as a measure of latent cognitive skills) for individual i at time t. $\mu_{\omega,t,j}$ and $\lambda_{\omega,t,j}$, respectively, are the location and scale of this measure and are constant across individuals. $\epsilon_{\omega,i,t,j}$ denotes an idiosyncratic measurement error, assumed to be independent across individuals, measures, and time, and is also independent of the latent variables, all other controls, and shocks. Following Agostinelli and Wiswall (2024) and Cunha and Heckman (2008), we estimate the scaling parameters of the measurement system (the λs in equation (7)) by exploiting covariances between different measures. Using the results in Freyberger (2021), we normalize the variance of all log-latent variables to be one and normalize the mean of skills to be 0 in the initial period and the mean of investments to 0 in all periods. In Section 6.5 we investigate the sensitivity of alternative assumptions on the location and scale of our latent variables.[17]

In the procedures below, we assume that all measures are distributed as a mixture of normal variables. However, many of our measures are categorical, making the mixture of normals assumption implausible. As a result, we combine our measures to construct Bartlett scores (Heckman et al. (2013)), whose distri-

[17]Scale and location normalizations are potentially problematic and can lead to biased parameters when estimating CES production functions. To alleviate concerns regarding the scale of the log latent variables, we allow for non-constant returns to scale in the production function (4) via the parameters $\nu_{t,k}$. In terms of location normalizations, note that $E(\omega_{i,t})$ and the intercept term of the CES are not separately identified. We identify the mean of log skills using the intercept of CES in all periods other than the first period. We investigate alternative assumptions for $E(\omega_{i,t})$ in Appendix D with key results given in Section 6.5.

bution is reasonably well approximated by a mixture of normals.[18] In particular, we predict the latent variables for each individual using the Bartlett score method:

$$\hat{\omega}_{i,t} = (\lambda'_{\omega,\mathbf{t}}\mathbf{\Omega^{-1}}\lambda_{\omega,\mathbf{t}})^{-\mathbf{1}}\lambda'_{\omega,\mathbf{t}}\mathbf{\Omega^{-1}}\mathbf{Z}_{\omega,\mathbf{i},\mathbf{t}} \tag{8}$$

where $\hat{\omega}_{i,t}$ is a Bartlett score, and all the objects are replaced by their estimated counterparts. Here $\lambda_{\omega,\mathbf{t}}$ is a $J_{\omega,t} \times 1$ vector of scaling parameters $\lambda_{\omega,t,j}$ of all measures j for latent variable $\omega_{i,t}$, and $\mathbf{\Omega}$ is a $J_{\omega,t} \times J_{\omega,t}$ diagonal matrix with the variances of the measurement errors on the diagonal. Hence this step is equivalent to estimating a weighted regression of the measures $Z_{\omega,i,t,j}$ on the coefficients $\lambda_{\omega,t,j}$ in equation (7) for each individual, where the coefficient of interest is $\omega_{i,t}$. The weights ensure that noisier measures receive a lower weight. Because Bartlett scores are a weighted average of these measures, they reduce, but do not eliminate, measurement error. Hence, they are a noisy measure of the true latent variable. We account for the remaining measurement error in the Bartlett scores using a method proposed by Attanasio et al. (2020) and described in Section 5.2.

Parental income is observed only when the NCDS cohort member is 16. We treat this as a measurement error problem and model parents' log income when the cohort members were 16 as a noisy measure of their log lifetime income:

$$\ln Y_{P,i,16} = \mu_P + \lambda_P \ln Y_{P,i} + \epsilon_{P,i}. \tag{9}$$

As with the other measurement errors, $\epsilon_{P,i}$ is assumed to be independent of parental lifetime income and all other controls and shocks. We cannot estimate equation (9) for the parent's generation, but we can do so for the NCDS sample member's generation (for whom we have both point-in-time measures of income as well as lifetime income). We estimate it for the latter and assume that λ_P and the reliability ratio (the share of variance in point-in-time income explained by lifetime income) are constant across the two generations. This allows us to obtain the variance of measurement error in point-in-time income of the parents. Details can be found in Appendix B.

5.2 Approximating the Joint Distribution of Our Data Using a Normal Mixture

This subsection shows how we obtain the joint distribution of the variables that are relevant to our analysis. Let W_i be a $J \times 1$ vector of these variables, which we either observe without error (child income, child education, parental education, number of siblings) or with error (parental income and age 7, 11, and 16 skills and investments). Following Attanasio et al. (2020), we assume that the distribution of these

[18] We found that when assuming all measures are distributed as a mixture of normal variables, the parameters of the normal mixture in equation (13) are driven by a small subset of measures. Because Bartlett scores are a weighted sum of many measures, they are reasonably well approximated by a mixture of normals. As a result, using Bartlett scores made our procedure less sensitive to any particular measure.

variables, F_W, can be approximated by a mixture of two normals:

$$F_W = \tau\Phi\left(\kappa_A, \mathbf{\Omega}_A\right) + (1-\tau)\Phi\left(\kappa_B, \mathbf{\Omega}_B\right) \tag{10}$$

where $\tau \in [0,1]$ is the mixture weight and $\Phi(.,.)$ is the CDF of a normal distribution; e.g., $\Phi(\kappa_A, \mathbf{\Omega}_A)$ is a CDF with a $(L \times 1)$ vector of means κ_A and $(L \times L)$ variance-covariance matrix $\mathbf{\Omega_A}$. Many of these variables are measured with error.

The relationship between observed variables and underlying measurement error-free variables in vector form is as follows:

$$\mathcal{Z}_i = W_i + E_i \tag{11}$$

where $\mathcal{Z}_i$ is the $(J \times 1)$ vector of observed variables and E_i is the $(J \times 1)$ vector of all measurement errors for individual i. For variables observed without measurement error (child income, child education, parental education, and number of siblings), the corresponding element of E_i is 0. Assuming that measurement error is independent and normally distributed, inserting equation (10) into equation (11) yields the distribution of observed variables:

$$F_{\mathcal{Z}} = \tau\Phi\left(\Pi_A, \mathbf{\Psi}_A\right) + (1-\tau)\Phi\left(\Pi_B, \mathbf{\Psi}_B\right) \tag{12}$$

where

$$\begin{aligned} \mathbf{\Psi}_A = \mathbf{\Omega}_A + \mathbf{\Sigma}; \quad \mathbf{\Psi}_B = \mathbf{\Omega}_B + \mathbf{\Sigma} \\ \Pi_A = \kappa_A; \qquad \Pi_B = \kappa_B \end{aligned} \tag{13}$$

and $\mathbf{\Sigma} = E[E_i E_i^T]$ is a (diagonal $J \times J$) covariance matrix of the measurement errors. For the variables without measurement error, the corresponding variance is 0. For the latent variables which we measure using Bartlett scores, the variance of the measurement error (the elements of $\mathbf{\Sigma}$) equals the variance of the observed Bartlett score minus the variance of the log latent variable (which has been normalized to unity). Following Attanasio et al. (2020), we use an Expectation-Maximization (EM) algorithm to estimate the parameters of equation (12): τ, Π_A, Π_B, $\mathbf{\Psi}_A$, $\mathbf{\Psi}_B$. In the Expectation step, we calculate τ holding all other parameters fixed. Given τ, in the Maximization step, we maximize the likelihood function to estimate the parameters Π_A, Π_B, $\mathbf{\Psi}_A$, $\mathbf{\Psi}_B$. Because $\mathbf{\Sigma}$ has been previously estimated and is thus known, equation (13) shows that we can also recover $\mathbf{\Omega}_A, \mathbf{\Omega}_B$, κ_A, κ_B. Thus, we have all the parameters we need to recover the joint distribution of all the variables in our model, as shown in equation (10). These parameters allow us to generate a measurement error-free dataset of all variables in the model, W_i, using equation (10).

5.3 Generating a Synthetic Data Set and Estimating and Simulating the Model

With the estimated parameters of the normal mixture for the variables in hand, we generate a synthetic (measurement error-free) data set of 50 synthetic observations per individual in our NCDS data. Using this synthetic data set, we estimate the production functions (4) and the lifetime earnings equation (2) using non-linear least squares, and we estimate the education choice (3) and parental investment choices (5), (6) using OLS. We also estimate the variance of shocks to each of these equations.

With the synthetic data in hand, we simulate the model by feeding in initial conditions (family background characteristics and parental income) from our synthetic data set. We then use the estimated model equations and estimated distributions of shocks to simulate the trajectories of investments, skills, and ultimately earnings of each synthetic individual. Upon simulating the model, we can perform counterfactuals and estimate the IGE on the simulated data.

6 Results

In this section, we first present our estimates of the IGE. We then show estimates of our model equations: lifetime earnings, educational choice, skill formation, and investment choices. Finally, we show the results from our counterfactual decomposition exercise, which quantifies the importance of different channels for the intergenerational elasticity of earnings.

6.1 Estimates of the IGE

Table 3 shows estimates of the IGE, both when using the raw data and using our model. Without correcting for measurement error, the estimated IGE is 0.272 and 0.247 for males and females respectively. These estimates are similar to estimates in other studies using the same data (Belfield et al. (2017), Gregg et al. (2016)), and are robust to alternative measures of earnings (see Appendix C). The estimates increase modestly to 0.344 and 0.309 when we estimate the IGE using the simulated data on *lifetime* income generated by the model. While Haider and Solon (2006) find that using point-in-time income can bias the estimate of the IGE downwards if parents' income is measured when very young or very old, they also show that the bias is modest if parental income is measured in their 40s. Our estimates are consistent with this finding. The table also shows a version of the IGE that accounts for measurement error in a different manner – by using an errors-in-variables correction (described in Appendix B.1). These estimates are almost identical to the IGE that we obtain using the model-simulated data. The IGE is our primary object of interest, and will be the basis for our decomposition, so it is reassuring that the model simulated data replicates the relationship between (latent) parents' income and children's earnings.

Table 3: IGE estimates

	Male model	Male corrected(EIV)	Male uncorrected	Female model	Female corrected(EIV)	Female uncorrected
IGE	0.344	0.335	0.272	0.309	0.298	0.247
	(0.049)	(0.049)	(0.039)	(0.070)	(0.067)	(0.048)

Note: The first and fourth column show the measurement error-corrected IGE as predicted by simulating our model. The second and fifth column shows the IGE after applying an errors-in-variables correction, using the raw data. The third and sixth columns report the IGE estimates with no correction for measurement error in parental income, using the raw data.

6.2 Estimation Results: Earnings, Education, Skills, and Investments

Lifetime earnings We model the lifetime earnings equation (2) as a CES function of skills at 16, parental time and school quality investments, family background characteristics, and parental income. To help interpret the magnitude of the CES coefficients, Table 4 presents the average effects of an increase in each input for men and women, respectively, holding all other inputs constant at their original values. Because the log-latent variables (skills and investments) have no natural scale, we evaluate a 1 standard deviation increase in them. For individual's education, parental years of completed education, number of siblings, and log parental income, we evaluate a 1 unit increase. The underlying coefficients for the CES function are reported in Appendix Table 13.

An additional year of education increases earnings by 4.2% for men and 11.6% for women, which falls within the range of commonly reported returns to schooling, as summarized in Card (1999). An additional standard deviation of log cognitive skill increases earnings by 15% for men and 10% for women, similar to the estimates in Heckman et al. (2006). We find no significant effect of non-cognitive skills on earnings.

We test whether parental investments affect lifetime earnings beyond their impact on skills and education and find some evidence that age 7 investments are important for earnings of males. However, when we jointly test for the role of all investments, we cannot reject the null hypothesis of no effect of investments on lifetime earnings over and above their effect on cognitive skills. This confirms the usual view that parental time investments affect lifetime earnings primarily through their impact on cognitive skills and educational attainment. This is an attractive aspect of both our data and our framework. Whereas most of the literature (Huggett et al. (2011), Lee and Seshadri (2019), Daruich (2018)) *assumes* that parental time and school quality investments impact lifetime earnings only through their role in promoting higher cognitive skills and educational attainment, we formally test to see if that is the case. Furthermore, when we test for a joint effect of the family background variables on lifetime earnings, we find no significant joint effect of family background, conditional on cognitive skill and educational attainment. Parental income, however, has a significant effect on earnings of men. A 1 log point increase in parental income is associated with a 15% significant increase in earnings for men and a 10% increase for women (albeit that the latter is not statistically different from 0), controlling for all other variables.

The lessons we take from these results are as follows. First, human capital (i.e., cognitive skill and educational attainment) matters for earnings. Second, conditional on parents' income, we find little evidence that parental investments affect earnings beyond the effect that they have on human capital, which we show below. Third, while parental education is not quantitatively important, parental income is a quantitatively important determinant of earnings, even after controlling for human capital. Whether this link represents higher occupational attainment, better networks, or other unmeasured components of human capital we leave for future research.

For both men and women, ϕ is not significantly different from 0, which implies an elasticity of substitution close to 1. Thus, we cannot reject the hypothesis that earnings are a log-linear function of inputs. To further assess whether non-linearity implied by the CES production function is quantitatively important, we evaluate whether the marginal effects of inputs differ depending on age 16 skills and education. Consistent with the hypothesis that earnings are a log-linear function of inputs, Appendix Figure 7 shows that the marginal effects of inputs do not change much depending on the level of age 16 skills and education. Finally, while we cannot reject constant returns to scale for men, for women $\nu = 2.48$, indicating increasing returns to scale in the earnings equation.

Education In line with Arcidiacono (2005), Stinebrickner and Stinebrickner (2008), Carneiro and Heckman (2002) and Carneiro et al. (2011), we find a large effect of cognitive skills on educational attainment. Table 4 shows that a standard deviation increase in log cognitive skills increases educational attainment by 1.12 years for men and 1.08 years for women. This is consistent with the view that those with higher cognitive skills experience potentially lower disutility from obtaining additional education or are more productive in attaining education. For men, there is a small but statistically significant positive effect of non-cognitive skills on education - a standard deviation increase in log non-cognitive skills leads to a 1.16 month increase in education. For women, there is no significant effect. Once we control for skills, there is no significant effect of parental income on education. This is of interest, since many studies use parental income as a measure of liquidity. Our results indicate that for our cohort (who faced no tuition fees), the correlation of parental income and educational attainment arises not because of liquidity constraints, but because high-income parents have children with higher cognitive skills. This is consistent with Belley and Lochner (2007), who find that conditional on ability, parental income did not matter for the schooling decisions of the NLSY79 cohort (although they find that it does for more recent cohorts).

The F-tests reported at the bottom of the table show that time investments matter for educational outcomes even conditional on skills. For women (men), we can reject at the 1% (10%) level that time

Table 4: Life time earnings and educational attainment: males & females

	Men		Women	
	Lifetime Earnings	Education	Lifetime Earnings	Education
Education	**0.042**		**0.116**	
	[0.026, 0.054]		[0.090, 0.139]	
Cognitive Skills at 16	**0.148**	**1.119**	**0.096**	**1.081**
	[0.108, 0.195]	[1.004, 1.205]	[0.043, 0.162]	[0.957, 1.181]
Non-Cognitive Skills at 16	-0.013	**0.097**	-0.024	-0.005
	[-0.044, 0.009]	[0.019, 0.182]	[-0.055, 0.002]	[-0.082, 0.070]
School Quality				
Age 7	0.016	0.029	-0.019	**-0.119**
	[-0.021, 0.055]	[-0.071, 0.146]	[-0.066, 0.038]	[-0.239, -0.034]
Age 11	0.018	-0.025	-0.002	**0.076**
	[-0.016, 0.050]	[-0.095, 0.047]	[-0.044, 0.044]	[0.003, 0.156]
Age 16	-0.016	-0.025	-0.002	**0.076**
	[-0.048, 0.008]	[-0.084, 0.059]	[-0.015, 0.064]	[0.023, 0.186]
Time Investments				
Age 7	**0.044**	0.061	0.043	**0.139**
	[0.001, 0.077]	[-0.070, 0.160]	[-0.017, 0.084]	[0.046, 0.252]
Age 11	0.002	0.093	-0.027	0.015
	[-0.029, 0.040]	[-0.009, 0.189]	[-0.070, 0.011]	[-0.093, 0.079]
Age 16	0.015	0.020	-0.030	**0.226**
	[-0.019, 0.045]	[-0.072, 0.128]	[-0.067, 0.015]	[0.138, 0.303]
Family Background				
Mother's education	0.007	0.009	0.012	-0.006
	[-0.007, 0.024]	[-0.057, 0.074]	[-0.011, 0.036]	[-0.056, 0.052]
Father's education	**-0.026**	0.047	0.011	-0.007
	[-0.044, -0.008]	[-0.011, 0.105]	[-0.010, 0.047]	[-0.049, 0.049]
Number of Siblings	0.000	0.001	0.000	0.032
	[0.000, 0.000]	[-0.044, 0.042]	[0.000, 0.000]	[-0.013, 0.070]
Log Parental Income	**0.152**	-0.015	0.103	0.114
	[0.073, 0.245]	[-0.250, 0.200]	[-0.031, 0.212]	[-0.115, 0.326]
Returns to scale	**0.733**		**2.480**	
	[0.358;1.037]		[2.004;3.158]	
Elasticity of Subst.	**1.305**		**0.911**	
	[0.980, 1.967]		[0.728, 1.226]	
P-values for joint significance of:				
School Quality	0.656	0.705	0.836	0.040
Time Investments	0.542	0.093	0.846	0.000
Family Background	0.370	0.392	0.697	0.756

Note: This Table shows the impact of changing different inputs on earnings and education; it uses estimates of equations (2) and (3) for men and women, respectively. The elasticity of substitution is $\frac{1}{1-\phi}$. Bottom panel shows p-values of F-tests for joint significance of time investments at all ages, school quality at all ages, and all family background variables. The null hypothesis is that the relevant group of variables jointly have zero coefficient in the corresponding regression. 90% confidence intervals, constructed using 250 bootstrapped repetitions, are in brackets.

investments have no direct effect on educational outcomes. Furthermore, we find some evidence that school quality matters for educational outcomes for women (but not men) even conditional on skills. Thus, parental investments matter for education, beyond skill formation. This reflects an early result by Sewell and Hauser (1972) who find that aspirations or the influence of others (e.g., teachers) affect educational outcomes, but not earnings.

Table 5: Skill Production: Marginal Effects

(a) Males

	Cognitive			Non-Cognitive		
	Age 7	Age 11	Age 16	Age 7	Age 11	Age 16
Cognitive Skills Lag		**0.995**	**0.904**		**0.113**	**0.083**
		[0.922, 1.057]	[0.840, 0.940]		[0.023, 0.208]	[0.018, 0.122]
Non-Cognitive Skills Lag		-0.024	0.021		**0.327**	**0.217**
		[-0.063, 0.020]	[-0.009, 0.055]		[0.239, 0.511]	[0.168, 0.316]
Time Investments	**0.187**	**0.116**	**0.116**	**0.197**	**0.040**	**0.112**
	[0.143, 0.256]	[0.055, 0.151]	[0.078, 0.143]	[0.157, 0.269]	[0.009, 0.085]	[0.051, 0.174]
School Quality	**0.100**	0.002	0.004	-0.005	-0.007	**-0.037**
	[0.014, 0.177]	[-0.048, 0.058]	[-0.028, 0.041]	[-0.061, 0.050]	[-0.019, 0.028]	[-0.077, -0.007]
Mother's Education	**0.060**	**0.034**	-0.005	-0.013	-0.002	0.002
	[0.035, 0.109]	[0.016, 0.050]	[-0.023, 0.020]	[-0.029, 0.039]	[-0.007, 0.025]	[-0.011, 0.026]
Father's Education	**0.071**	**0.033**	-0.006	**0.030**	0.000	0.004
	[0.037, 0.101]	[0.017, 0.050]	[-0.017, 0.011]	[0.007, 0.063]	[-0.011, 0.008]	[-0.008, 0.027]
Number of Siblings	-0.020	**-0.052**	-0.006	0.035	**-0.051**	**-0.049**
	[-0.060, 0.011]	[-0.076, -0.026]	[-0.023, 0.008]	[-0.002, 0.075]	[-0.081, -0.016]	[-0.080, -0.009]
Log Parental Income	**0.284**	-0.022	-0.014	-0.111	**-0.192**	-0.049
	[0.108, 0.461]	[-0.141, 0.068]	[-0.117, 0.040]	[-0.282, 0.032]	[-0.360, -0.037]	[-0.186, 0.087]
Returns to Scale	**2.435**	**2.096**	**0.849**	**0.509**	**0.554**	**0.525**
	[2.076, 3.079]	[1.743, 2.408]	[0.632, 1.318]	[0.432, 1.258]	[0.469, 1.017]	[0.392, 1.062]
Elasticity of Subst.	**0.710**	**1.356**	1.124	**0.405**	**0.517**	**0.691**
	[0.632, 0.882]	[1.095, 1.701]	[0.832, 1.215]	[0.179, 0.720]	[0.458, 0.916]	[0.519, 0.835]

(b) Females

	Cognitive			Non-Cognitive		
	Age 7	Age 11	Age 16	Age 7	Age 11	Age 16
Cognitive Skills Lag		**0.884**	**0.806**		**0.125**	**0.091**
		[0.839, 0.944]	[0.761, 0.851]		[0.023, 0.165]	[0.040, 0.147]
Non-Cognitive Skills Lag		-0.044	0.004		**0.242**	**0.157**
		[-0.075, 0.012]	[-0.022, 0.034]		[0.173, 0.340]	[0.100, 0.230]
Time Investments	**0.230**	**0.065**	**0.114**	**0.111**	**0.111**	**0.133**
	[0.168, 0.287]	[0.017, 0.112]	[0.088, 0.148]	[0.078, 0.161]	[0.013, 0.141]	[0.095, 0.177]
School Quality	0.032	0.051	-0.033	-0.016	0.008	**-0.050**
	[-0.030, 0.090]	[-0.003, 0.087]	[-0.062, 0.002]	[-0.061, 0.004]	[-0.026, 0.059]	[-0.082, -0.022]
Mother's Education	**0.063**	**0.024**	0.002	**0.021**	0.002	**0.020**
	[0.034, 0.101]	[0.012, 0.043]	[-0.022, 0.017]	[0.002, 0.042]	[-0.016, 0.034]	[0.002, 0.044]
Father's Education	**0.042**	**0.015**	0.009	0.015	-0.038	0.004
	[0.011, 0.072]	[0.004, 0.030]	[-0.006, 0.023]	[-0.005, 0.034]	[-0.054, 0.002]	[-0.012, 0.021]
Number of Siblings	**-0.040**	**-0.028**	-0.006	-0.008	0.000	**-0.032**
	[-0.076, -0.007]	[-0.049, -0.010]	[-0.018, 0.011]	[-0.034, 0.018]	[-0.030, 0.020]	[-0.054, -0.006]
Log Parental Income	0.092	**0.117**	-0.035	**-0.135**	0.119	-0.101
	[-0.063, 0.259]	[0.018, 0.193]	[-0.102, 0.038]	[-0.234, -0.033]	[-0.005, 0.183]	[-0.217, 0.011]
Returns to Scale	**2.010**	**1.649**	**1.115**	**0.708**	**0.035**	**0.837**
	[1.482, 2.619]	[1.467, 2.012]	[0.761, 1.402]	[0.417, 1.017]	[0.045, 0.804]	[0.643, 1.112]
Elasticity of Subst	**0.701**	**1.276**	0.963	**0.501**	1.013	**0.643**
	[0.596, 0.815]	[1.146, 1.745]	[0.893, 1.107]	[0.340, 0.673]	[0.435, 1.184]	[0.584, 0.745]

Notes: This table uses estimates of equation (4) to show the average effect of increasing inputs into the skill production functions. For skills and investments, we evaluate a 1 standard deviation increase, for individual's education, parental education number of siblings, and log parental income, we evaluate a 1 unit increase. Investment measures are contemporaneous, e.g., we use age investments measured at age 16 (which should capture investments ages 11-16) in the age 16 skills equation. The elasticity of substitution is $\frac{1}{1-\phi}$. All coefficients for the CES function are reported in Appendix Table 13. 90% confidence intervals, constructed using 250 bootstrapped repetitions, are in brackets.

Skills We model the production function for both cognitive and non-cognitive skills as CES functions of lagged skill, time and school quality investments, family background characteristics, and parental income.

We again allow for a free returns-to-scale parameter.

As we showed for the earnings equations, Table 5 presents the average effects of an increase in each input for men and women, respectively, holding all other inputs constant at their original values. We evaluate a 1 standard deviation increase in skills and investments, and a 1 unit increase in individual's education, parental education, number of siblings, and log parental income. The raw coefficients for the CES function are reported in Appendix Table 14.

For males, time investments positively affect cognitive and non-cognitive skills and are most productive at age 7. School quality is less productive for men in producing either skill compared to time investments. Paternal and maternal education tend to increase cognitive skills, especially at age 7 and age 11. This may be due to a direct transmission of cognitive skill from parents to children or the efficiency of those parental investments. Growing up in a smaller family is better for both cognitive and non-cognitive skills. Finally, parental income increases cognitive skills at age 7, but otherwise has small and mostly insignificant effects on both types of skills at other ages. This is akin to Caucutt and Lochner (2020) and Eshaghnia et al. (2024)'s finding that parental resources in early childhood are particularly important for children's cognitive skills.

For females, the patterns are largely similar. Time investments in girls are most productive for cognitive skills at age 0-7, whilst they are equally productive at all ages for non-cognitive skills. Parental education improves cognitive skills, whereas having more siblings reduces both cognitive and non-cognitive skills. Lastly, parental income increases cognitive skills at younger ages.

The elasticity of substitution, $\frac{1}{1-\phi}$, ranges from 0.71 to 1.35 for cognitive skills and 0.41 to 1.01 for non-cognitive skills. To investigate and illustrate the effect of this non-linearity we evaluate the marginal effects of each input at the 25th, 50th and 75th percentile of cognitive skills and maternal education. Results can be found in Appendix Figures 4-5. Given that our estimates of the elasticity of substitution are close to 1 (implying a log linear production function), we find that marginal effects of different inputs do not change much depending on previous skills or parental education.

Whilst we assume our investments are independent of the error term in the production function in the results described above, in Section 6.5 we relax this assumption and consider the possibility that some individuals have permanent unobserved traits that are productive for outcomes. We allow these permanent traits to be correlated with investments received and show that allowing for these unobservables does not change the main results of this paper.

Investments We model time and school quality investments as log-linear functions of previous period log-skills, parental education, number of siblings, and log parental income. Table 6 presents results. We find that that children with better cognitive and non-cognitive skills in one period receive higher investments in the next period. Thus, early investments which increase cognitive skills can lead to an amplification effect, as they beget higher subsequent investments.

Educated parents invest more in their children, both in terms of time and school quality. One more year of education for the mother increases time investments by 0.06 (0.12) standard deviations at age 0-7 for males (females), echoing results in Carneiro et al. (2013). Paternal education also matters. Consistent with resource constraints, having more children reduces both time investments and school quality, similar to the findings in Bhalotra and Clarke (2020).

Finally, higher parental income increases time investments and school quality. For example, a 10% increase in parental income increases time investments by 0.045 (0.032) standard deviations at ages 0-7 for boys (girls). Importantly, parental income increases investments at all ages, conditional on family background and other variables. Our finding that it is not only family background, but parental income itself which matters for parental investments is consistent with empirical evidence (Duncan et al. (2011), Milligan and Stabile (2011), Dahl and Lochner (2012)) on the impact of financial transfers on the human capital development of children.

Table 6: Investment equations

(a) Males

	Time investment			School Quality		
	Age 0-7	Age 7-11	Age 11-16	Age 0-7	Age 7-11	Age 11-16
Cognitive Skills Lag		**0.124**	**0.340**		0.014	**0.559**
		[0.070, 0.213]	[0.293, 0.404]		[-0.055, 0.065]	[0.504, 0.609]
Non-Cognitive Skills Lag		**0.100**	**0.053**		0.014	-0.035
		[0.040, 0.159]	[0.013, 0.098]		[-0.034, 0.060]	[-0.074, 0.019]
Mother's Education	**0.060**	0.028	0.015	**0.113**	**0.090**	**0.046**
	[0.024, 0.096]	[-0.006, 0.064]	[-0.005, 0.053]	[0.057, 0.162]	[0.047, 0.154]	[0.012, 0.086]
Father's Education	**0.074**	0.011	**0.071**	**0.082**	**0.163**	**0.075**
	[0.043, 0.103]	[-0.028, 0.034]	[0.045, 0.097]	[0.044, 0.128]	[0.104, 0.222]	[0.039, 0.107]
Number of Siblings	**-0.242**	**-0.155**	**-0.078**	**-0.071**	**-0.045**	0.003
	[-0.270, -0.208]	[-0.180, -0.119]	[-0.103, -0.046]	[-0.114, -0.017]	[-0.078, -0.013]	[-0.030, 0.023]
Log Parental Income	**0.453**	**0.480**	**0.232**	**0.357**	0.187	**0.139**
	[0.314, 0.626]	[0.337, 0.653]	[0.106, 0.363]	[0.097, 0.555]	[-0.033, 0.387]	[0.012, 0.263]

(b) Females

	Time investment			School Quality		
	Age 0-7	Age 7-11	Age 11-16	Age 0-7	Age 7-11	Age 11-16
Cognitive Skills Lag		**0.225**	**0.369**		0.057	**0.583**
		[0.132, 0.322]	[0.306, 0.425]		[-0.005, 0.135]	[0.525, 0.638]
Non-Cognitive Skills Lag		0.001	**0.056**		-0.031	-0.043
		[-0.100, 0.095]	[0.006, 0.118]		[-0.103, 0.022]	[-0.089, 0.001]
Mother's Educ.	**0.119**	**0.105**	**0.101**	0.015	**0.098**	0.023
	[0.081, 0.150]	[0.058, 0.128]	[0.069, 0.132]	[-0.026, 0.075]	[0.047, 0.164]	[-0.007, 0.060]
Father's Educ	**0.083**	**0.027**	**0.061**	**0.109**	**0.132**	**0.029**
	[0.048, 0.117]	[0.001, 0.061]	[0.035, 0.083]	[0.056, 0.156]	[0.072, 0.187]	[0.002, 0.056]
Number of Siblings	**-0.232**	**-0.146**	**-0.104**	**-0.093**	**-0.038**	**0.048**
	[-0.264, -0.203]	[-0.169, -0.111]	[-0.136, -0.074]	[-0.141, -0.047]	[-0.066, -0.010]	[0.017, 0.071]
Log Parental Income	**0.316**	0.128	0.110	**0.400**	**0.185**	0.107
	[0.188, 0.455]	[-0.010, 0.309]	[-0.012, 0.249]	[0.184, 0.612]	[0.040, 0.398]	[-0.013, 0.227]

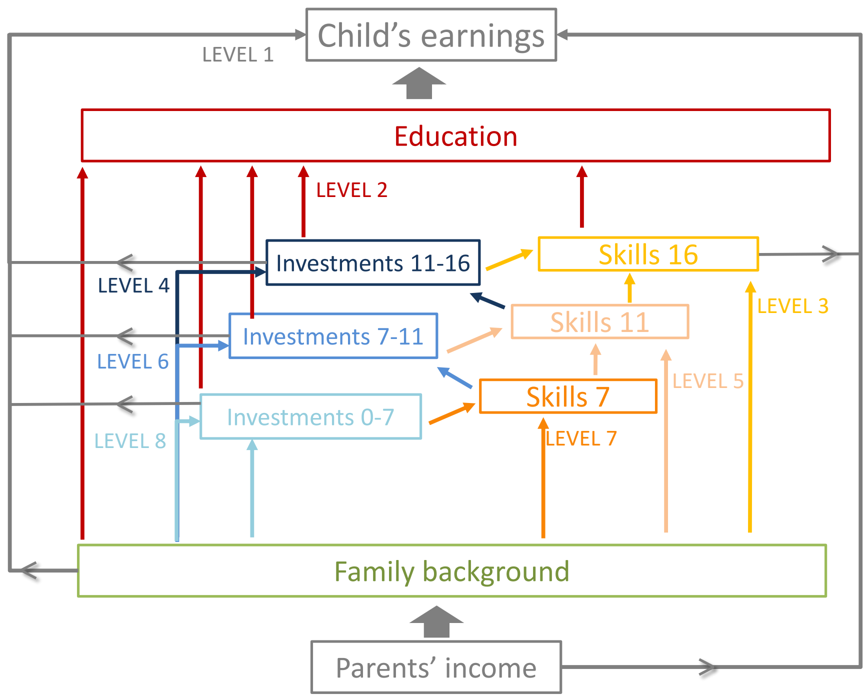
Notes: This table shows estimates of the investment equations (5) and (6). 90% confidence intervals, constructed using 250 bootstrapped repetitions, are in brackets.

6.3 Decomposing the Sources of Intergenerational Persistence

We use the estimated model to evaluate how parental income gradients in education, skills, investments, and family background contribute to the IGE and how their effect is mediated by other variables. To do this we equalize each variable by giving everyone its mean value in the equations of interest (thereby eliminating the parental income gradient in that variable), re-simulate lifetime earnings, and re-estimate the IGE on the re-simulated data.

In the following, a *direct* effect is the effect of a variable on the IGE when only accounting for its impact in the earnings equation, holding constant other variables. An *indirect effect* is the effect of a variable on the IGE when accounting for its impact on earnings through an intermediate variable. For example, while cognitive skills have a *direct* effect as they enter the earnings equation, they may also

Figure 1: Overview of Mediation Approach



have an *indirect* effect on the IGE as they affect education which in turn affects earnings. Figure 1 shows the variables which affect child earnings and the pathways through which they contribute to the IGE, in the spirit of path diagrams in the quantitative sociology literature (see, for example, Sewell and Hauser (1972)).

To illustrate our approach, we will describe how we measure the contribution of parental education (one of our family background variables) to the IGE. To determine the *direct* effect of parental education on the IGE, we assign all individuals the mean values of maternal and paternal education ($\overline{ed}_m$, $\overline{ed}_f$) in the lifetime earnings equation (2), re-simulate the model, and predict each individual's earnings in the re-simulated data:

$$\hat{Y} = [\hat{\alpha}_0 ed^{\hat{\phi}} + \hat{\alpha}_1 \theta_C^{\hat{\phi}} + \hat{\alpha}_2 \theta_N^{\hat{\phi}} + \hat{\alpha}_3 \mathbf{I}^{\hat{\phi}} + \hat{\alpha}_4 \overline{ed}_m^{\hat{\phi}} + \hat{\alpha}_5 \overline{ed}_f^{\hat{\phi}}]^{\frac{\hat{\nu}}{\hat{\phi}}} \cdot \hat{A}, \tag{14}$$
$$\hat{A} = \exp(\hat{\alpha}_6 + \hat{\alpha}_7 sib + \hat{\alpha}_8 \ln Y_P + \hat{u^Y}).$$

We then re-estimate the IGE on the re-simulated data. We take the percentage difference between the baseline IGE and the one where parental education has been equalized as the contribution of parental education to the IGE. This tells us to what extent differences in parental education affect the IGE through the earnings equation. This direct effect is the first level of mediation and is illustrated as 'Level 1' in Figure 1 by the grey arrow from family background to child's earnings.

Parental education might not only affect earnings directly, but also indirectly through its impact on educational attainment. To quantify this indirect effect alongside the direct effect, we equalize parental education in the lifetime earnings equation (2) as before. In addition, we now equalize parental education in the child's education equation (3) which we denote $\widetilde{ed}$, which in turn also enters the earnings equation. Thus, children's earnings will change for two reasons: 1) due to the direct effect of parents' education in the earnings equation and 2) due to the change in their own education which in turn enters the earnings equation:

$$\widetilde{ed} = \hat{\gamma}_{0,ed} + \hat{\gamma}_{1,ed} \ln \theta_C + \hat{\gamma}_{2,ed} \ln \theta_{NC} + \hat{\gamma}_{3,ed} \ln \mathbf{I} + \hat{\gamma}_{4,ed} \overline{ed}_m + \hat{\gamma}_{5,ed} \overline{ed}_f + \hat{\gamma}_{6,ed} sib + \hat{\gamma}_{7,ed} \ln Y_P + \hat{u}^{ed} \quad (15)$$

$$\hat{Y} = [\hat{\alpha}_0 \widetilde{ed}^{\hat{\phi}} + \hat{\alpha}_1 \theta_C^{\hat{\phi}} + \hat{\alpha}_2 \theta_N^{\hat{\phi}} + \hat{\alpha}_3 \mathbf{I}^{\hat{\phi}} + \hat{\alpha}_4 \overline{ed}_m^{\hat{\phi}} + \hat{\alpha}_5 \overline{ed}_f^{\hat{\phi}}]^{\frac{\hat{\nu}}{\hat{\phi}}} \cdot \hat{A}, \quad (16)$$

$$\hat{A} = \exp(\hat{\alpha}_6 + \hat{\alpha}_7 sib + \hat{\alpha}_8 \ln Y_P + \hat{u^Y})$$

This sum of the direct effect and the indirect effect via education constitutes the share of the IGE explained by parental education at the second level of mediation. Level 2 is illustrated in Figure 1 by bringing in the red arrows. Thus, the indirect effect of parental education via child's educational attainment is captured by the path traced out by the red arrow from family background to education and the grey arrow on to child's earnings.

We then calculate the share of the IGE explained by parental education due to its effect on an increasing number of other variables which, in turn, affect earnings. In particular, we additionally equalize parental education in the age 16 skills equations (level 3), the age 11-16 investment equations (level 4), the age 11 skills equations (level 5), the age 7-11 investments equations (level 6), the age 7 skills equations (level 7), and the age 0-7 investments equations (level 8). That is, we respectively equalize parental education in the equations that constitute a given level, re-simulate the model, and re-estimate the IGE on the simulated data. We perform a similar analysis for all other variables.

Figure 1 illustrates all of the direct and indirect effects a variable can have on the IGE at a given level. To see this, one needs to consider all arrows, from Level 1 up to the level of interest, which originate from the variable of interest. For example, to see all the effects family background has on the IGE at level 3, one can trace the Level 1 (grey) arrow, which illustrates the direct effect of family background on child's earnings, the Level 2 (red) arrow, which illustrates the indirect effect on child's earnings via education, and the Level 3 (yellow) arrow which illustrates the indirect effect on child's earnings via skills at age 16.

6.4 Mediation Results

Figure 2 displays the results of our mediation analysis. Overall, variation in the channels we consider – education, skills, investments and family background – explain 55% (68%) of the intergenerational elasticity in earnings of males (females). The eight bars in the figure show the shares of the IGE explained by different variables at each of the eight levels of mediation. Table 11 in Appendix G gives the detailed numbers underlying our baseline analysis along with their statistical significance.

Level 1 - Direct effects on lifetime earnings The "direct effect" columns in Figure 2 decompose the IGE, allowing only for the direct effect of each channel on the IGE. This is the first level of mediation. Differences in cognitive skills and educational attainment explain large fractions of the IGE for both males and females. For males, 14% of the IGE is explained by educational attainment (coloured in dark red) and 32% by cognitive skill at 16 (coloured in yellow). For females, 39% of the IGE is explained by educational attainment and 23% by cognitive skill. Non-cognitive skills explain a negligible share of the IGE for both genders. Parental investments at all ages, coloured in different shades of blue, explain in total 14% (1%) of the IGE for men (women); age 0-7 investments explain a significant share of the IGE for men, but not for women.[19] Lastly, family background has a small and insignificant effect on the IGE once education, skills, and investments are accounted for. Thus, having better educated parents or more siblings does not affect earnings beyond their impact on skill formation and educational attainment.

Level 2 - Allowing for indirect effects via educational attainment The second columns of Figure 2 show the fractions of the IGE explained by each channel when allowing age 16 skills, investments, and family background to additionally have indirect effects through their impact on educational attainment. To do this, we equalize skills, investments, and family background (in turn) in both the education and earnings equations, re-simulate the model, re-estimate the IGE on the re-simulated data, and calculate the resulting percent decline in the IGE. Thus the reported share explained by skills, investments and family background now include both direct effects and indirect effects via their impact on educational attainment. Once we allow for these indirect effects, the share of the IGE explained by educational attainment becomes small and no longer statistically different from zero for both genders (in the figure, we can see the red block disappearing).[20] This indicates that for both men and women, the higher educational

[19]In our main specification, we simultaneously equalize school quality and time investments. Appendix Table 12 shows results when we separately equalize investments. At most ages and at most levels of mediation, parental time investments are more important than school quality investments for boys. For girls, school quality investments are slightly more important from age 7 onwards. Due to the modest degree of complementarity that we estimate, the sum of shares explained by time investments and school quality are very similar to the share explained by both when equalizing them simultaneously.

[20]To calculate the remaining share of the IGE explained by education in this level, we equalize parental income in the education equation and calculate the percentage change of the IGE. This is because parental income is the only remaining driver of differences in education after accounting for the effect of skills, investments, and family background on education.

attainment of individuals from high-income households is fully explained by their greater skills and investments, as well as more advantaged family background. Of skills, investments, and family background, age 16 cognitive skills matter the most. In fact, while cognitive skills explain 32% (23%) of the IGE through their direct effect on lifetime earnings, they also explain the IGE through an indirect effect via educational attainment, thus explaining a total share of 43% (49%) of the IGE for men (women). This is consistent with previous studies showing that those with greater cognitive skills are more likely to attain higher levels of education (Keane and Wolpin (2001), Carneiro and Heckman (2002), Arcidiacono (2005)).

Neither the education of parents nor the number of siblings has a significant impact on education once cognitive skill and investments are controlled for. Lastly, the explanatory power of non-cognitive skills remains low. Although non-cognitive skills do have a positive effect on education for men, the effect is much smaller than for cognitive skills. Furthermore, there is only a small gradient in non-cognitive skills by parental income. As a result, the overall share of the IGE explained by non-cognitive skills is small.

Levels 3 to 8 - Allowing for effects of human capital formation Columns 3-8 of Figure 2, corresponding to mediation levels 3-8, additionally account for the formation of skills and investments. Mediation level 3 accounts for additional indirect effects of age 11 skills, investments, and family background on the IGE through their effect on skills at age 16. Comparing column 3 to column 2 reveals that age 16 cognitive skills are largely explained by differences in age 11-16 investments and age 11 cognitive skills (the yellow bars disappear and the peach and blue-coloured bars increase). Thus, the lion's share of the effect of age 16 cognitive skills in transmitting earnings across generations is actually determined by earlier life skills and investments.

Level 4 allows for age 11 skills and family background variables to have an additional indirect effect on the IGE via their impact on age 11-16 investments. Investments at 11-16 are largely driven by the age-11 skills. This can be seen by the decrease in the dark blue shade (investments at 11-16) and the increase in the peach shade (cognitive skills at 11) when moving from the third to the fourth column. Continuing on through the fifth and sixth column, differences in age 11 skills and age 7-11 investments can largely be explained by differences in age 7 skills: age 7 skills have sizeable indirect effects on the IGE through their effect on subsequent skills and investments (i.e., the orange bars become sizable). The effect of these age 7 skills on the IGE, in turn, can largely be explained by age 0-7 investments and family background; the orange bars (showing the contribution of age 7 skills to the IGE) shrink between level 6 and 7, and the light blue and green bars increase. The final column shows that the share of the IGE explained by investments can in part be explained by differences in parental education driving differences

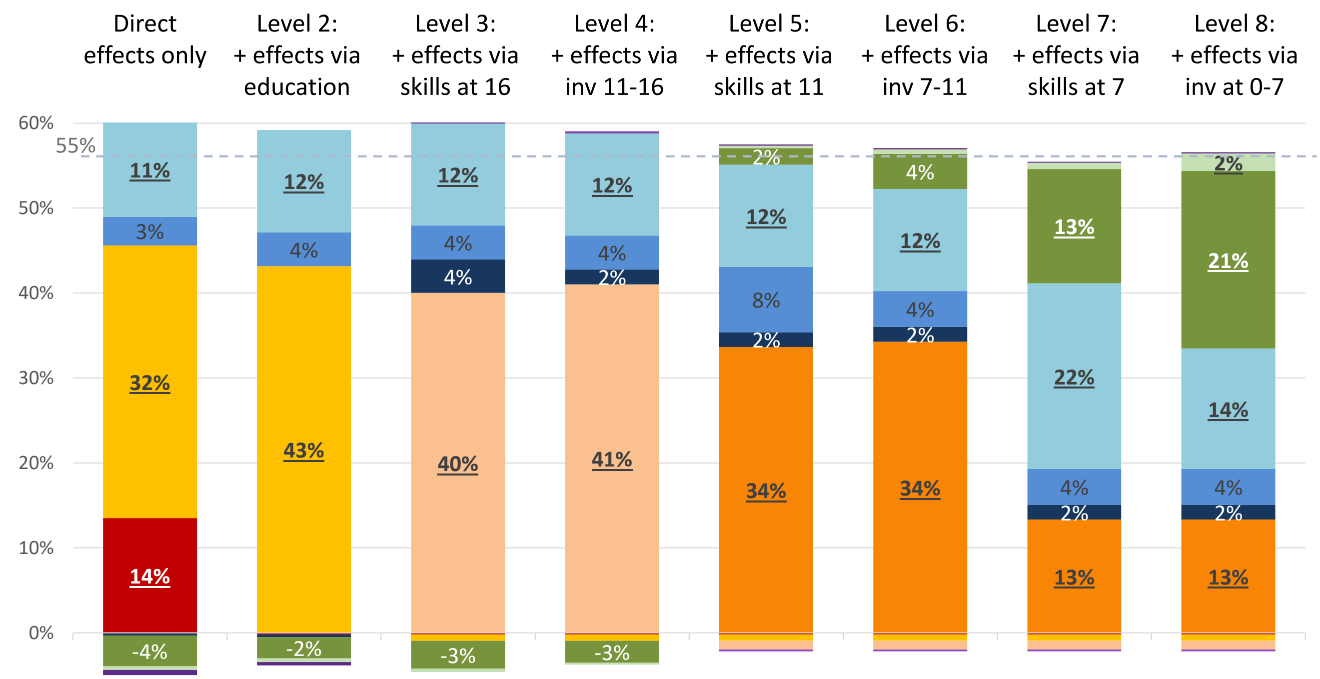
Thus, the decline in the red bar for women between Level 1 and Level 2 of Figure 2 shows that there is a small effect of parental income on education and thus the IGE, even after accounting for all other possible channels which may affect the IGE.

in investments. However, school quality and parental time investments at age 0-7 continue to explain a significant share of the IGE, indicating there is some direct or unexplained relationship between parental income and school quality/ parental time investments at age 0-7. In contrast, the relationship between parental income and investments at later ages has little predictive power for the IGE. To the extent that financial resources are key for explaining the relationship between parents' and childrens' earnings, it is through the role of these resources early in life, not late in life.

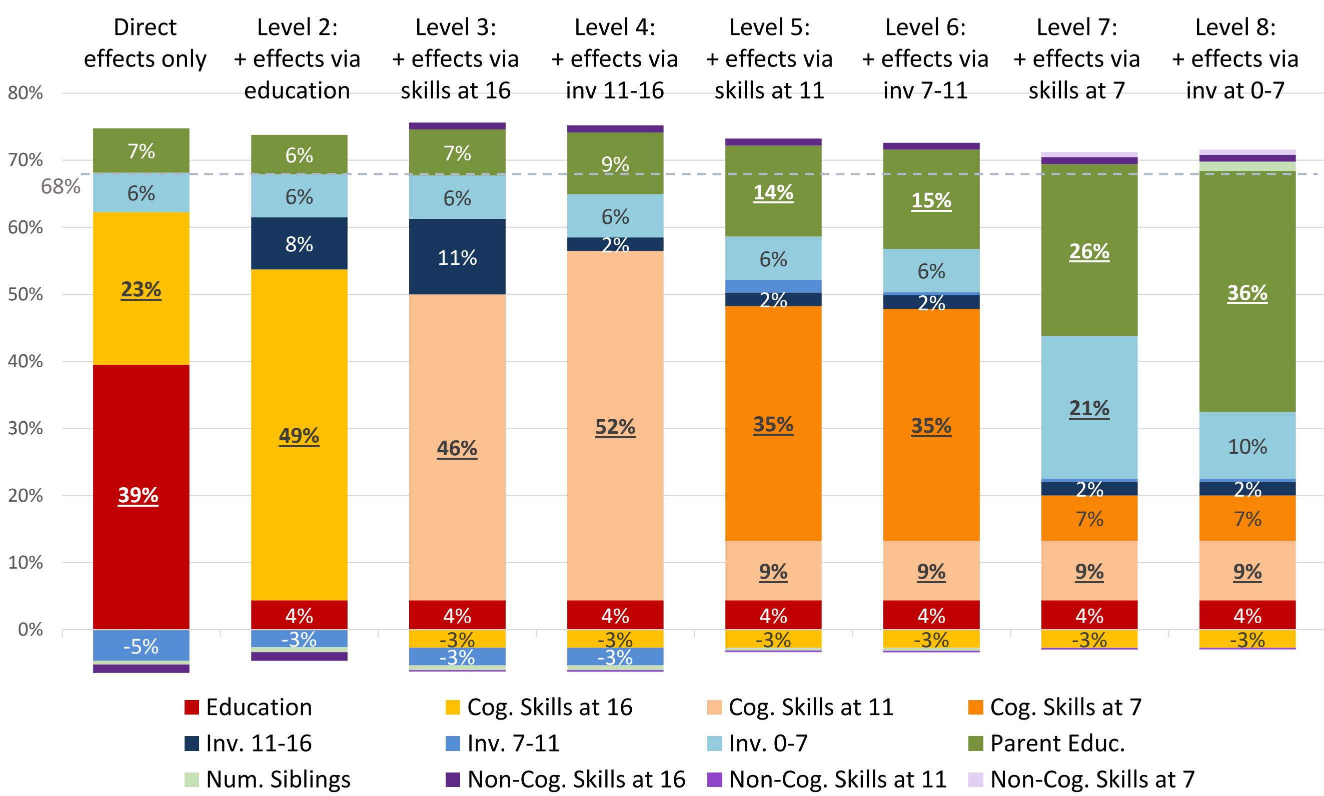
Summary Figure 2 illustrates that which variables are considered most consequential for the IGE depends on whether we look at Level 1 (direct effects only) or Level 8 (which accounts for the effect of early-life variables on those realized later in life). For example, parental education has a very small direct effect on the IGE. However, when we account for its role in shaping investments and childhood skills, it plays a dominant role: it accounts for 21% of the IGE for men and 36% for women. This echoes earlier results in the literature on family background and economic outcomes; Leibowitz (1977) notes that the key channel by which family background affects earnings is via its impact on the human capital accumulation of the child. Similarly, investments do not matter much when one only accounts for their direct effect on lifetime earnings. However, once we consider their effect on early-life skills (a channel which has recently been emphasized in economics by Cunha et al. (2010) among others), which in turn beget further investments and further skills, differences in investments become a crucial driver of the IGE: differences in investments over the first 7 years of life between those from rich and poor families account for 22% and 21% of the IGE for men and women, respectively.

Figure 2: Mediation analysis results: share of IGE explained

(a) Men



(b) Women

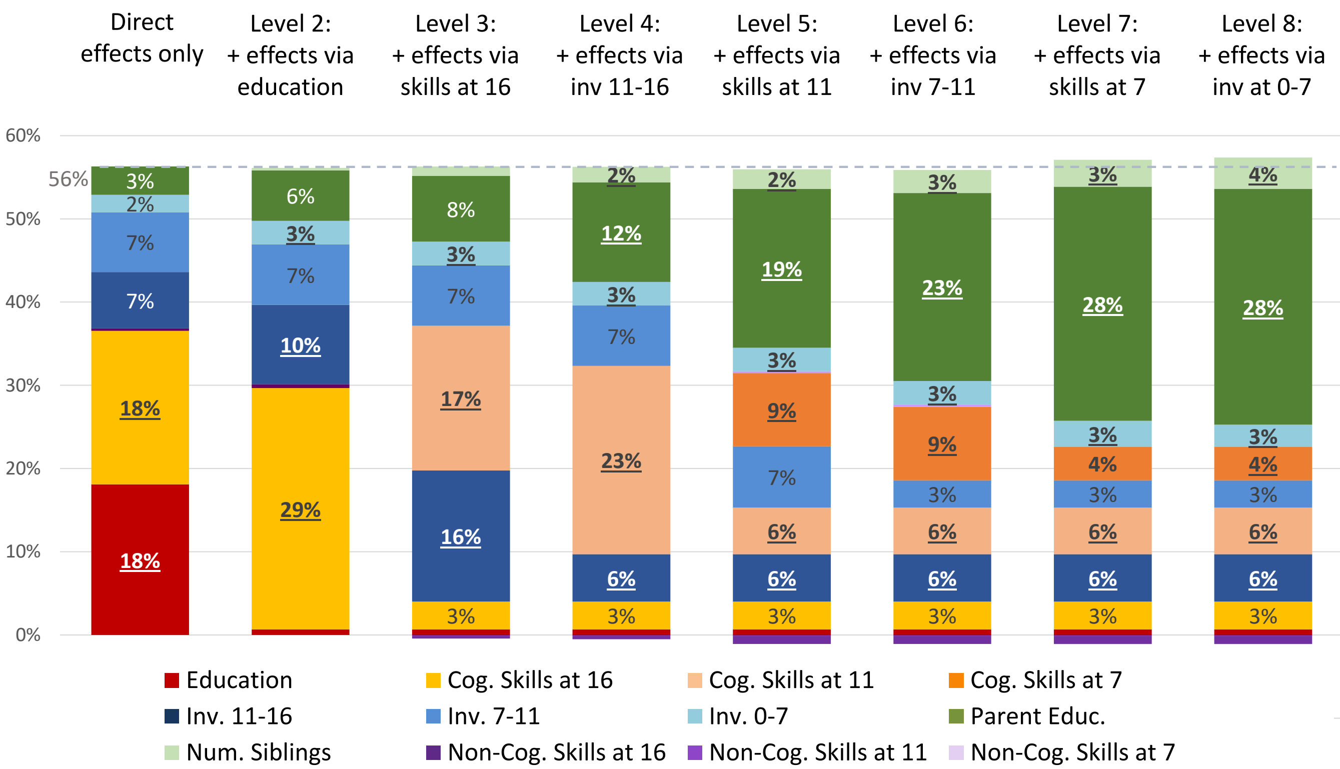


Note: These graphs show Levels 1-8 of the mediation analysis. The horizontal dashed line shows the share of the IGE explained by the variables we consider jointly in level 1 (55% for men and 68% for women). Note that this line does not lie at the top of the bars due to the negative contributions of some variables which are shown below the horizontal axis. The dashed line is approximately equal to the sum of all the positive and the negative contributions. The total share of the IGE explained differs by level since the model is non-linear; differences are small, however. Further details, including confidence intervals, can be found in Table 11 of the appendix.

6.5 Robustness Checks

In this section, we summarize the results of the following robustness checks: (i) ignoring measurement error, (ii) allowing for unobserved individual-level heterogeneity, (iii) increasing the mixture of normals from two to three, (iv) changing the location and scale of our unobserved variables, and (v) using different measures of non-cognitive skills. We show that while accounting for measurement error is critical, the other modifications have little impact on our results.

Figure 3: Mediation analysis results for men when ignoring measurement error: share of IGE explained



These graphs show Levels 1-8 of the mediation analysis for men when not accounting for measurement error. The horizontal dashed line shows the share of the IGE explained by the variables we consider jointly in level 1 (56%). Note that this line does not lie at the top of the bars due to the negative contributions of some variables which are shown below horizontal axis. The dashed line is approximately equal to the sum of all the positive and the negative contributions. The total share of the IGE explained differs by level since the model is non-linear; differences are small, however. Further details, including confidence intervals, can be found in Table 15 of the appendix.

The importance of correcting for measurement error Throughout this analysis, we have confronted the fact that parental income, skills, and time and school quality investments are all measured with error. In this section we discuss the importance of allowing for measurement error in these variables. Figure 3 gives results of our mediation analysis for men when *not* accounting for measurement error. In this analysis, instead of combining multiple measures to extract a factor, we use the single measure with the highest signal-to-noise ratio for cognitive skill, non-cognitive skill, school quality, and time investment. As we do not wish to correct for measurement error, we do not use the Attanasio et al. (2020) procedure, but instead directly use the single measure of each factor in the estimation of the lifetime earnings equation, education equation, production functions, and investment equations. We then conduct the same decomposition exercise as outlined in Section 6.3, but on the actual, rather than simulated data.

Although the overall share of the IGE explained is not substantially affected by controlling for measurement error, there are two key differences between the results in Figures 2 and 3. First, consistent with the usual attenuating role of measurement error, the estimated coefficients on the error-ridden variables are smaller when not accounting for measurement error. As a result, these variables explain a smaller share of the IGE. For example, ignoring measurement error attenuates the fraction of the IGE explained by parental investment by over half. Recall that for all of the latent variables, we select the measure with the highest signal-to-noise ratio. If we were to pick less well measured variables with lower signal-to-noise ratios, these variables would explain an even smaller share of the IGE. In this sense the results we present here should be considered a conservative assessment of the importance of controlling for measurement error. Second, the objects not measured with error explain a larger share of the IGE when not accounting for measurement error. This is as expected. Since all the variables considered are correlated with one another, erroneously understating the impact of one variable will lead us to erroneously overstate the impact of the other variables. Table 15 in Appendix I contains the full decomposition results excluding the measurement error correction. It also shows decomposition results for women. As with men, failure to correct for measurement error understates the importance of error-ridden variables in explaining the IGE.

Unobserved heterogeneity Our main analysis does not allow for unobserved heterogeneity to be driving investments, skills, education, or earnings. In this section, we relax that assumption and estimate a version that allows for unobserved heterogeneity that is correlated with investments and outcomes. To do so, we follow Cunha et al. (2010) and exploit multiple skill outcome measures to identify an individual-specific fixed effect that is correlated both with investments and earnings.[21]

Specifically, we take $S = 7$ adult skill measures which are not included in the baseline model. We posit that those skill measures are related to the variables in our mediation analysis (schooling, skills, parental investments, and family background), and an unobserved individual-specific factor π, in the following

[21] An alternative approach would be to use the discrete factor approximation developed by Heckman and Singer (1984) and used in Gilleskie (1998) and Mroz (1999). But given the similarity of our approach to Cunha et al. (2010), we chose to use the approaches suggested in that paper.

manner:

$$\ln Skill_s = \mu_{s,0} + \mu_{s,ed} ed + \mu_{s,C} \ln \theta_C + \mu_{s,N} \ln \theta_N + \mu_{s,inv} \ln \boldsymbol{I} + \mu_{s,ed_m} ed_m + \mu_{s,ed_f} ed_f + \mu_{s,sib} sib + \mu_{s,Y_P} \ln Y_P + \mu_{s,\pi} \pi + \varepsilon_s \tag{17}$$

for skill measures $s \in \{1, ..., S\}$. The skill measures we use are respondents' self-assessed skills covering several dimensions, such as problem-solving and communicating. The full list of adult skill measures can be found in Appendix Table 16.

We augment the investment equations (5)-(6), the educational attainment equation (3), and production function (4) to also include π as follows:

$$ti_t = \tilde{\gamma}_{0,ti_t} + \tilde{\gamma}_{1,ti_t} \theta_{C,t-1} + \tilde{\gamma}_{2,ti_t} \theta_{NC,t-1} + \tilde{\gamma}_{3,ti_t} \mathbf{F} + \tilde{\gamma}_{4,ti_t} \ln Y_P + \tilde{\gamma}_{5,ti_t} \pi + \tilde{u}_t^{ti}, \tag{18}$$

$$sq_t = \tilde{\gamma}_{0,sq_t} + \tilde{\gamma}_{1,sq_t} \theta_{C,t-1} + \tilde{\gamma}_{2,sq_t} \theta_{NC,t-1} + \tilde{\gamma}_{3,sq_t} \mathbf{F} + \tilde{\gamma}_{4,sq_t} \ln Y_P + \tilde{\gamma}_{5,sq_t} \pi + \tilde{u}_t^{sq}, \tag{19}$$

$$ed = \tilde{\gamma}_{0,ed} + \tilde{\gamma}_{1,ed} \theta_{C,t} + \tilde{\gamma}_{2,ed} \theta_{NC,t} + \tilde{\gamma}_{3,ed} \mathbf{F} + \tilde{\gamma}_{4,ed} \mathbf{I} + \tilde{\gamma}_{5,ed} \ln Y_P + \tilde{\gamma}_{6,S} \pi + \tilde{u}^{ed}, \tag{20}$$

$$\begin{aligned} \theta_{k,t+1} &= [\tilde{\gamma}_{1,k,t} \theta_{C,t}^{\phi_{t,k}} + \tilde{\gamma}_{2,k,t} \theta_{N,t}^{\phi_{t,k}} + \tilde{\gamma}_{3,k,t} ti_t^{\phi_{t,k}} + \tilde{\gamma}_{4,k,t} sq_t^{\phi_{t,k}} + \tilde{\gamma}_{5,k,t} ed_m^{\phi_{t,k}} + \tilde{\gamma}_{6,k,t} ed_f^{\phi_{t,k}}]^{\frac{1}{\phi_{t,k}}} \cdot A_{k,t+1}, \\ A_{k,t+1} &= \exp(\tilde{\gamma}_{7,k,t} + \tilde{\gamma}_{8,k,t} sib + \tilde{\gamma}_{9,k,t} \ln Y_P + \tilde{\gamma}_{10,k,t} \pi + \tilde{u}_{t+1}^k) \end{aligned} \tag{21}$$

for $k \in \{C, NC\}$.

Finally, we include π in an adapted version of the lifetime earnings equations (2). To achieve identification, we restrict the elasticity of substitution to be unity (and recall that above we found that the estimated elasticity is close to unity).

$$\ln Y = \tilde{\alpha}_6 + \tilde{\alpha}_0 ed + \tilde{\alpha}_1 \ln \theta_C + \tilde{\alpha}_2 \ln \theta_N + \tilde{\alpha}_3 \ln \boldsymbol{I} + \tilde{\alpha}_4 ed_m + \tilde{\alpha}_5 ed_f + \tilde{\alpha}_7 sib + \tilde{\alpha}_8 \ln Y_P + \tilde{\alpha}_9 \pi + \tilde{\varepsilon}_Y. \tag{22}$$

To identify the joint distribution of all variables with π, we follow the approach suggested in Cunha et al. (2010) and exploit variances and covariances between the different adult skill measures and the variables contained in our final earnings equation. We must make the (strong) assumption that $\tilde{\gamma}_{\pi,s} = 1$ for each of the skill measures, and that $\tilde{\alpha}_9 = 1$. These restrictions, combined with the restriction that only age 16 skills enter the earnings equation (and not skills at 7 and 11), allows identification of the parameters in equations (17) and (22) which we estimate using OLS. With parameters of equations (17) and (22) in hand, we take the difference between the left hand side variables and their predicted values in these equations to obtain residuals for each of our seven adult skill measures ($\hat{\pi} + \hat{\varepsilon}_s$) for each observation in our synthetic dataset. Averaging over these seven residuals for each observation yields an estimate of $\hat{\pi}$ for that observation, which we include in our synthetic data set. We then estimate the production functions, investment equations, and educational attainment equation in equations (18)-(21).

Table 17 in the appendix reports the average effects of increases in inputs into the production function, once unobserved heterogeneity is accounted for. The productivity of parental time and school quality investments hardly change compared to the baseline results in Table 5, providing reassurance that the endogeneity of investments does not greatly bias our skill development equations.

The decompositions in Appendix Table 18 show that accounting for unobserved heterogeneity reduces the fraction of the IGE explained by cognitive skills and parental education for men, although not for women. The fraction explained by the unobserved heterogeneity itself is negative. This is because the correlation between parental income and π is negative, i.e., π captures a skill that increases earnings that is more prevalent in those from poorer families.

Note that whilst we can account for unobserved fixed heterogeneity, there may still be unobserved period-specific shocks affecting parental investment decisions. Several papers have found parents compensate for shocks during childhood (Attanasio et al. (2017), Attanasio et al. (2020)) – that is, parents invest more in children who have lower skills. If this dynamic is at work in our cohort, our estimates of the effect of time investments on cognitive skill will be downward biased and our results regarding the impact of time investments on the IGE would be a lower bound.

Using different time investment and school quality measures Whilst the NCDS is unique in that it collected information on childhood investments for individuals who were followed many decades later, these investment measures are not as rich as some of the measures contained in more recent surveys (such as those used by Cunha et al. (2010)). To check whether our results are sensitive to our time investment measures, we drop some of the measures which may capture parental preferences rather than parental time (e.g., parental interest in education). Likewise, we drop school quality measures that may primarily reflect preferences of peers rather than school quality itself (e.g., share of children at an individual's school that continue education).

Appendix Table 23 lists the alternative measures we use and Table 24 shows the resulting decomposition. It shows that the share of the IGE explained for men remains the same, whereas the share explained for women increases somewhat due to increases in the shares explained by investments, skills, and parental education. Qualitatively, the results of the mediation analysis in the table remains unchanged.

Using different non-cognitive skill measures The decomposition in Figure 2 indicated no major role for non-cognitive skills in explaining intergenerational earnings persistence. To check whether this is due to the teacher-reported measures we used, in Appendix Table 20, we use mother-reported measures of non-cognitive skills at ages 7, 11, and 16. We use the six measures with the strongest signal-to-noise ratio:

Child is (1) irritable, (2) often miserable, (3) disobedient, (4) unconcentrated, (5) fights with others, (6) fidgety. Using these measures slightly increases the share of IGE explained by non-cognitive skills in level 1 from -0.6% to 0.9% for men and from -1.2% to 3% for women. Compared to cognitive skills, the share explained by non-cognitive skills remains small even with this different set of measures.

Allowing for a mixture of three normals In Section 6.3, we followed Attanasio et al. (2020) and approximated the underlying joint distribution of latent factors using a mixture of two normals. To assess whether our results are sensitive to this, we increase the number of normal mixtures to three and re-run the analysis. Appendix Table 19 presents the decomposition results based on the generating data from the joint distribution with a mixture of three normals. We find that whilst for women, the share explained increases slightly to 72%, for men the results hardly change. We are thus confident that our results are not sensitive to this assumption.

Using a different normalization Finally, we confirm that our results are not sensitive to changes in the scaling and location assumptions of our skill variables.[22] To do so, we estimate one version in which we multiply all our synthetic log-cognitive skill variables by a factor of 1.5 and add 0.5 and another version in which we multiply all our synthetic log-cognitive skill variables by a factor of 2/3 and add 2. Our decomposition results remain almost completely unchanged, as can be seen in Tables 21 and 22 in the appendix.

7 Conclusion

In this paper, we estimate a model of intergenerational earnings persistence to quantify the direct and indirect effects of a large number of potential drivers of the IGE. Our approach provides a bridge between two literatures studying intergenerational persistence: a literature pioneered in sociology which explored a large number of mechanisms and was agnostic as to how each variable affected earnings, and a recent literature in economics which exploits the restrictions implied by human capital theory as to how variables enter the model. Our framework nests the older models in sociology using flexible functional forms, and tests the restrictions imposed by human capital theory.

Our model explains 55% of the IGE for males and 68% for females. The model mechanisms that generate a link between earnings of parents and children are: educational attainment, cognitive and non-cognitive skills of children, parental time and school quality investments in children, and family

[22] An alternative approach would be to use a limited set of measures which were unchanged across survey waves. However, recent research establishes that age-invariance of measures rarely holds (Heckman and Zhou, 2022). Thus, we do not exploit the age-invariance assumption and instead check that our results are not sensitive to changes in the scaling and location assumptions.

background. Of these, cognitive skill and educational attainment play the most important role when all mechanisms are considered to have only a direct effect on transmission of earnings across generations. However, once we allow for investments at earlier ages to affect cognitive skill and educational attainment at later ages, the perspective changes. The role of educational attainment in explaining the relationship between parents' income and children's earnings can be fully explained by differences in cognitive skill. Furthermore, the role of cognitive skill is substantially explained by differences in investments. Finally, differences in investments by rich and poor parents can in part be attributed to differences in family background, and in part to differences in parental income. While parental income has little predictive power for educational attainment conditional on skills, it has significant predictive power for investments and thus skill. Thus, if financial constraints are important for the persistence in income across generations, it is because they constrain early-in-life investments, not educational attainment, at least for this cohort that faced no university tuition.

We find that parental education is a key driver of the IGE. However, parental education mainly affects children's earnings through the skill formation process and not through other channels. Thus, the implicit assumption in human capital theory that family influence does not impact earnings beyond skills cannot be rejected.

Our paper focuses on the effect of early-life circumstances on lifetime earnings via their impact on human capital. Our approach allows for variables to impact earnings through more channels than previous studies. However, there are potentially important channels beyond those that we study, such as the quality of neighborhoods, family networks, and occupation. While the channels we consider explain most of the persistence in earnings across generations, they do not explain it all. It would be valuable to consider what channels beyond human capital explain the persistence of earnings across generations. Building on the current framework to further investigate these issues would be a fruitful direction for future research.

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A Data

We use only one dataset - the National Child Development Study (NCDS) - to estimate the IGE, our model and the decomposition. The NCDS is a panel tracking a cohort of individuals born in the UK in a particular week in March 1958. In this section, we describe how the parental income and children's lifetime earnings variables are constructed from the NCDS data, as well as how we select our analytical sample.

A.1 Variable Construction

A.1.1 Parental Income

Parental income variables are only observed in the third wave of the NCDS, when cohort members are aged 16. There are three relevant variables: fathers' net earnings, mothers' net earnings, and other net income. We drop individuals whose parents did not answer any of the earnings questions. Adopting Blanden et al. (2013)'s procedure, we also drop households where at least one parent is working but that parent's earnings are unobserved. Finally, we restrict age of father at the time of birth to be between 20 and 45, to ensure that the point-in-time income measure is a reasonable proxy for lifetime income (a detailed breakdown of how we arrive to the final sample can be found in A.2).

Fathers' and mothers' earnings and other net income are recorded as interval, or "banded" data. We use the continuous parental income variables which were imputed by the Institute for Fiscal Studies as part of an effort to harmonize income variables in different cohort studies (Belfield et al. (2017)). This procedure can be summarized by three steps. First, income bands identical to the NCDS are created for the 1973, 1974, and 1975 Family Expenditure Survey (FES) data. Second, within each income band, net male, net female, and net other income data are estimated using variables that are correlated with income.[23] Third, using these prediction equations, each of the three income components are separately predicted within each income band in the NCDS, using the same covariates. The sum of the three predicted income variables in the NCDS is the measure of parental income that we use.

A.1.2 Children's Earnings

NCDS cohort members' gross earnings are observed at ages 23, 33, 42, 50, and 55. Gross earnings are calculated using usual earnings and pay period on the respondent's main job. Current or last earnings

[23]The following variables are used to estimate income data within each band: year of interview, age left school of mother and father, employment status of mother and father, age of mother and father, occupation of mother and father, number of siblings of the cohort member, housing tenure, region, number of rooms in household, number of cars, marital status, whether benefits are received by household, type of school cohort member attends, interactions between age left school and occupation of mother and father, interactions between age left school and employment status of mother and father, and interactions between year of interview and occupation of mother and father

variables are used where usual earnings are unavailable.

Based on NCDS employment spells data from 1974-2008, we apply three criteria for sample selection as in Gregg et al. (2016). Firstly, cohort members are excluded if less than 61 months of working history is observed. Secondly, cohort members with fewer than two earnings observations across the five survey waves are excluded. Finally, cohort members who do not have parental income observation from childhood are not considered in our analysis.

The crucial step in dealing with this sample is in how we interpret missing and zero earnings figures for cohort members, which could be due to attrition, item non-response, or non-employment. To address this, we adapt Gregg et al. (2016)'s method of imputing missing earnings at the time of a survey. For this imputation, earnings are modeled as a function of an individual-specific fixed effect, age, and a categorical education variable interacted with age of cohort member:

$$\ln Y_{it} = f_i + \chi_0 t + \chi_1 ed_i \cdot t + \zeta_{it}$$

where $ed_i = 1$ if less than O level, 2 if O level qualification, 3 if A level qualification, 4 if some college or above.[24] Once earnings at ages 23, 33, 42, 50, and 55 have been predicted as $\widehat{\ln Y_{it}} = \hat{f}_i + \hat{\chi}_0 t + \hat{\chi}_1 ed_i \cdot t$, the earnings value for individuals recorded as being out of work at the time of a survey is replaced with zero. This accounts for the fact that missing earnings in those cases represented non-employment, as opposed to attrition. Monthly earnings are calculated from earnings at each survey date by imputing a linear trajectory between each earnings data point. Aggregating monthly earnings provides an estimate of children's lifetime earnings.

A.2 Sample Selection

The initial wave of the NCDS consists of 18,558 individuals. We impose the following requirements for individuals to be in the sample:

- Parental income available (see section A.1.1 for details) - drop 9,407 observations
- Father's age is between 20 and 45 at the time child was born - drop 939 observations
- Information on child skills, school quality, time investments available - drop 2,591 observations
- Children's lifetime earnings available (see section A.1.2 for details) - drop 2,205 observations
- Children's years of school available - drop 48 observations
- Other variables missing: parental education, number of siblings - drop 60 observations

[24] O levels and A levels were national exams taken at approximately age 16 and 18 respectively.

The final sample consists of 1,635 males and 1,673 females.

A.3 Further Descriptives

Table 7 includes descriptive statistics on parental investment measures which we use for our analysis. We also report the gradients by parental income tertile, and F-tests on mean-equivalence across the groups.

Table 7: Investments: Descriptive Statistics and Means by Parental Income Tertile

	Avg	SD	Bottom	Middle	Top	*F-test*
% Parents had PT meeting	60.31	48.93	56.52	59.71	64.72	0.00
Avg social class in classroom	2.92	0.67	3.06	2.97	2.72	0.00
% Schools with PTA	17.80	38.26	17.58	15.99	19.85	0.06
% Parents who met teacher	51.23	31.75	47.35	50.57	55.82	0.00
class size11	35.12	6.66	34.87	35.22	35.27	0.32
%Attended private school 11	2.30	14.98	1.18	0.91	4.81	0.00
% Students suitable for GCE	26.47	16.51	23.57	24.64	31.26	0.00
Student-teacher ratio	24.22	9.38	25.09	24.23	23.33	0.00
Did teacher initiate discussion	41.07	49.20	37.38	42.19	43.65	0.01
% of experiences teachers	1.54	0.77	1.55	1.52	1.54	0.58
% Private school	3.87	19.29	1.72	1.90	7.99	0.00
% students who cont' educ	60.64	26.89	55.62	57.77	68.54	0.00
% students who cont' FT deg	1.37	2.03	1.05	1.26	1.81	0.00
% students with GCE last year	2.43	3.20	1.87	2.22	3.21	0.00
% students study for GCE	52.20	32.84	46.10	49.24	61.23	0.00
Student-teacher ratio	17.01	1.94	17.17	17.07	16.78	0.00
% Dads v interested in educ	30.77	46.16	22.67	29.12	40.49	0.00
% Mums v interested in educ	43.70	49.61	35.43	42.29	53.36	0.00
% Mums frequent outings w child	87.60	32.97	86.79	84.85	91.18	0.00
% Dads frequent outings w child	73.87	43.94	69.02	73.32	79.17	0.00
% Mums read often to child	51.78	49.98	49.95	49.67	55.77	0.01
% Dads read often to child	38.50	48.67	37.25	36.57	41.65	0.04
% Mums frequent outings w child	55.97	49.65	52.90	57.80	57.21	0.05
% Dads frequent outings w child	53.75	49.87	49.03	55.21	56.80	0.00
% Dads v interested in educ	34.14	47.43	23.36	33.02	45.67	0.00
% Mums v interested in educ	43.90	49.63	33.49	44.21	53.95	0.00
%Dads v involved in upbringing	66.67	47.15	63.11	69.59	67.12	0.01
% Dads v interested in educ	40.59	49.11	31.06	37.92	51.88	0.00
% Mums v interested in educ	42.98	49.51	34.65	41.51	52.42	0.00
% parents want child go to uni	38.05	48.56	26.01	34.56	53.26	0.00

Note: This table presents descriptive statistics and means by parental income tertile for all of the investment measures we use. The relevant sample consists of 3,308 individuals. The final column reports *p-values* from the *F-tests* testing the null hypothesis of equality of means across income tertiles.

B Measurement Error in Parental Income

Our goal is to estimate the IGE, which is the slope coefficient ρ in the OLS regression of cohort member's log lifetime earnings on parent's log lifetime income:

$$\ln Y_i = \rho_0 + \rho \ln Y_{P,i} + u_i \tag{23}$$

However, parent's lifetime income is unobserved in the NCDS. It is proxied using parental income when the children are 16 (and median age of their parents is close to 42). Previous research has shown that attenuation bias from such proxying can be significant (Haider and Solon (2006)). To address this problem, we use the errors-in-variables framework described below.

First, consider the log-linear projection of age 42 income (when the child is 16) on lifetime income for parents:

$$\ln Y_{P,i,16} = \mu_P + \ \lambda_P \ln Y_{P,i} + \epsilon_{P,i} \tag{24}$$

Allowing λ_P to be different than one makes this framework more general than the textbook errors-in-variables framework. We assume the following:

- $Cov(\ln Y_{P,i}, u_i) = 0$
- $Cov(\ln Y_{P,i}, \epsilon_{P,i}) = 0$
- $Cov(u_i, \epsilon_{P,i}) = 0$

The slope coefficient that we can estimate using observables is ρ^* from the regression of child's lifetime earnings on parents' age 42 (and children's age 16) income:

$$\ln Y_i = \rho_0^* + \rho^* \ln Y_{P,i,16} + u_i$$

Note that by substituting for child's earnings ($\ln Y_i$) using the IGE equation (23) and then substituting for parents' income when the child is 16 ($\ln Y_{P,i,16}$) using the projection in equation (24), we can rewrite ρ^* to be:

$$\rho^* = \frac{\mathbb{E}[\ln Y \cdot \ln Y_{P,16} - \mathbb{E}[\ln Y]\mathbb{E}[\ln Y_{P,16}]]}{\mathbb{E}[\ln {Y_{P,16}}^2 - \mathbb{E}^2[\ln Y_{P,16}]]} = \rho \frac{\lambda_P Var(Y_P)}{\lambda_P^2 Var(Y_P) + Var(\epsilon_P)} \tag{25}$$

Thus, ρ^* is equal to the true IGE multiplied by the reliability ratio, defined as:

$$RR_P = \frac{\lambda_P Var(Y_P)}{\lambda_P^2 Var(Y_P) + Var(\epsilon_P)}$$

We can estimate ρ^* using available NCDS data. However, this does not identify ρ because the reliability ratio for the parent generation, RR_P, is unobserved. Moreover, to be able to uncover the joint distribution of parental income with all other factors, we need to know the variance of measurement error in parental income: $Var(\epsilon_P)$. To identify these two parameters, we assume that the reliability ratio stays constant across generations, $RR_P = RR_{Child}$, and that the relationship between point-in-time and lifetime income stays constant in time too, $\lambda_P = \lambda_{Child}$. Using these assumptions and equation (25), we can back out $Var(\epsilon_P)$ which we use in the Attanasio et. al (2020) algorithm.

B.1 Errors-in-Variables approach

For the Errors-in-Variables approach, we first divide parental income observed when the cohort member is aged 16 by the loading parameter λ_P.

$$\ln Y_{P,i,16} = \mu_P + \ \lambda_P \ln Y_{P,i} + \epsilon_{P,i} \tag{26}$$

$$\underbrace{\frac{\ln Y_{P,i,16} - \mu_P}{\lambda_P}}_{\tilde{Z}_{Y_P}} = \ \ln Y_{P,i} + \underbrace{\frac{\epsilon_{P,i}}{\lambda_P}}_{\tilde{\epsilon}} \tag{27}$$

Regressing the child's log lifetime income on observed $\tilde{Z}_{Y_P}$ gives:

$$\hat{\rho} = \frac{Cov(\ln Y, Z_Y)}{Var(\tilde{Z}_{Y_P})} = \frac{Cov(\ln Y, \ln Y_P)}{Var(\tilde{Z}_{Y_P})} \rho \frac{Var(\ln Y_P)}{Cov(\ln Y, \ln Y_P)} = \rho \frac{Var(\ln Y_P)}{Var(\tilde{Z}_{Y_P})}$$

and so we can use the following correction:

$$\rho = \hat{\rho} \frac{Var(\tilde{Z}_{Y_P})}{Var(\ln Y_P)}$$

C Measures of Intergenerational Elasticity of Earnings and Income

In our estimates of the intergenerational elasticity of earnings, we use children's gross (pre-tax) lifetime earnings and net (post-tax) parental income (father's and mother's net earnings, and other net income) when children are 16. This choice is made because the NCDS does not report gross earnings for parents. Moreover, whilst information on net income of the cohort members is available, we are missing earnings information for many spouses, and thus using household income for them would entail the loss of many observations.

Table 8 reports four alternative estimates of the IGE, and compares them to our preferred measures. None of the measures here are corrected for measurement error in parental income.

Table 8: Different measures of the IGE

	Measure of children's earnings	Measure of parent's earnings	IGE for Males	IGE for Females
(1)	Gross lifetime earnings	Within-band imputed net income	0.272***	0.248***
			(0.035)	(0.048)
	N		1635	1673
(2)	Gross mean annual earnings	Within-band imputed net income	0.271***	0.225***
			(0.041)	(0.048)
	N		1635	1673
(3)	Gross lifetime earnings	Within-band median net income	0.240***	0.223***
			(0.035)	(0.047)
	N		1635	1673
(4)	Net lifetime earnings	Within-band imputed net income	0.271***	0.202***
			(0.041)	(0.041)
	N		1635	1668
(5)	Net family lifetime earnings	Within-band imputed net income	0.197***	0.163***
			(0.033)	(0.049)
	N		1000	1040

Note: Row (1) presents our main baseline estimates of the IGE using children's gross lifetime earnings and net parental income when children are 16. Each subsequent row changes one aspect of the estimation, holding all other aspects constant. Gross mean annual earnings is the simple average of children's gross earnings at 23, 33, 42, 50, and 55 multiplied by the length of child's working life. Within-band median income uses medians for each band from the FES when imputing for net parental income at 16. Net lifetime earnings is constructed by using take-home pay at 23, 33, 42, and 50 for children and our fixed-effects imputation. Net lifetime family earnings sums across the imputed net lifetime earnings of the child and their partner.

Our main estimates without measurement error corrections for parental income are 0.272 and 0.248 for males and females, respectively. As we discuss in the main text, corrected for measurement error, the estimates become 0.344 and 0.309.

In our main estimates, we impute earnings at each month between ages 23 and 55. Row 2 of Table 8 shows that if instead we use a simple mean of point-in-time earnings for each of the 5 times we observe them, we obtain an almost identical IGE for males and a slightly lower IGE for females.

In our main estimate, we predict the three components of parents' income within each income band, using characteristics that are correlated with income. An alternative procedure is to directly calculate median income within each income band from the FES, and replace interval data in the NCDS with the corresponding medians. Row (3) of Table 8 presents the IGE using this alternative measure of parents' income. This reduces our estimate of the IGE by no more than 3 percentage points.

Belfield et. al (2017) make a distinction between net and gross earnings for children. Our baseline uses gross lifetime earnings, while the estimate in row (4) of Table 8 uses the child's net lifetime earnings. To construct net lifetime earnings, we simply use take-home pay at ages 23, 33, 42, and 50 instead of the gross wage. The NCDS measures take-home pay as "pay after deductions for tax and National Insurance, including any overtime, bonus, commission or tips". Using net instead of gross lifetime earnings leads to an almost identical IGE for males, whereas for females the IGE goes down to 0.202.

A final way to estimate the IGE is to use family income for the children as well as for the parents. We find estimates of 0.197 for males and 0.163 for females but we use net lifetime family income for children, which is the sum of net lifetime earnings of the NCDS cohort member and their partner.

Overall, we find that the uncorrected IGE is relatively robust to the measure of child's earnings used. We prefer using our fixed effect imputed child gross lifetime earnings measure, as it is the most accurate reflection of lifetime earnings of the child.

D Estimation

D.1 Estimation Details for Skills, Investment, Education, and Lifetime Earnings Equations

Here we discuss how to estimate the skill production functions, investment decision rules, schooling choices, and lifetime earnings equations. Estimating these equations is not straightforward because both the left- and right-hand-side variables in the equations are latent variables that we only observe through multiple error ridden measures; moreover, the production functions and lifetime earnings equation are non-linear.

There are five main steps when using our noisy measures of skills, school quality, investments, and parental income. First, we establish how each individual measure relates to the underlying unobserved latent variable. In Sections D.1.1, D.1.2, and D.1.3, we describe the measurement system, the statistical assumptions on the measurement system, and estimation of the measurement system. Second, we combine these different measures into comprehensive indices that can be used for estimation. We do this by estimating Bartlett scores, described in Section 5.1. Then, we follow Attanasio et al. (2020) and extract the underlying joint distribution of latent variables and generate a new measurement error-free data set. Lastly, we estimate the equations using OLS and non-linear least squares.

D.1.1 Measurement System

We do not observe parental income (Y_P), children's skills (C, NC), parental time investments (ti), or school quality (sq) directly. Instead, we observe multiple error-ridden measurements of each.[25] These measures have arbitrary scale and location. In particular:

$$Z_{\omega,i,t,j} = \mu_{\omega,t,j} + \lambda_{\omega,t,j}\omega_{i,t} + \epsilon_{\omega,i,t,j} \tag{28}$$

[25] We do not have multiple measures of parents' income, but we show that we can use multiple measures of children's earnings in our errors in variables framework in appendix B.

for $\omega \in \{Y_P, C, NC, ti, sq\}$ and each $j = \{1, ..., J_{\omega,t}\}$ error-ridden measurements of each latent variable ω.

D.1.2 Assumptions on Measurement Errors

Measurement errors are assumed to be independent across individuals, measures, and time. Measurement errors are also assumed to be independent of the latent variables, and all other controls and shocks. In particular, we make the following assumptions on our measurement model:

1. $\epsilon_{\omega,t,j} \perp \epsilon_{\omega,t,j'}$ for all t, ω and $j \neq j'$
2. $\epsilon_{\omega,t,j} \perp \epsilon_{\omega,t',j'}$ for all ω and $t \neq t'$ and j, j'
3. $\epsilon_{\omega,t,j} \perp \omega'_{t'}$ for all ω, ω', t, t', and j
4. $\epsilon_{\omega,t,j} \perp X_{t'}$ for all ω, X, t, t'
5. $\epsilon_{\omega,t,j} \perp u_{t'}$ for all ω, t, t' where $u_{t'}$ represents a structural shock (for investment, skills, education, earnings)

Although we drop the i subscripts for notational convenience, all of the above independence assumptions hold for each individual i. Furthermore, all measurement errors are assumed independent across individuals.

Assumption 1 is that measurement errors are independent contemporaneously across measures. Assumption 2 is that measurement errors are independent over time. Assumption 3-5 are that measurement errors in any period are independent of the latent variables (Assumption 3), covariates (Assumption 4), and structural shocks (Assumption 5) in any period. While these assumptions are strong, they are common in the literature.

D.1.3 Estimation of Measurement Parameters

Using the measurement system in appendix D.1.1 and the statistical assumptions made in appendix D.1.2, here we describe the procedure to estimate the measurement parameters. We have multiple measures of cognitive skill, time investments, and school quality. In this section, which borrows heavily from Heckman et al. (2013), we show how to use the Bartlett score method to take a weighted average of these measurements. In the Bartlett score method, the weights are constructed so that noise from measurement error is minimized. In particular, the procedure is as follows:

1. **Scaling parameters**

Using equation (28) and normalizing the variance of the latent variable ω_t to 1, we can derive the scale parameters of each of the latent variables from the covariances of the observed measures:

$$Cov(Z_{\omega,t,j}, Z_{\omega,t,j^*}) = \lambda_{\omega,t,j}\lambda_{\omega,t,j^*}\ Var(\omega_t) = \lambda_{\omega,t,j}\lambda_{\omega,t,j^*} \tag{29}$$

Note that as long as we have at least three measures, we can identify the scaling parameters. For example, if we have three measures, we have three covariances available, and three λs to estimate.

To avoid bias arising from the unit variance assumption, we allow for free returns to scale in the production function (see below for more details).

2. **Variance of the measurement error**

   Finally, we can estimate the measurement error variance for each measure using the observed variance of our measures, our estimated scaling parameters, and the normalization of the latent variable:

$$Var(Z_{\omega,t,j}) = \lambda^2_{\omega,t,j} Var(\omega_t) + Var(\epsilon_{\omega,t,j}) \tag{30}$$

   Since $Var(Z_{\omega,t,j})$ is estimated directly from the data, $\lambda_{\omega,t,j}$ is estimated in the previous step, and $Var(\omega_t) = 1$, it is straightforward to recover $Var(\epsilon_{\omega,t,j})$.

3. **Bartlett score**

   For each individual, predict Bartlett score (after demeaning): $\mathcal{Z}_{i,t} = (\lambda'_{\omega,\mathbf{t}}\mathbf{\Omega^{-1}}\lambda_{\omega,\mathbf{t}})^{\mathbf{-1}}\lambda'_{\omega,\mathbf{t}}\mathbf{\Omega^{-1}}\mathbf{Z}_{\omega,\mathbf{i},\mathbf{t}}$ - where all the objects are replaced by their estimated counterparts. Here $\lambda_{\omega,\mathbf{t}}$ is a $J_{\omega,t} \times 1$ vector of scaling parameters $\lambda_{\omega,t,j}$ of all measures j for latent variable ω, and $\mathbf{\Omega}$ is a $J_{\omega,t} \times J_{\omega,t}$ diagonal matrix with the variances of the measurement errors on the diagonal. Hence this step is equivalent to estimating a weighted regression of the measurement equation for each individual where the coefficient of interest is $\omega_{i,t}$. The weights ensure that noisier measures receive a lower weight.

Note, however, that the Bartlett scores are still contaminated with measurement error. Taking a weighted average reduces but does not eliminate measurement error, so the Bartlett scores themselves can thus be seen as a measure of the true latent variable.

D.2 Scale and Location Normalizations

Our latent variables do not have a natural scale or location. We normalize:

- $E(ti_t) = 0$, $E(sq_t) = 0$ for all t
- $E(\ln C_t) = 0$, $E(\ln NC_t) = 0$ for $t = 1$

- $Var(ti_t) = 1$, $Var(sq_t) = 1$ for all t
- $Var(\ln C_t) = 1$, $Var(\ln NC_t) = 1$ for all t
- Free returns to scale in the CES production function $\nu_{t,k}$
- No TFP growth in production functions (i.e., $\gamma_{t,k,6} = 0$)

We normalize the variance of cognitive and non-cognitive skills to have variance 1. To avoid this causing bias in the production function, we allow for a free returns to scale parameter in the CES aggregator. Alternatively, one could normalize returns to scale to be 1 and derive the scale of the latent factors (Freyberger (2021)). These are observationally equivalent. To see this, note the equivalence between equations (31) and (32) below:

$$\begin{aligned}\ln(\theta_{k,t+1}) &= \frac{\nu_{t,k}}{\phi_{t,k}} \ln[\gamma_{t,k,1}\theta_{C,t}^{\phi_{t,k}} + \gamma_{t,k,2}\theta_{N,t}^{\phi_{t,k}} + \gamma_{t,k,3}\mathbf{I}_t^{\phi_{t,k}} + \gamma_{t,k,4}ed_m^{\phi_{t,k}} + \gamma_{t,k,5}ed_f^{\phi_{t,k}}] \\ &\quad + \gamma_{t,k,6} + \gamma_{t,k,7}sib + \gamma_{t,k,8}\ln Y_P + u_{t+1}^k\end{aligned} \tag{31}$$

$$\begin{aligned}\ln(\theta_{k,t+1}) &= \frac{\lambda_{\theta,k,t+1}}{\phi_{t,k}} \ln[\gamma_{t,k,1}\theta_{C,t}^{\phi_{t,k}} + \gamma_{t,k,2}\theta_{N,t}^{\phi_{t,k}} + \gamma_{t,k,3}\mathbf{I}_t^{\phi_{t,k}} + \gamma_{t,k,4}ed_m^{\phi_{t,k}} + \gamma_{t,k,5}ed_f^{\phi_{t,k}}] \\ &\quad + \mu_{\theta,k,t+1} + \gamma_{t,k,7}sib + \gamma_{t,k,8}\ln Y_P + u_{t+1}^k\end{aligned} \tag{32}$$

where $\nu_{t,k}$ and $\gamma_{t,k,6}$ are the returns to scale and TFP growth parameters in the production functions, and $\lambda_{\theta,k,t+1}$ and $\mu_{\theta,k,t+1}$ are the scale and location parameters in the measurement equations. Setting $\lambda_{\theta,k,t+1} = 1$ and $\mu_{\theta,k,t+1}$=0 in equation (31) is observationally equivalent to setting $\nu_{t,k} = 1$ and $\gamma_{t,k,6} = 0$ in equation (32).

In our implementation, to pin down the location of log-skills, we assume that TFP growth ($\gamma_{t,k,6}$) is zero and identify the location ($\mu_{\theta,k,t+1}$) from the constant in the production function. Doing so allows us to have log-skills that are non-zero mean (and thus, we do not implicitly assume a Cobb-Douglas production function).

To evaluate whether our analysis is sensitive to these normalization assumptions, we conduct robustness checks where we change the scale and location of skills in Section I.

As pointed out in Freyberger (2021), whilst most of the production function parameters ($\gamma_{t,k,1}$, $\gamma_{t,k,2}$, $\gamma_{t,k,3}$, $\gamma_{t,k,4}$, $\gamma_{t,k,5}$, and $\phi_{t,k}$) are invariant to which of equations (31) or (32) are estimated, there can be important consequences for the production function in the subsequent period. For example, if the parameter $\gamma_{t,k,6}$ was interpreted as a TFP parameter, then arbitrary changes to the location of $\ln(\theta_{k,t+1})$ by adding $\tilde{\mu}_{\theta,k,t+1}$ means that the scale of the level factor $\theta_{k,t+1}$ may change since $\exp(\ln(\theta_{k,t+1}) + \tilde{\mu}_{\theta,k,t+1}) =$

$\theta_{k,t+1}\exp(\tilde{\mu}_{\theta,k,t+1})$. That is, arbitrary changes in $\tilde{\mu}_{\theta,k,t+1}$ also change $\theta_{k,t+1}$. Entering the rescaled factor $\theta_{k,t+1}\exp(\tilde{\mu}_{\theta,k,t+1})$ into the next period's production function will affect next period's production function estimates ($\gamma_{t+1,k,1}$ to $\gamma_{t+1,k,5}$), as one of the inputs into the production function for the next period now has a different scale.

A similar argument holds for the scaling parameter $\lambda_{\theta,k,t+1}$, which we set equal to 1. Whilst we found that interpreting the constant in the production functions as TFP growth made our parameters very sensitive to changes in the location of log skills, interpreting $\nu_{t,k}$ as the returns to scale parameter did not lead to parameters that were particularly sensitive to changes in the scale of log skills. We thus used the following estimating equation:

$$
\begin{aligned}
\ln(\theta_{k,t+1}) \quad = \quad & \frac{\nu_{t,k}}{\phi_{t,k}}\ln[\gamma_{t,k,1}\theta_{C,t}^{\phi_{t,k}} + \gamma_{t,k,2}\theta_{N,t}^{\phi_{t,k}} + \gamma_{t,k,3}\mathbf{I}_t^{\phi_{t,k}} + \gamma_{t,k,4}ed_m^{\phi_{t,k}} + \gamma_{t,k,5}ed_f^{\phi_{t,k}}] \\
& + \mu_{\theta,k,t+1} + \gamma_{t,k,7}sib + \gamma_{t,k,8}\ln Y_P + u_{t+1}^k. \qquad (33)
\end{aligned}
$$

D.3 Signal-to-Noise Ratios

Table 9 presents the signal-to-noise ratios for the variables included in our final analysis. The signal-to-noise ratio is defined as $SN_{\omega,t,j} = \frac{\lambda^2_{\omega,t,j}Var(\omega_t)}{Var(Z_{\omega,t,j})}$. Intuitively, this is the appropriately scaled variance of the latent variable (signal) to the variance of the measure (signal+noise) and thus describes the information content of each measure.

E Testing Restrictions in the Presence of Measurement Error

To test commonly used restrictions, we calculate the F-statistic on the simulated data,

$$F = \frac{(SSR_R - SSR_{UR})/q}{SSR_{UR}/(n-k-1)},$$

where SSR_R is the sum of squares of the restricted model and SSR_{UR} is the sum of squares of the unrestricted model, $q = 1$ is the number of restrictions, n is the sample size, and $k = 1$ is the number of independent variables in the unrestricted model. We bootstrap the (centered) distribution of the statistic because the use of simulated data based on an estimated joint distribution of variables complicates the derivation of an asymptotic distribution of this statistic.

Table 9: Signal-to-Noise Ratio for Measures Used

		Cognitive skills			
Age 7		Age 11		Age 16	
copying 7	0.223	reading 11	0.620	reading 16	0.613
reading 7	0.371	maths 11	0.651	maths 16	0.655
maths 7	0.366	copying 11	0.113	teacher maths16	0.783
drawaman 7	0.255			teacher english16	0.740
		Non-cognitive skills			
Age 7		Age 11		Age 16	
bsag inconsequential	0.463	bsag inconsequential	0.483	unconcentrated	0.466
bsag hostile to children	0.388	bsag hostile to children	0.411	fights	0.156
bsag writes off adults	0.379	bsag writes off adults	0.404	disobedient	0.603
bsag hostile to adults	0.449	bsag hostile to adults	0.508	irritable	0.395
bsag depression	0.295	bsag depression	0.315	miserable	0.453
		Time investments			
Age 7		Age 11		Age 16	
mother outings	0.263	mother outings 11	0.504	father interest in ed	0.781
father outings	0.328	father outings 11	0.562	mother interest in ed	0.767
mother reads	0.275	father interest in ed 11	0.237	parents' ambitions for child	0.202
father reads	0.295	mother interest in ed 11	0.238		
mother interest in ed	0.258	fathers role 11	0.067		
father interest in ed	0.216				
		School quality			
Age 7		Age 11		Age 16	
school avg social class	0.091	class size	0.141	school type	0.145
parent teacher meetings	0.257	type of school	0.496	%of children in child's school who:	
school has PTA	0.166	% in class suitable for GCEs	0.251	ct' educ	0.387
%parents meeting teacher	0.137	teacher-student ratio	0.249	ct' to full-time degrees	0.831
		teacher shows initiative to meet	0.001	passed GCEs	0.878
		% experienced teachers	0.189	studying towards GCEs	0.474
				teacher-student ratio	0.200

Note: the Signal to Noise ratio is defined as $SN_{\omega,t,j} = \frac{\lambda^2_{\omega,t,j} Var(\omega_t)}{Var(Z_{\omega,t,j})}$

F Effect of Parental Income on Mediating Variables

The share of the IGE explained by different variables depends not only on the effect that that variable has on lifetime earnings, but also on how strong the relationship between the variable and parental income is. In Table 10 we show correlations between the simulated variables and log parental income.

Table 10: Correlation of variables with log parental income

Correlations with log parental income					
Education & skills		**Investments**		**Family background**	
education	0.212	ln inv 16	0.239	mother educ	0.318
	(0.020)		(0.023)		(0.021)
ln cog 16	0.274	ln inv 11	0.206	father educ	0.372
	(0.020)		(0.026)		(0.021)
ln cog 11	0.283	ln inv 7	0.257	siblings	-0.049
	(0.021)		(0.025)		(0.020)
ln cog 7	0.226	ln sq 16	0.244		
	(0.024)		(0.023)		
ln nc 16	0.057	ln sq 11	0.216		
	(0.023)		(0.026)		
ln nc 11	0.046	ln sq 7	0.231		
	(0.021)		(0.034)		
ln nc 7	0.020				
	(0.019)				

Note: Standard errors bootstrapped with 250 repetitions.

G Further Tables

This section contains:

1. Tables of the full decomposition results in Table 11
2. Tables of the full decomposition results separating time investments and school quality in Table 12
3. Coefficients of the CES lifetime earnings equation in Table 13
4. Coefficients of the production functions in Table 14

Table 11: Mediation results

(a) Males

LEVEL	Direct Effect (1)	*Educ* (2)	*Skills at 16* (3)	*Inv. 11-16* (4)	*Skills at 11* (5)	*Inv. 7-11* (6)	*Skills at 7* (7)	*Inv. 0-7* (8)
		Indirect effects (cumulative) via:						
Education	**13.5%**	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Cog. skills at 16	**32.1%**	**43.2%**	*-0.7%*	*-0.7%*	*-0.7%*	*-0.7%*	*-0.7%*	*-0.7%*
Non-cog. skills at 16	-0.6%	-0.4%	*0.1%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*
Inv. at 11-16	-0.3%	-0.3%	3.9%	*1.7%*	*1.7%*	*1.7%*	*1.7%*	*1.7%*
Cog. skills at 11			**40.0%**	**41.0%**	*-1.0%*	*-1.0%*	*-1.0%*	*-1.0%*
Non-cog. skills at 11			0.1%	0.1%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 7-11	3.4%	4.0%	4.0%	4.0%	7.7%	*4.2%*	*4.2%*	*4.2%*
Cog. skills at 7			0.0%	0.0%	**33.6%**	**34.3%**	***13.3%***	***13.3%***
Non-cog. skills at 7			0.0%	0.0%	-0.1%	-0.1%	*0.0%*	*0.0%*
Inv. at 0-7	**11.2%**	**12.0%**	**12.0%**	**12.0%**	**12.0%**	**12.0%**	**21.9%**	***14.2%***
Parental educ.	-3.6%	-2.5%	-3.3%	-2.6%	2.0%	4.1%	**13.5%**	**20.9%**
Num. siblings	-0.4%	-0.4%	-0.4%	-0.2%	0.3%	0.5%	0.7%	**2.1%**
TOTAL	55.2%	55.4%	55.6%	55.3%	55.2%	54.8%	53.3%	54.4%

(b) Females

LEVEL	Direct Effect (1)	*Educ* (2)	*Skills at 16* (3)	*Inv. 11-16* (4)	*Skills at 11* (5)	*Inv. 7-11* (6)	*Skills at 7* (7)	*Inv. 0-7* (8)
		Indirect effects (cumulative) via:						
Education	**39.5%**	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*
Cog. skills at 16	**22.8%**	**49.3%**	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*
Non-cog. skills at 16	-1.2%	-1.3%	*1.0%*	*1.0%*	*1.0%*	*1.0%*	*1.0%*	*1.0%*
Inv. at 11-16	0.0%	7.8%	11.3%	*2.0%*	*2.0%*	*2.0%*	*2.0%*	*2.0%*
Cog. skills at 11			**45.6%**	**52.1%**	***8.9%***	***8.9%***	***8.9%***	***8.9%***
Non-cog. skills at 11			-0.2%	-0.3%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 7-11	-4.6%	-2.6%	-2.6%	-2.6%	1.9%	*0.5%*	*0.5%*	*0.5%*
Cog. skills at 7			0.0%	0.0%	**35.0%**	**34.6%**	*6.8%*	*6.8%*
Non-cog. skills at 7			0.0%	0.0%	-0.1%	-0.1%	*0.8%*	*0.8%*
Inv. at 0-7	5.9%	6.4%	6.4%	6.4%	6.4%	6.4%	**21.3%**	*9.9%*
Parental educ.	6.6%	5.9%	6.9%	9.2%	**13.6%**	**14.8%**	**25.6%**	**35.9%**
Num. siblings	-0.6%	-0.7%	-0.7%	-0.7%	-0.4%	-0.4%	0.0%	1.4%
TOTAL	68.3%	69.1%	69.4%	68.9%	69.8%	69.1%	68.3%	68.6%

Note: This table shows the detailed results of our mediation analysis for males and females. Coefficients that are significant at the 10% level are bold. Each column displays the share explained by each variable at different levels of mediation. E.g., column 1 accounts only for direct effects of each variable on earnings. Column 2 additionally accounts for indirect effects, where each variable can additionally affect earnings by its effect on educational attainment, etc.

Table 12: Results when equalizing time investments and school quality separately

(a) Men

	Direct	Indirect effects (cumulative) via:						
	Effect	*Educ*	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**13.5%**	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Cog. skills 16	**32.1%**	***43.2%***	*-0.7%*	*-0.7%*	*-0.7%*	*-0.7%*	*-0.7%*	*-0.7%*
Non-cog. skills 16	-0.6%	*-0.4%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*
Time investments 11-16	2.8%	*3.0%*	***7.0%***	***2.3%***	***2.3%***	***2.3%***	***2.3%***	***2.3%***
School quality 11-16	-3.1%	*-3.4%*	*-3.1%*	*1.7%*	*1.7%*	*1.7%*	*1.7%*	*1.7%*
Cog. skills 11	0.0%	*0.0%*	***40.0%***	***41.0%***	*-1.0%*	*-1.0%*	*-1.0%*	*-1.0%*
Non-cog. skills 11	0.0%	*0.0%*	*0.1%*	*0.1%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Time investments 7-11	0.4%	*1.2%*	*1.2%*	*1.2%*	*4.9%*	*3.4%*	*3.4%*	*3.4%*
School quality 7-11	3.0%	*2.8%*	*2.8%*	*2.8%*	*2.9%*	*0.8%*	*0.8%*	*0.8%*
Cog. skills 7	0.0%	*0.0%*	*0.0%*	*0.0%*	***33.6%***	***34.3%***	***13.3%***	***13.3%***
Non-cog. skills 7	0.0%	*0.0%*	*0.0%*	*0.0%*	*-0.1%*	*-0.1%*	*0.0%*	*0.0%*
Time investments 0-7	**8.5%**	***9.1%***	***9.1%***	***9.1%***	***9.1%***	***9.1%***	***15.7%***	***10.6%***
School quality 0-7	2.7%	*2.9%*	*2.9%*	*2.9%*	*2.9%*	*2.9%*	*6.0%*	*3.5%*
Parental Educ.	-3.6%	*-2.5%*	*-3.3%*	*-2.6%*	*2.0%*	*4.1%*	***13.5%***	***20.9%***
Num. Siblings	-0.4%	*-0.4%*	*-0.4%*	*-0.2%*	*0.3%*	*0.5%*	*0.7%*	***2.1%***
TOTAL	55.2%	55.4%	55.6%	57.6%	57.5%	57.1%	55.4%	56.7%

(b) Women

	Direct	Indirect effects (cumulative) via:						
	Effect	*Educ*	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**39.5%**	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*
Cog. skills 16	**22.8%**	***49.3%***	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*
Non-cog. skills 16	-1.2%	*-1.3%*	*1.0%*	*1.0%*	*1.0%*	*1.0%*	*1.0%*	*1.0%*
Time investments 11-16	-6.2%	*-0.7%*	*4.1%*	*0.7%*	*0.7%*	*0.7%*	*0.7%*	*0.7%*
School quality 11-16	6.2%	*8.5%*	*7.2%*	*2.0%*	*2.0%*	*2.0%*	*2.0%*	*2.0%*
Cog. skills 11	0.0%	*0.0%*	***45.6%***	***52.1%***	***8.9%***	***8.9%***	***8.9%***	***8.9%***
Non-cog. skills 11	0.0%	*0.0%*	*-0.2%*	*-0.3%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Time investments 7-11	-4.2%	*-3.9%*	*-3.9%*	*-3.9%*	*-1.7%*	*-0.6%*	*-0.6%*	*-0.6%*
School quality 7-11	-0.4%	*1.3%*	*1.3%*	*1.3%*	*3.6%*	*1.1%*	*1.1%*	*1.1%*
Cog. skills 7	0.0%	*0.0%*	*0.0%*	*0.0%*	***35.0%***	***34.6%***	*6.8%*	*6.8%*
Non-cog. skills 7	0.0%	*0.0%*	*0.0%*	*0.0%*	*-0.1%*	*-0.1%*	*0.8%*	*0.8%*
Time investments 0-7	10.0%	*13.5%*	*13.5%*	*13.5%*	*13.5%*	*13.5%*	***26.3%***	***13.2%***
School quality 0-7	-4.1%	*-7.1%*	*-7.1%*	*-7.1%*	*-7.1%*	*-7.1%*	*-5.2%*	*-3.3%*
Parental Educ.	6.6%	*5.9%*	*6.9%*	*9.2%*	***13.6%***	***14.8%***	***25.6%***	***35.9%***
Num. Siblings	-0.6%	*-0.7%*	*-0.7%*	*-0.7%*	*-0.4%*	*-0.4%*	*0.0%*	***1.4%***
TOTAL	68.3%	69.2%	69.4%	69.6%	70.5%	69.8%	68.7%	69.3%

Note: This table shows results when separately equalizing time investments and school quality. Each column displays the share explained by each variable at different levels of mediation. E.g., column 1 accounts only for direct effects of each variable on earnings. Column 2 additionally accounts for indirect effects, where each variable can additionally affect earnings by its effect on educational attainment, etc. We can see that results are similar to equalizing investment variables jointly as in the main text. This is due to the small amount of complementarity in the equations.

Table 13: Coefficients of CES lifetime earnings equation: Men and women

	Men	Women
Education	**1.108**	**0.859**
	[0.702;2.08]	[0.676;1.009]
Cognitive skills 16	**0.085**	**0.062**
	[0.022;0.325]	[0.019;0.167]
Non-cognitive skills 16	-0.022	-0.012
	[-0.106;0.015]	[-0.028;0.001]
School quality 7	0.037	-0.006
	[-0.06;0.156]	[-0.034;0.014]
School quality 11	0.044	-0.001
	[-0.043;0.158]	[-0.015;0.017]
School quality 16	-0.034	0.01
	[-0.157;0.02]	[-0.004;0.03]
Time investments 7	**0.109**	0.015
	[0.002;0.28]	[-0.005;0.041]
Time investments 11	0.005	-0.009
	[-0.093;0.121]	[-0.036;0.003]
Time investments 16	0.036	-0.01
	[-0.047;0.148]	[-0.035;0.003]
Mother's education	**-0.598**	0.068
	[-1.856;-0.149]	[-0.067;0.245]
Father's education	0.231	0.023
	[-0.171;0.708]	[-0.12;0.154]
Num. siblings	0.007	0.012
	[-0.007;0.024]	[-0.011;0.036]
Log Parental income	**0.152**	0.103
	[0.073;0.245]	[-0.031;0.212]
Returns to Scale	**0.733**	**2.48**
	[0.358;1.037]	[2.004;3.158]
Elasticity of Subst.	1.305	0.911
	[0.979;1.969]	[0.728;1.225]

Note: This table shows estimates of the lifetime earnings equation (2). Confidence intervals are from a clustered bootstrap with 250 repetitions.

Table 14: Coefficients of skill production functions

(a) Males

	Cognitive Skills			Non-Cognitive Skills		
	Age 7	Age 11	Age 16	Age 7	Age 11	Age 16
Cognitive Lag		**0.194** [0.073, 0.389]	**0.971** [0.719, 1.539]		**0.998** [0.284, 1.002]	**0.766**
Non-Cognitive Lag		-0.027 [-0.085, 0.021]	0.041 [-0.012, 0.102]		**0.004** [0.000, 0.238]	**0.134** [0.016, 0.389]
Time Investments	**0.034** [0.016, 0.071]	**0.144** [0.053, 0.231]	**0.298** [0.019, 0.504]	**0.023** [0.000, 0.131]	**0.000** [0.000, 0.055]	**0.030** [0.001, 0.138]
School Quality	**0.017** [0.002, 0.048]	0.002 [-0.070, 0.068]	0.009 [-0.058, 0.112]	0.000 [-0.022, 0.019]	0.000 [-0.001, 0.021]	**-0.009** [-0.037, 0.000]
Mother's Educ.	**0.435** [0.266, 0.687]	**0.354** [0.190, 0.480]	-0.143 [-0.943, 0.209]	-0.818 [-1.287, 0.758]	-0.003 [-0.036, 0.362]	0.029 [-0.175, 0.434]
Father's Educ	**0.513** [0.209, 0.481]	**0.333** [0.209, 0.481]	-0.176 [-0.632, 0.232]	**1.795** [0.136, 2.151]	0.001 [-0.129, 0.101]	0.050 [-0.133, 0.433]
Number of Siblings	-0.020 [-0.060, 0.011]	**-0.052** [-0.076, -0.026]	-0.006 [-0.023, 0.008]	0.035 [-0.002, 0.075]	**-0.051** [-0.081, -0.016]	**-0.049** [-0.080, -0.009]
Log Parental Income	**0.284** [0.108, 0.461]	-0.022 [-0.141, 0.068]	-0.014 [-0.117, 0.040]	-0.111 [-0.282, 0.032]	**-0.192** [-0.360, -0.037]	-0.049 [-0.186, 0.087]
Returns to Scale	**2.435** [2.076, 3.079]	**2.096** [1.743, 2.408]	**0.849** [0.632, 1.318]	**0.509** [0.432, 1.258]	**0.554** [0.469, 1.017]	**0.525** [0.392, 1.062]
Elasticity of Subst.	**0.710** [0.632, 0.882]	**1.356** [1.095, 1.701]	1.124 [0.832, 1.215]	**0.405** [0.179, 0.720]	**0.517** [0.458, 0.916]	**0.691** [0.519, 0.835]

(b) Females

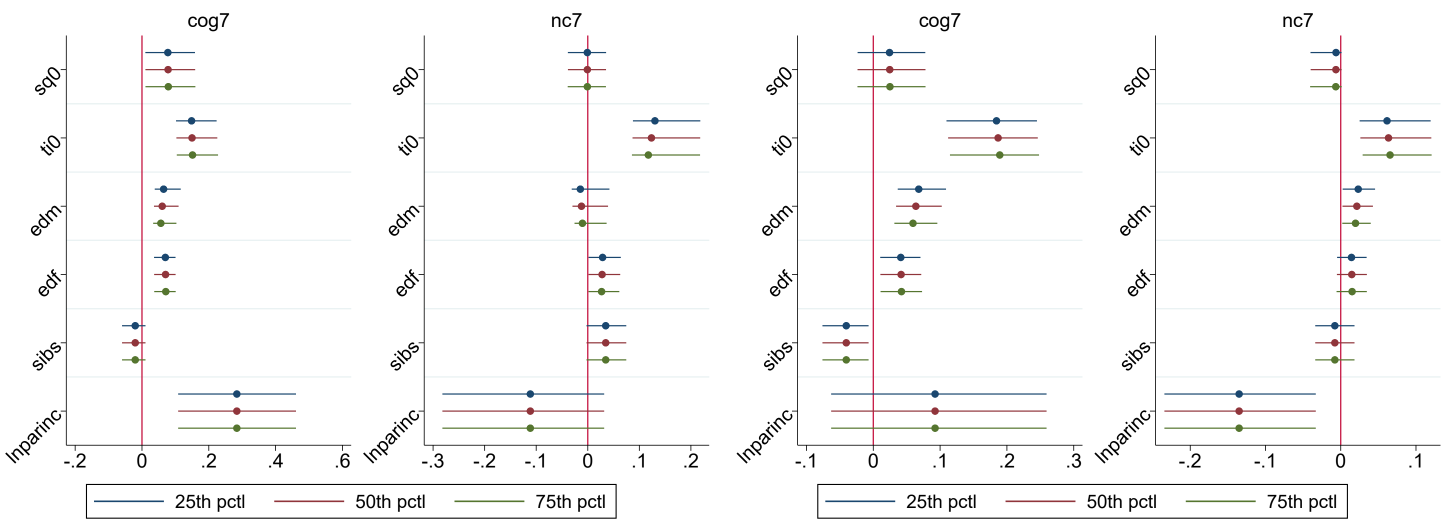
	Cognitive Skills			Non-Cognitive Skills		
	Age 7	Age 11	Age 16	Age 7	Age 11	Age 16
Cognitive Lag		**0.444** [0.231, 0.531]	**0.804** [0.635, 1.177]		**3.064** [0.081, 2.010]	**0.703**
Non-Cognitive Lag		-0.067 [-0.203, 0.016]	0.004 [-0.026, 0.043]		**7.382** [0.005, 5.741]	**0.031** [0.014, 0.206]
Time Investments	**0.051** [0.020, 0.100]	**0.086** [0.019, 0.195]	**0.086** [0.047, 0.312]	**0.017** [0.002, 0.083]	**2.722** [0.000, 2.043]	**0.024** [0.008, 0.069]
School Quality	0.006 [-0.006, 0.025]	0.066 [-0.004, 0.136]	-0.026 [-0.108, 0.001]	-0.002 [-0.026, 0.000]	0.181 [-0.007, 0.477]	**-0.009** [-0.026, -0.002]
Mother's Educ.	**0.567** [0.347, 0.803]	**0.291** [0.176, 0.503]	0.019 [-0.603, 0.198]	**0.580** [0.091, 1.246]	0.604 [-1.602, 1.976]	**0.211** [0.015, 0.539]
Father's Educ	**0.375** [0.113, 0.597]	**0.180** [0.053, 0.347]	0.112 [-0.104, 0.325]	0.405 [-0.256, 0.898]	-12.952 [-9.899, 0.030]	0.040 [-0.191, 0.258]
Number of Siblings	**-0.040** [-0.076, -0.007]	**-0.028** [-0.049, -0.010]	-0.006 [-0.018, 0.011]	-0.008 [-0.034, 0.018]	0.000 [-0.030, 0.020]	**-0.032** [-0.054, -0.006]
Log Parental Income	0.092 [-0.063, 0.259]	**0.117** [0.018, 0.193]	-0.035 [-0.102, 0.038]	**-0.135** [-0.234, -0.033]	0.119 [-0.005, 0.183]	-0.101 [-0.217, 0.011]
Returns to Scale	**2.010** [1.482, 2.619]	**1.649** [1.467, 2.012]	**1.115** [0.761, 1.402]	**0.708** [0.417, 1.017]	**0.035** [0.045, 0.804]	**0.837** [0.643, 1.112]
Elasticity of Subst	**0.701** [0.596, 0.815]	**1.276** [1.146, 1.745]	0.963 [0.893, 1.107]	**0.501** [0.340, 0.673]	1.013 [0.435, 1.184]	**0.643** [0.584, 0.745]

Note: This table shows estimates of the production function, described in equation 4 of the main text. Confidence intervals are constructed using 250 clustered bootstrap replications.

H Complementarities in CES equations

The below figures show the extent of non-linearity in our production function and lifetime earnings equations. For each variable, we evaluate the effect of an increase in input at the bottom 25%, middle 50% and top 75% of maternal education, lagged cognitive and lagged non-cognitive skills. All other variables are held constant at the mean. For example, in Figure 4, we can see that the returns to time investments do not differ depending on maternal education for cognitive skills, but they are higher for low educated mothers when it comes to the production of non-cognitive skills. Overall, in line with our production function estimates, we find that the production of non-cognitive skills displays more non-linearity. For the log-lifetime earnings equation, we again find little complementarity between inputs.

Figure 4: Evaluating complementarities in the age 7 skill production functions

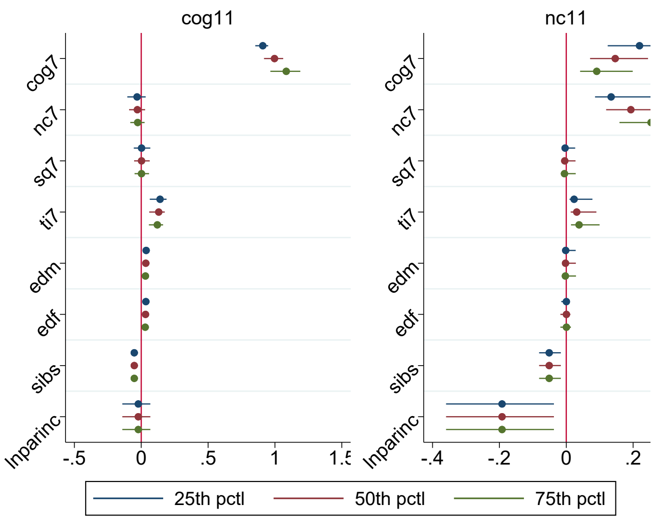


(a) Men, evaluated at levels of mother's educ

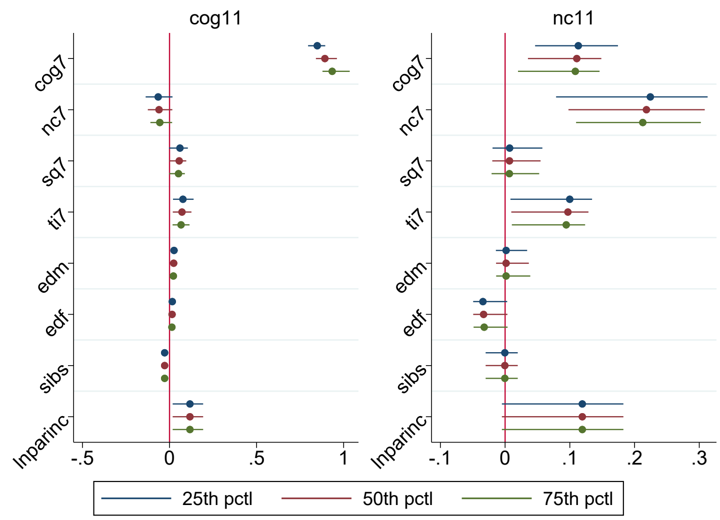
(b) Women, evaluated at levels of mother's educ

Note: This figure displays the extent of non-linearity in our age 7 production functions. Each dot shows the point estimates of an increase in the input displayed on the y axis, holding all other inputs constant at the mean, evaluated at the 25th percentile, 50th percentile, and 75th percentile of maternal education. Lines display 90% confidence intervals. For skills and investments, we evaluate a 1 SD increase, for individual's education, parental education, number of siblings, and log parental income, we evaluate a 1 unit increase. "sq0" stands for school quality investments from 0-7 (which are measured at age 7), "ti0" for time investments from 0-7 (also measured at age 7), "edm" for education of the mother, "edf" for education of the father, "sibs" for the number of siblings, "lnparinc" for log parental income. The graphs with "cog7" in the title evaluate complementarity in the production function of age 7 cognitive skill, the graphs with "nc7" in the title evaluate complementarity in the production function of age 7 non-cognitive skill.

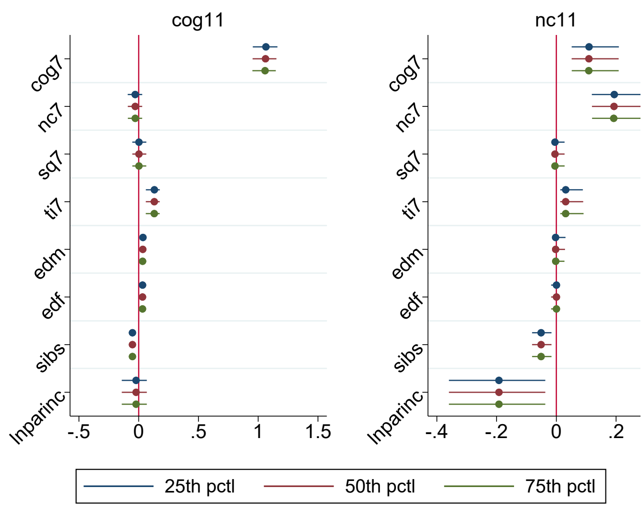
Figure 5: Evaluating complementarities in the age 11 skill production functions



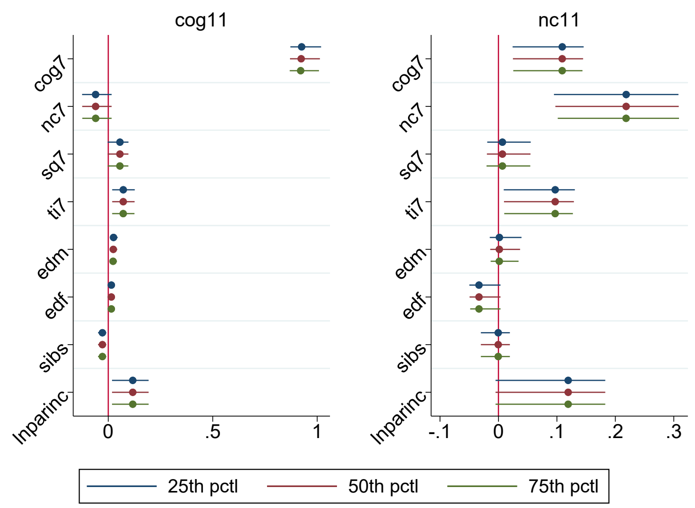
(a) Men, evaluated at pctls of lagged cog skills



(b) Women, evaluated at pctls of lagged cog skills



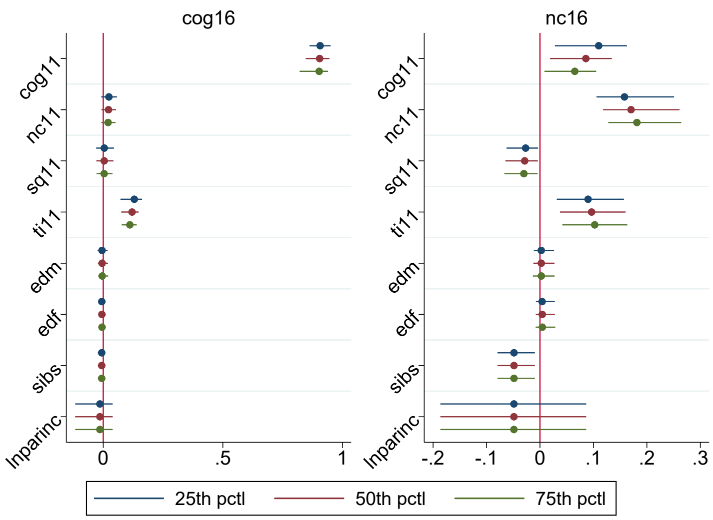
(c) Men, evaluated at levels of mother's educ



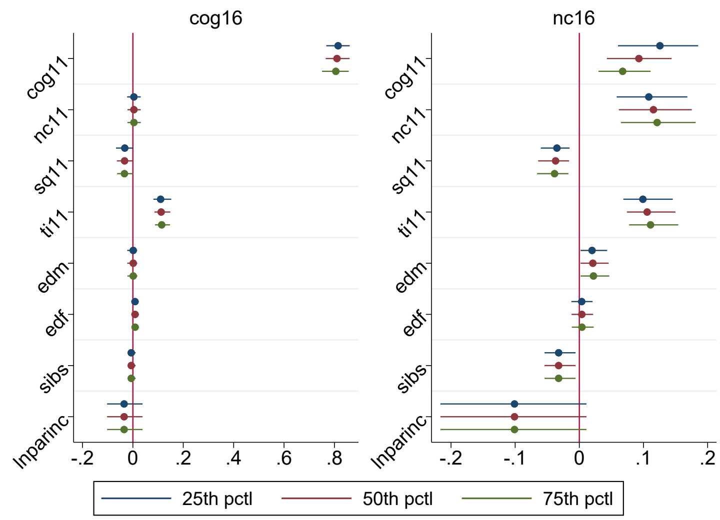
(d) Women, evaluated at levels of mother's educ

Note: This figure displays the extent of non-linearity in our age 11 production function. Each dot shows the point estimates of an increase in the input displayed on the y axis, holding all other inputs constant at the mean, evaluated at the 25th percentile, 50th percentile, and 75th percentile of maternal education. Lines display 90% confidence intervals. For skills and investments, we evaluate a 1 SD increase, for individual's education, parental education, number of siblings, and log parental income, we evaluate a 1 unit increase. "cog7" stands for cognitive skills at age 7, "nc7" for non-cognitive skills at age 7, "sq7" for school quality investments from 7-11 (measured at 11), "ti7" stands for time investments from 7-11 (also measured at 11), "edm" for education of the mother, "edf" for education of the father, "sibs" for the number of siblings, "lnparinc" for log parental income. The graphs with "cog11" in the title evaluate complementarity in the production function of age 11 cognitive skill, the graphs with "nc11" in the title evaluate complementarity in the production function of age 11 non-cognitive skill.

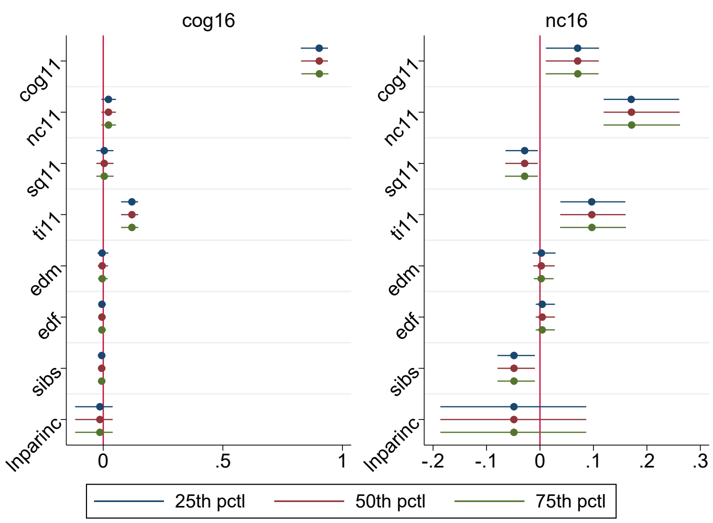
Figure 6: Evaluating complementarities for production functions at 16



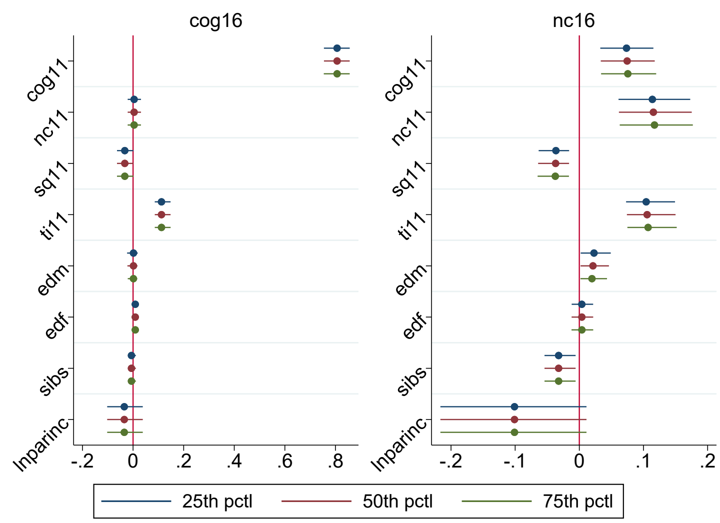
(a) Men, evaluated at pctls of lagged cog skills



(b) Women, evaluated at pctls of lagged cog skills



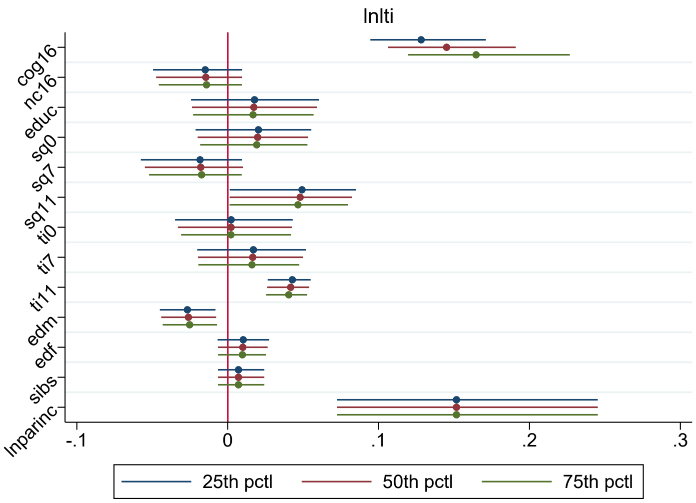
(c) Men, evaluated at levels of mother's educ



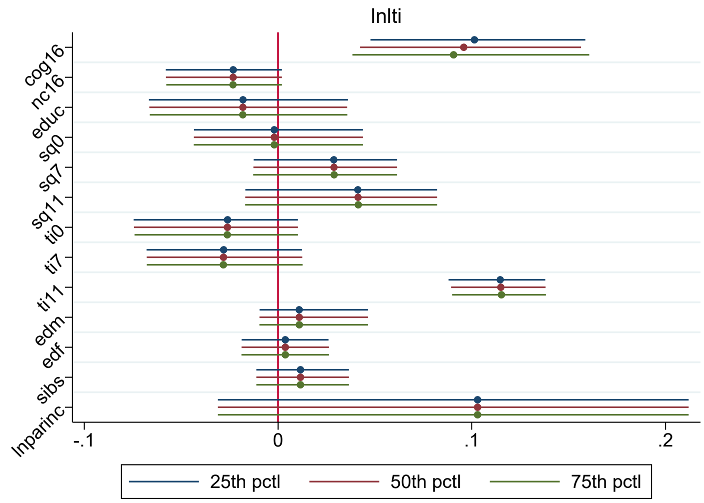
(d) Women, evaluated at levels of mother's educ

Note: This figure displays the extent of non-linearity in our age 16 production function. Each dot shows the point estimates of an increase in the input displayed on the y axis, holding all other inputs constant at the mean, evaluated at the 25th percentile, 50th percentile, and 75th percentile of maternal education. Lines display 90% confidence intervals. For skills and investments, we evaluate a 1 SD increase, for individual's education, parental education, number of siblings, and log parental income, we evaluate a 1 unit increase. "cog11" stands for cognitive skills at age 11, "nc11" for non-cognitive skills at age 11, "sq11" for school quality investments from 11-16 (measured at 16), "ti11" stands for time investments from 11-16 (also measured at 16), "edm" for education of the mother, "edf" for education of the father, "sibs" for the number of siblings, "lnparinc" for log parental income. The graphs with "cog16" in the title evaluate complementarity in the production function of age 16 cognitive skill, the graphs with "nc16" in the title evaluate complementarity in the production function of age 16 non-cognitive skill.

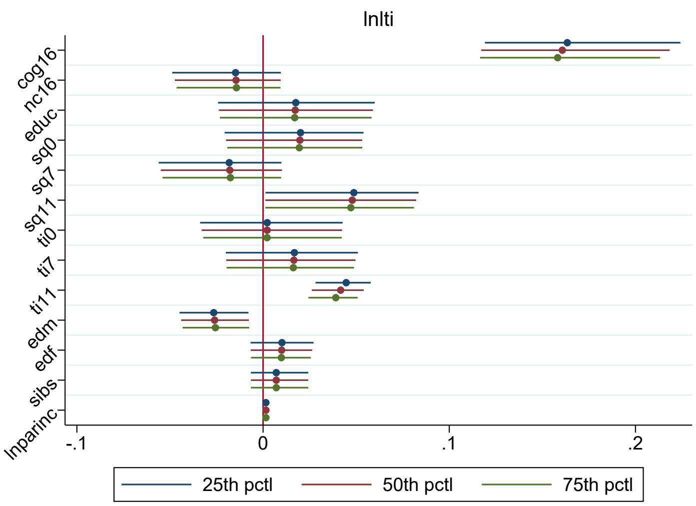
Figure 7: Evaluating complementarities in lifetime earnings equation



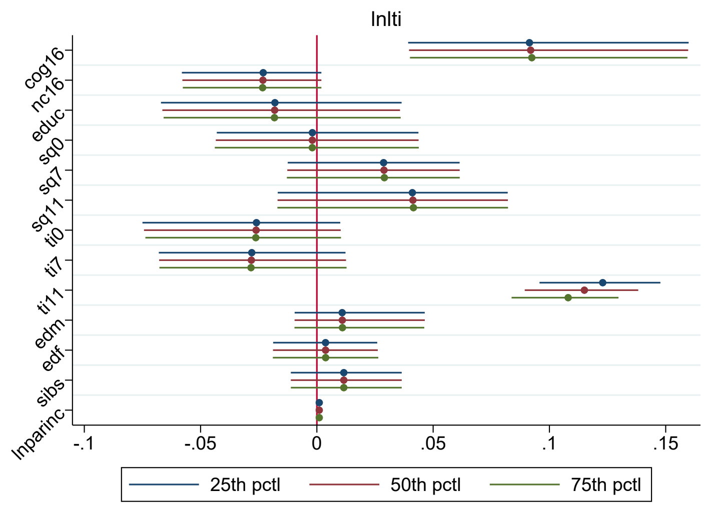
(a) Men, evaluated at pctls of cog skills 16



(b) Women, evaluated at pctls of cog skills 16



(c) Men, evaluated at pctls of education



(d) Women, evaluated at pctls of education

Note: This figure displays the extent of non-linearity in our earnings equation. Each dot shows the point estimates of an increase in the input displayed on the y axis, holding all other inputs constant at the mean, evaluated at the 25th percentile, 50th percentile, and 75th percentile of maternal education. Lines display 90% confidence intervals. For skills and investments, we evaluate a 1 SD increase, for individual's education, parental education, number of siblings, and log parental income, we evaluate a 1 unit increase. "educ" stands for education of the individual, "cog16" for cognitive skills at age 16, "nc16" for non-cognitive skills at age 16; "sq0" and "ti0" stand for school quality and time investments from 0-7 and measured at 7, respectively; "sq7" and "ti7" stand for school quality and time investments from 7-11 and measured at 11, respectively; "sq11" and "ti11" stand for school quality and time investments from 11-16 and measured at 16, respectively; "edm" stands for education of the mother, "edf" for education of the father, "sibs" for the number of siblings, "lnparinc" for log parental income. The graphs with "cog16" in the title evaluate complementarity in the production function of age 16 cognitive skill, the graphs with "nc16" in the title evaluate complementarity in the production function of age 16 non-cognitive skill.

I Results for Robustness Checks

This section contains:

1. Decomposition results when not correcting for measurement error in Table 15
2. List of adult measures used for identification of unobserved heterogeneity in Table 16
3. Average effects of increasing inputs in the production function when accounting for unobserved heterogeneity in Table 17
4. Decomposition results accounting for unobserved heterogeneity in Table 18
5. Decomposition results when using a mixture of three normals in Table 19
6. Decomposition results when using a different set of non-cognitive skill measures in Table 20
7. Decomposition results when changing the normalizations in Tables 21 and 22
8. List of alternative set of time investment and school quality measures in Table 23
9. Decomposition results when using the alternative set of time investment and school quality measures in Table 24

Table 15: Results when not correcting for measurement error

(a) Men

LEVEL	Direct Effect (1)	Indirect effects (cumulative) via: *Educ* (2)	*Skills at 16* (3)	*Inv. 11-16* (4)	*Skills at 11* (5)	*Inv. 7-11* (6)	*Skills at 7* (7)	*Inv. 0-7* (8)
Education	**18.1%**	*0.7%*	*0.7%*	*0.7%*	*0.7%*	*0.7%*	*0.7%*	*0.7%*
Cog. skills at 16	**18.4%**	**29.0%**	*3.3%*	*3.3%*	*3.3%*	*3.3%*	*3.3%*	*3.3%*
Non-cog. skills at 16	0.3%	0.5%	*-0.1%*	*-0.1%*	*-0.1%*	*-0.1%*	*-0.1%*	*-0.1%*
Inv. at 11-16	6.8%	**9.5%**	**15.8%**	***5.7%***	***5.7%***	***5.7%***	***5.7%***	***5.7%***
Cog. skills at 11			**17.4%**	**22.6%**	***5.6%***	***5.6%***	***5.6%***	***5.6%***
Non-cog. skills at 11			-0.3%	-0.4%	***-1.0%***	***-1.0%***	***-1.0%***	***-1.0%***
Inv. at 7-11	7.2%	7.3%	7.3%	7.3%	7.4%	*3.3%*	*3.3%*	*3.3%*
Cog. skills at 7			0.0%	0.0%	**8.8%**	**8.8%**	***4.0%***	***4.0%***
Non-cog. skills at 7			0.0%	0.0%	**0.2%**	**0.3%**	*0.0%*	*0.0%*
Inv. at 0-7	2.1%	**2.8%**	**2.8%**	**2.8%**	**2.8%**	**2.8%**	**3.1%**	***2.6%***
Parental educ.	3.4%	6.1%	7.9%	**12.0%**	**19.1%**	**22.6%**	**28.1%**	**28.3%**
Num. siblings	0.0%	0.3%	1.1%	**1.9%**	**2.4%**	**2.8%**	**3.2%**	**3.8%**
TOTAL	56.3%	56.1%	55.9%	55.7%	54.9%	54.8%	56.0%	56.3%

(b) Women

LEVEL	Direct Effect (1)	Indirect effects (cumulative) via: *Educ* (2)	*Skills at 16* (3)	*Inv. 11-16* (4)	*Skills at 11* (5)	*Inv. 7-11* (6)	*Skills at 7* (7)	*Inv. 0-7* (8)
Education	**49.7%**	*10.3%*	*10.3%*	*10.3%*	*10.3%*	*10.3%*	*10.3%*	*10.3%*
Cog. skills at 16	5.6%	**22.7%**	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Non-cog. skills at 16	0.9%	1.6%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 11-16	-2.6%	**11.7%**	**18.0%**	*3.0%*	*3.0%*	*3.0%*	*3.0%*	*3.0%*
Cog. skills at 11			**15.3%**	**22.2%**	***7.4%***	***7.4%***	***7.4%***	***7.4%***
Non-cog. skills at 11			0.7%	**0.8%**	*0.5%*	*0.5%*	*0.5%*	*0.5%*
Inv. at 7-11	-1.5%	-0.3%	-0.3%	-0.3%	-0.2%	*0.0%*	*0.0%*	*0.0%*
Cog. skills at 7			0.0%	0.0%	**7.1%**	**7.0%**	*2.3%*	*2.3%*
Non-cog. skills at 7			0.0%	0.0%	0.3%	0.3%	*0.0%*	*0.0%*
Inv. at 0-7	2.1%	1.8%	1.8%	1.8%	1.8%	1.8%	2.3%	*1.4%*
Parental educ.	**15.4%**	**21.2%**	**25.2%**	**31.6%**	**38.6%**	**38.4%**	**42.6%**	**43.5%**
Num. siblings	-0.4%	0.2%	0.7%	1.2%	1.6%	1.5%	**2.1%**	**2.2%**
TOTAL	69.1%	69.4%	71.3%	70.3%	70.1%	70.0%	70.2%	70.3%

Note: For this version, we ignore measurement error and use the measure with the highest signal-to-noise ratio as described in Section 6.5. Each column displays the share explained by each variable at different levels of mediation. E.g., column 1 accounts only for direct effects of each variable on earnings. Column 2 additionally accounts for indirect effects, where each variable can additionally affect earnings by its effect on educational attainment, etc. Coefficients that are significant at the 10% level are bold.

Table 16: List of adult measures used for identification of unobserved heterogeneity

How good are you at communicating with others?
How good are you at the use of numbers and calculations?
How good are you at the use of computers and information technology?
How good are you at working in a team?
How good are you at learning new skills?
How good are you at problem solving?
How good are you at looking after people who need care?

Table 17: Skill production functions: average effects of increasing inputs in production function with individual fixed effect

(a) Men

	Cognitive			Non-Cognitive		
	Age 7	Age 11	Age 16	Age 7	Age 11	Age 16
Cognitive Lag		**0.994** [0.904, 1.045]	**0.866** [0.816, 0.929]		**0.143** [0.089, 0.236]	**0.105** [0.041, 0.167]
Non-Cognitive Lag		-0.019 [-0.053, 0.027]	0.023 [-0.007, 0.055]		**0.403** [0.265, 0.504]	**0.268** [0.185, 0.336]
Time Investments	**0.217** [0.148, 0.280]	**0.117** [0.057, 0.156]	**0.105** [0.082, 0.158]	**0.226** [0.174, 0.295]	**0.082** [0.042, 0.142]	**0.076** [0.038, 0.136]
School Quality	**0.135** [0.039, 0.210]	0.000 [-0.055, 0.055]	-0.001 [-0.027, 0.043]	-0.022 [-0.070, 0.037]	-0.008 [-0.032, 0.047]	**-0.060** [-0.108, -0.025]
Mother's Educ.	**0.068** [0.038, 0.118]	**0.036** [0.014, 0.051]	0.011 [-0.026, 0.024]	0.016 [-0.011, 0.042]	0.017 [0.000, 0.048]	-0.006 [-0.018, 0.019]
Father's Educ	**0.055** [0.020, 0.084]	**0.033** [0.019, 0.050]	0.001 [-0.016, 0.011]	**0.030** [0.005, 0.058]	0.002 [-0.028, 0.019]	0.013 [-0.001, 0.039]
Number of Siblings	0.014 [-0.037, 0.042]	**-0.045** [-0.067, -0.015]	-0.003 [-0.022, 0.014]	**0.047** [0.007, 0.086]	**-0.046** [-0.079, -0.010]	**-0.082** [-0.120, -0.041]
Log Parental Income	**0.333** [0.158, 0.510]	-0.050 [-0.157, 0.056]	-0.035 [-0.118, 0.050]	-0.128 [-0.308, 0.025]	**-0.259** [-0.414, -0.073]	-0.093 [-0.238, 0.066]

(b) Women

	Cognitive			Non-Cognitive		
	Age 7	Age 11	Age 16	Age 7	Age 11	Age 16
Cognitive Lag		**0.866** [0.814, 0.904]	**0.794** [0.738, 0.836]		**0.051** [0.021, 0.086]	**0.099** [0.050, 0.160]
Non-Cognitive Lag		-0.030 [-0.072, 0.014]	0.005 [-0.023, 0.034]		**0.340** [0.235, 0.405]	**0.197** [0.116, 0.255]
Time Investments	**0.220** [0.163, 0.285]	**0.072** [0.023, 0.120]	**0.114** [0.086, 0.152]	**0.111** [0.081, 0.176]	**0.034** [0.015, 0.076]	**0.093** [0.063, 0.143]
School Quality	0.033 [-0.024, 0.110]	**0.065** [0.012, 0.094]	-0.028 [-0.057, 0.007]	-0.027 [-0.076, 0.003]	**-0.019** [-0.033, -0.008]	**-0.050** [-0.084, -0.025]
Mother's Educ.	**0.073** [0.041, 0.112]	**0.025** [0.011, 0.043]	-0.003 [-0.025, 0.015]	**0.034** [0.017, 0.050]	**0.025** [0.012, 0.044]	0.015 [0.000, 0.038]
Father's Educ	0.031 [0.000, 0.062]	**0.013** [0.002, 0.027]	0.011 [-0.005, 0.026]	**0.021** [0.004, 0.037]	-0.002 [-0.016, 0.009]	0.006 [-0.011, 0.022]
Number of Siblings	-0.020 [-0.057, 0.012]	**-0.019** [-0.043, -0.002]	0.000 [-0.016, 0.014]	0.002 [-0.022, 0.034]	-0.013 [-0.040, 0.007]	**-0.053** [-0.075, -0.022]
Log Parental Income	0.135 [-0.022, 0.308]	**0.101** [0.006, 0.184]	-0.029 [-0.098, 0.044]	**-0.165** [-0.260, -0.073]	0.038 [-0.050, 0.136]	-0.097 [-0.217, 0.000]

Note: Coefficients that are significant at the 10% level are bold. This table replicates Table 5, but accounts for unobserved heterogeneity as described in Section 6.5. For skills and investments, we evaluate a 1 SD increase; for individual's education, parental education, number of siblings, and log parental income, we evaluate a 1 unit increase.

Table 18: Decomposition results including individual fixed effect

(a) Men

	Direct	Indirect effects (cumulative) via:						
	Effect	*Educ.*	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**8.8%**	*0.2%*	*0.2%*	*0.2%*	*0.2%*	*0.2%*	*0.2%*	*0.2%*
Cog. skills at 16	**16.0%**	**22.6%**	*-1.0%*	*-1.0%*	*-1.0%*	*-1.0%*	*-1.0%*	*-1.0%*
Non-cog. skills at 16	0.8%	0.9%	*-0.7%*	*-0.7%*	*-0.7%*	*-0.7%*	*-0.7%*	*-0.7%*
Inv. at 11-16	**10.4%**	**10.6%**	**12.8%**	***3.7%***	***3.7%***	***3.7%***	***3.7%***	***3.7%***
Cog. skills at 11			**21.6%**	**27.7%**	*-1.7%*	*-1.7%*	*-1.7%*	*-1.7%*
Non-cog. skills at 11			-0.1%	0.0%	***-0.8%***	***-0.8%***	***-0.8%***	***-0.8%***
Inv. at 7-11	**15.4%**	**16.0%**	**16.0%**	**16.0%**	**18.9%**	***7.6%***	***7.6%***	***7.6%***
Cog. skills at 7			0.0%	0.0%	**24.1%**	**26.4%**	***12.0%***	***12.0%***
Non-cog. skills at 7			0.0%	0.0%	-0.1%	0.0%	*-0.2%*	*-0.2%*
Inv. at 0-7	**19.2%**	**20.1%**	**20.1%**	**20.1%**	**20.1%**	**20.1%**	**30.0%**	***16.9%***
Parental educ.	**-10.5%**	-9.9%	-9.3%	-6.6%	-3.2%	3.5%	**10.0%**	**20.6%**
Num. siblings	-2.4%	-2.5%	-2.4%	-2.2%	-1.9%	-1.2%	-1.3%	0.1%
Fixed effect	**-11.4%**	**-11.7%**	**-11.5%**	**-11.2%**	**-11.0%**	**-9.8%**	**-11.5%**	**-10.2%**
TOTAL	46.2%	46.3%	45.7%	46.1%	46.5%	56.1%	46.4%	46.6%

(b) Women

	Direct	Indirect effects (cumulative) via:						
	Effect	*Educ.*	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**26.1%**	*0.0%*	***-21.4%***	***-6.3%***	*9.1%*	***28.1%***	*-0.1%*	*6.9%*
Cog. skills at 16	-0.3%	2.8%	*0.0%*	***-20.8%***	***-5.9%***	*12.2%*	***28.1%***	*0.2%*
Non-cog. skills at 16	**3.8%**	**15.6%**	*2.8%*	*0.0%*	***-20.1%***	***-5.7%***	***19.1%***	***38.5%***
Inv. at 11-16	**23.8%**	**4.0%**	-0.7%	*2.8%*	*0.0%*	***-20.3%***	***-5.5%***	***26.5%***
Cog. skills at 11			-2.5%	-0.7%	*2.8%*	*0.0%*	***-19.9%***	***-5.3%***
Non-cog. skills at 11			**32.0%**	-2.5%	*-0.7%*	*2.8%*	*0.0%*	***-20.5%***
Inv. at 7-11	6.2%	0.0%	**17.2%**	4.4%	-2.5%	*-0.7%*	*2.8%*	*0.0%*
Cog. skills at 7			**0.6%**	**35.9%**	4.4%	-2.5%	*-0.7%*	*2.8%*
Non-cog. skills at 7			8.1%	**0.7%**	**5.1%**	4.4%	*-2.5%*	*-0.7%*
Inv. at 0-7	**27.0%**	0.0%	0.0%	8.1%	0.2%	**5.1%**	4.4%	*-2.5%*
Parental educ.	-0.1%	**28.1%**	0.0%	0.0%	**11.9%**	0.2%	**5.1%**	4.4%
Num. siblings	**-6.2%**	-0.3%	**28.1%**	0.0%	**25.4%**	**3.8%**	0.2%	**5.1%**
Fixed effect	**-20.6%**	**-6.6%**	1.0%	**28.1%**	-0.1%	**25.5%**	**3.8%**	0.2%
TOTAL	-20.6%	-6.6%	1.0%	28.1%	-0.1%	25.5%	3.8%	0.2%

Note: For this version, we accounted for unobserved heterogeneity as described in Section 6.5. Each column displays the share explained by each variable at different levels of mediation. E.g., column 1 accounts only for direct effects of each variable on earnings. Column 2 additionally accounts for indirect effects, where each variable can additionally affect earnings by its effect on educational attainment, etc. Coefficients that are significant at the 10% level are bold.

Table 19: Results when using a mixture of 3 normals

(a) Men

	Direct Effect	Indirect effects (cumulative) via:						
		Education	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**11.7%**	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Cog. skills at 16	**32.3%**	**41.4%**	*-2.5%*	*-2.5%*	*-2.5%*	*-2.5%*	*-2.5%*	*-2.5%*
Non-cog. skills at 16	-0.6%	-0.3%	*0.1%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*
Inv. at 11-16	-2.4%	-1.9%	2.3%	*1.5%*	*1.5%*	*1.5%*	*1.5%*	*1.5%*
Cog. skills at 11			**40.1%**	**40.3%**	*-0.6%*	*-0.6%*	*-0.6%*	*-0.6%*
Non-cog. skills at 11			0.2%	0.3%	*-0.3%*	*-0.3%*	*-0.3%*	*-0.3%*
Inv. at 7-11	4.7%	5.4%	5.4%	5.4%	8.9%	*5.3%*	*5.3%*	*5.3%*
Cog. skills at 7			0.0%	0.0%	**31.7%**	**32.6%**	***14.2%***	***14.2%***
Non-cog. skills at 7			0.0%	0.0%	0.0%	0.2%	*-0.1%*	*-0.1%*
Inv. at 0-7	**8.7%**	**9.2%**	**9.2%**	**9.2%**	**9.2%**	**9.2%**	**18.1%**	***11.7%***
Parental educ.	-2.2%	-1.2%	-1.8%	-1.6%	3.7%	5.9%	**15.0%**	**20.9%**
Num. siblings	-0.5%	-0.5%	-0.5%	-0.4%	0.0%	0.2%	0.5%	**1.5%**
TOTAL	51.8%	51.9%	52.2%	52.0%	51.5%	51.5%	51.0%	51.6%

(b) Women

	Direct Effect	Indirect effects (cumulative) via:						
		Education	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**44.6%**	*6.1%*	*6.1%*	*6.1%*	*6.1%*	*6.1%*	*6.1%*	*6.1%*
Cog. skills at 16	**13.4%**	**32.8%**	*-1.2%*	*-1.2%*	*-1.2%*	*-1.2%*	*-1.2%*	*-1.2%*
Non-cog. skills at 16	-0.8%	-0.5%	*0.4%*	*0.4%*	*0.4%*	*0.4%*	*0.4%*	*0.4%*
Inv. at 11-16	3.9%	**19.1%**	**24.8%**	***5.6%***	***5.6%***	***5.6%***	***5.6%***	***5.6%***
Cog. skills at 11			**25.9%**	**37.2%**	***10.6%***	***10.6%***	***10.6%***	***10.6%***
Non-cog. skills at 11			0.1%	0.3%	*0.1%*	*0.1%*	*0.1%*	*0.1%*
Inv. at 7-11	-4.2%	-2.8%	-2.8%	-2.8%	0.2%	*-0.1%*	*-0.1%*	*-0.1%*
Cog. skills at 7			0.0%	0.0%	**18.3%**	**18.1%**	*2.5%*	*2.5%*
Non-cog. skills at 7			0.0%	0.0%	0.1%	0.2%	*-0.1%*	*-0.1%*
Inv. at 0-7	0.2%	1.3%	1.3%	1.3%	1.3%	1.3%	9.5%	*4.8%*
Parental educ.	11.2%	13.0%	14.2%	**20.9%**	**26.8%**	**27.0%**	**33.6%**	**37.9%**
Num. siblings	-0.3%	-0.4%	-0.3%	-0.1%	0.2%	0.1%	0.4%	1.1%
TOTAL	68.0%	68.8%	68.6%	67.8%	68.6%	68.4%	67.4%	67.7%

Note: For this version, we approximated the underlying distribution using a mixture of three instead of two normals. Each column displays the share explained by each variable at different levels of mediation. E.g., column 1 accounts only for direct effects of each variable on earnings. Column 2 additionally accounts for indirect effects, where each variable can additionally affect earnings by its effect on educational attainment, etc. Coefficients that are significant at the 10% level are bold.

Table 20: Results when using parent-reported non-cognitive skills

(a) Men

LEVEL	Direct Effect (1)	*Educ* (2)	*Skills at 16* (3)	*Inv. 11-16* (4)	*Skills at 11* (5)	*Inv. 7-11* (6)	*Skills at 7* (7)	*Inv. 0-7* (8)
		Indirect effects (cumulative) via:						
Education	**13.2%**	*0.4%*	*0.4%*	*0.4%*	*0.4%*	*0.4%*	*0.4%*	*0.4%*
Cog. skills at 16	**31.0%**	**41.3%**	*-2.1%*	*-2.1%*	*-2.1%*	*-2.1%*	*-2.1%*	*-2.1%*
Non-cog. skills at 16	0.9%	1.1%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 11-16	0.9%	1.1%	5.4%	*2.6%*	*2.6%*	*2.6%*	*2.6%*	*2.6%*
Cog. skills at 11			**40.5%**	**42.2%**	*-0.4%*	*-0.4%*	*-0.4%*	*-0.4%*
Non-cog. skills at 11			0.5%	0.4%	*-0.7%*	*-0.7%*	*-0.7%*	*-0.7%*
Inv. at 7-11	1.8%	2.6%	2.6%	2.6%	6.1%	*2.7%*	*2.7%*	*2.7%*
Cog. skills at 7			0.0%	0.0%	**33.1%**	**33.6%**	***12.9%***	***12.9%***
Non-cog. skills at 7			0.0%	0.0%	0.6%	0.7%	*-0.4%*	*-0.4%*
Inv. at 0-7	8.1%	8.9%	8.9%	8.9%	8.9%	8.9%	**19.5%**	***11.7%***
Parental educ.	-0.3%	0.5%	-0.1%	0.5%	6.5%	8.9%	**20.1%**	**26.5%**
Num. siblings	-0.7%	-0.7%	-0.5%	-0.4%	0.2%	0.3%	0.6%	**1.9%**
TOTAL	55.0%	55.1%	55.3%	54.9%	54.9%	54.7%	55.0%	54.9%

(b) Women

LEVEL	Direct Effect (1)	*Educ* (2)	*Skills at 16* (3)	*Inv. 11-16* (4)	*Skills at 11* (5)	*Inv. 7-11* (6)	*Skills at 7* (7)	*Inv. 0-7* (8)
		Indirect effects (cumulative) via:						
Education	**35.1%**	*3.5%*	*3.5%*	*3.5%*	*3.5%*	*3.5%*	*3.5%*	*3.5%*
Cog. skills at 16	**22.2%**	**44.5%**	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*	*0.0%*
Non-cog. skills at 16	**3.0%**	**3.3%**	*-0.1%*	*-0.1%*	*-0.1%*	*-0.1%*	*-0.1%*	*-0.1%*
Inv. at 11-16	1.8%	9.0%	14.0%	*2.6%*	*2.6%*	*2.6%*	*2.6%*	*2.6%*
Cog. skills at 11			**41.2%**	**48.4%**	***11.5%***	***11.5%***	***11.5%***	***11.5%***
Non-cog. skills at 11			1.1%	1.1%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 7-11	-5.6%	-4.2%	-4.2%	-4.2%	-0.8%	*-0.5%*	*-0.5%*	*-0.5%*
Cog. skills at 7			0.0%	0.0%	**28.5%**	**27.9%**	*2.4%*	*2.4%*
Non-cog. skills at 7			0.0%	0.0%	1.2%	1.0%	*-0.5%*	*-0.5%*
Inv. at 0-7	-2.5%	-2.8%	-2.8%	-2.8%	-2.8%	-2.8%	11.0%	*3.9%*
Parental educ.	3.7%	5.0%	6.0%	9.5%	15.1%	**15.4%**	**27.0%**	**32.8%**
Num. siblings	-0.3%	-0.4%	-0.4%	-0.3%	0.2%	0.0%	0.6%	1.6%
TOTAL	57.4%	57.8%	58.3%	57.8%	58.8%	58.2%	57.2%	57.0%

Note: To construct non-cognitive skills, we used information on the following items reported by the mother at each of ages 7, 11, 16. Child is (1) irritable, (2) often miserable, (3) disobedient, (4) unconcentrated, (5) fights with others, (6) fidgety. These items were picked as they had the strongest signal-to-noise ratio in an exploratory factor analysis. Each column displays the share explained by each variable at different levels of mediation. E.g., column 1 accounts only for direct effects of each variable on earnings. Column 2 additionally accounts for indirect effects, where each variable can additionally affect earnings by its effect on educational attainment, etc. Coefficients that are significant at the 10% level are bold.

Table 21: Results when changing the normalization of the cognitive skill measure: Part I

(a) Men

	Direct	Indirect effects (cumulative) via:						
Men	Effect	*Education*	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**13.4%**	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Cog. skills at 16	**32.7%**	**43.6%**	*-1.4%*	*-1.4%*	*-1.4%*	*-1.4%*	*-1.4%*	*-1.4%*
Non-cog. skills at 16	-0.6%	-0.4%	*0.1%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*
Inv. at 11-16	-0.5%	-0.5%	3.1%	*1.7%*	*1.7%*	*1.7%*	*1.7%*	*1.7%*
Cog. skills at 11			**39.5%**	**40.7%**	*-1.0%*	*-1.0%*	*-1.0%*	*-1.0%*
Non-cog. skills at 11			-0.1%	-0.1%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 7-11	3.5%	4.1%	4.1%	4.1%	7.7%	*4.3%*	*4.3%*	*4.3%*
Cog. skills at 7			0.0%	0.0%	**33.4%**	**34.0%**	***13.3%***	***13.3%***
Non-cog. skills at 7			0.0%	0.0%	-0.2%	-0.2%	*0.0%*	*0.0%*
Inv. at 0-7	**11.3%**	**12.1%**	**12.1%**	**12.1%**	**12.1%**	**12.1%**	**21.7%**	***14.3%***
Parental educ.	-3.9%	-2.8%	-2.5%	-1.9%	2.5%	4.7%	**14.1%**	**21.5%**
Num. siblings	-0.4%	-0.4%	-0.4%	-0.2%	0.3%	0.5%	0.7%	**2.1%**
TOTAL	55.4%	55.5%	54.3%	55.0%	54.7%	54.5%	53.1%	54.5%

(b) Women

	Direct	Indirect effects (cumulative) via:						
	Effect	*Education*	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**39.5%**	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*
Cog. skills at 16	**22.6%**	**49.4%**	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*
Non-cog. skills at 16	-1.3%	-1.3%	*1.0%*	*1.0%*	*1.0%*	*1.0%*	*1.0%*	*1.0%*
Inv. at 11-16	0.0%	7.8%	11.3%	*2.0%*	*2.0%*	*2.0%*	*2.0%*	*2.0%*
Cog. skills at 11			**45.8%**	**52.2%**	***8.9%***	***8.9%***	***8.9%***	***8.9%***
Non-cog. skills at 11			-0.2%	-0.2%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 7-11	-4.6%	-2.6%	-2.6%	-2.6%	2.0%	*0.5%*	*0.5%*	*0.5%*
Cog. skills at 7			0.0%	0.0%	**35.4%**	**34.9%**	*6.7%*	*6.7%*
Non-cog. skills at 7			0.0%	0.0%	-0.1%	-0.1%	*0.7%*	*0.7%*
Inv. at 0-7	5.9%	6.4%	6.4%	6.4%	6.4%	6.4%	**21.3%**	*9.9%*
Parental educ.	6.6%	5.9%	6.9%	9.2%	**13.5%**	**14.8%**	**25.6%**	**35.9%**
Num. siblings	-0.6%	-0.7%	-0.7%	-0.7%	-0.4%	-0.4%	0.0%	1.4%
TOTAL	68.2%	69.2%	69.6%	69.1%	70.2%	69.5%	68.2%	68.6%

Note: In this version, we multiply log cognitive skills at ages 7, 11, and 16 by a factor of 1.5 and add 0.5. Each column displays the share explained by each variable at different levels of mediation. E.g., column 1 accounts only for direct effects of each variable on earnings. Column 2 additionally accounts for indirect effects, where each variable can additionally affect earnings by its effect on educational attainment, etc. Coefficients that are significant at the 10% level are bold.

Table 22: Results when changing the normalization of the cognitive skill measure: Part II

(a) Men

	Direct	Indirect effects (cumulative) via:						
	Effect	*Education*	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**13.4%**	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Cog. skills at 16	**32.7%**	**43.6%**	*-1.4%*	*-1.4%*	*-1.4%*	*-1.4%*	*-1.4%*	*-1.4%*
Non-cog. skills at 16	-0.6%	-0.4%	*0.1%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*	*0.1%*
Inv. at 11-16	-0.5%	-0.5%	3.1%	*1.7%*	*1.7%*	*1.7%*	*1.7%*	*1.7%*
Cog. skills at 11			**39.5%**	**40.7%**	*-1.0%*	*-1.0%*	*-1.0%*	*-1.0%*
Non-cog. skills at 11			-0.1%	-0.1%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 7-11	3.5%	4.1%	4.1%	4.1%	7.7%	*4.3%*	*4.3%*	*4.3%*
Cog. skills at 7			0.0%	0.0%	**33.4%**	**34.0%**	***13.3%***	***13.3%***
Non-cog. skills at 7			0.0%	0.0%	-0.2%	-0.2%	*0.0%*	*0.0%*
Inv. at 0-7	**11.3%**	**12.1%**	**12.1%**	**12.1%**	**12.1%**	**12.1%**	**21.7%**	***14.3%***
Parental educ.	-3.9%	-2.8%	-2.5%	-1.9%	2.5%	4.7%	**14.1%**	**21.5%**
Num. siblings	-0.4%	-0.4%	-0.4%	-0.2%	0.3%	0.5%	0.7%	**2.1%**
TOTAL	55.4%	55.5%	54.3%	55.0%	54.7%	54.5%	53.1%	54.5%

(b) Women

	Direct	Indirect effects (cumulative) via:						
	Effect	*Education*	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**39.5%**	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*	*4.4%*
Cog. skills at 16	**22.6%**	**49.4%**	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*	*-2.7%*
Non-cog. skills at 16	-1.3%	-1.3%	*1.0%*	*1.0%*	*1.0%*	*1.0%*	*1.0%*	*1.0%*
Inv. at 11-16	0.0%	7.8%	11.3%	*2.0%*	*2.0%*	*2.0%*	*2.0%*	*2.0%*
Cog. skills at 11			**45.8%**	**52.2%**	***8.9%***	***8.9%***	***8.9%***	***8.9%***
Non-cog. skills at 11			-0.2%	-0.2%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 7-11	-4.6%	-2.6%	-2.6%	-2.6%	2.0%	*0.5%*	*0.5%*	*0.5%*
Cog. skills at 7			0.0%	0.0%	**35.4%**	**34.9%**	*6.7%*	*6.7%*
Non-cog. skills at 7			0.0%	0.0%	-0.1%	-0.1%	*0.7%*	*0.7%*
Inv. at 0-7	5.9%	6.4%	6.4%	6.4%	6.4%	6.4%	**21.3%**	*9.9%*
Parental educ.	6.6%	5.9%	6.9%	9.2%	**13.5%**	**14.8%**	**25.6%**	**35.9%**
Num. siblings	-0.6%	-0.7%	-0.7%	-0.7%	-0.4%	-0.4%	0.0%	1.4%
TOTAL	68.2%	69.2%	69.6%	69.1%	70.2%	69.5%	68.2%	68.6%

Note: In this version, we multiply log cognitive skills at ages 7, 11, and 16 by a factor of 2/3 and add 2. Each column displays the share explained by each variable at different levels of mediation. E.g., column 1 accounts only for direct effects of each variable on earnings. Column 2 additionally accounts for indirect effects, where each variable can additionally affect earnings by its effect on educational attainment, etc. Coefficients that are significant at the 10% level are bold.

Table 23: Alternative list of time investments and school quality measures used

School quality, age 7:	Whether school has a parent-teacher association (PTA), whether PTA conducts educational meetings, fraction of parents in child's class that meet with teacher, social class of fathers in the child's class
School quality, age 11:	Class size, student-teacher ratio, type of school, fraction of experienced teachers
School quality, age 16:	Type of school, student-teacher ratio, number of teachers offering career guidance
Time investments, age 7:	How often father takes child on outings, how often mother takes child on outings, how often father reads to child, how often mother reads to child
Time investments, age 11:	How often father takes child on outings, how often mother takes child on outings, father's role in upbringing of child
Time investments, age 16:	Teacher's assessment of father's interest in child's education, teacher's assessment of mother's interest in child's education, parents' ambitions regarding child's educational attainment

Table 24: Results when using different measures of investments/school quality

(a) Men

	Direct	Indirect effects (cumulative) via:						
	Effect	*Education*	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**13.5%**	*-0.3%*	*-0.3%*	*-0.3%*	*-0.3%*	*-0.3%*	*-0.3%*	*-0.3%*
Cog. skills at 16	**25.9%**	**36.9%**	*-1.4%*	*-1.4%*	*-1.4%*	*-1.4%*	*-1.4%*	*-1.4%*
Non-cog. skills at 16	-0.8%	-0.7%	*0.3%*	*0.3%*	*0.3%*	*0.3%*	*0.3%*	*0.3%*
Inv. at 11-16	15.8%	15.8%	**20.7%**	*3.7%*	*3.7%*	*3.7%*	*3.7%*	*3.7%*
Cog. skills at 11			**34.4%**	**41.3%**	*0.1%*	*0.1%*	*0.1%*	*0.1%*
Non-cog. skills at 11			0.1%	0.2%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 7-11	1.7%	2.5%	2.5%	2.5%	4.9%	*3.9%*	*3.9%*	*3.9%*
Cog. skills at 7			0.0%	0.0%	**34.5%**	**34.2%**	***17.1%***	***17.1%***
Non-cog. skills at 7			0.0%	0.0%	0.0%	0.1%	*0.0%*	*0.0%*
Inv. at 0-7	5.6%	6.5%	6.5%	6.5%	6.5%	6.5%	**12.2%**	***8.2%***
Parental educ.	-7.3%	-6.0%	-7.4%	0.9%	5.2%	6.0%	**16.1%**	**19.7%**
Num. siblings	-0.6%	-0.6%	-0.6%	-0.4%	0.1%	0.3%	0.9%	1.6%
TOTAL	53.9%	54.2%	54.9%	53.3%	53.4%	53.2%	52.4%	52.6%

(b) Women

	Direct	Indirect effects (cumulative) via:						
	Effect	*Education*	*Skills at 16*	*Inv. 11-16*	*Skills at 11*	*Inv. 7-11*	*Skills at 7*	*Inv. 0-7*
LEVEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	**42.4%**	*4.9%*	*4.9%*	*4.9%*	*4.9%*	*4.9%*	*4.9%*	*4.9%*
Cog. skills at 16	17.4%	**47.0%**	*-2.2%*	*-2.2%*	*-2.2%*	*-2.2%*	*-2.2%*	*-2.2%*
Non-cog. skills at 16	-0.7%	-0.9%	*0.8%*	*0.8%*	*0.8%*	*0.8%*	*0.8%*	*0.8%*
Inv. at 11-16	33.0%	40.5%	43.4%	*16.7%*	*16.7%*	*16.7%*	*16.7%*	*16.7%*
Cog. skills at 11			**43.4%**	**57.5%**	*11.9%*	*11.9%*	*11.9%*	*11.9%*
Non-cog. skills at 11			-0.1%	-0.5%	*-0.2%*	*-0.2%*	*-0.2%*	*-0.2%*
Inv. at 7-11	-9.6%	-8.2%	-8.2%	-8.2%	-7.4%	*-1.2%*	*-1.2%*	*-1.2%*
Cog. skills at 7			0.0%	0.0%	**38.1%**	**38.4%**	***12.9%***	***12.9%***
Non-cog. skills at 7			0.0%	0.0%	-0.3%	-0.5%	*0.5%*	*0.5%*
Inv. at 0-7	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	3.8%	*2.0%*
Parental educ.	8.2%	8.1%	9.7%	23.7%	**30.5%**	**23.8%**	**43.6%**	**45.6%**
Num. siblings	-0.5%	-0.7%	-0.7%	-0.5%	0.0%	-0.2%	0.9%	1.5%
TOTAL	91.1%	91.7%	92.0%	93.1%	93.9%	93.2%	92.4%	93.1%

Note: This version uses the alternative set of investment and school quality measures described in Table 23. Each column displays the share explained by each variable at different levels of mediation. E.g., column 1 accounts only for direct effects of each variable on earnings. Column 2 additionally accounts for indirect effects, where each variable can additionally affect earnings by its effect on educational attainment, etc. Coefficients that are significant at the 10% level are bold.