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Abstract

We estimate a dynamic model of socio-emotional skill development between ages 8-22 for a Peruvian cohort born in 1994. At age 8 there is no wealth gradient, in contrast to cognitive skills. However, by age 12 inequalities emerge and widen through age 19, driven by differential household investments, and cross-productivity with cognitive skills. In early adulthood, we separate socio-emotional skills into two distinct domains – social skills and task effectiveness - that evolve differently, and are differently correlated with risky behaviours such as smoking or taking drugs. Unequal initial household resources perpetuate inequality across generations through cognitive and task effectiveness skills.

Keywords: Human capital, child development, dynamic factor analysis, socio-emotional skills
JEL codes: C38, J13, J24, O15, O54

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1 Introduction

Understanding how inequalities in skills emerge through childhood into adulthood is one of the most important questions for policy in both developed and developing countries. Inequalities appear very early in life and may perpetuate intergenerational differences in income. Economic research on the topic has evolved considerably over the past 25 years, moving from a narrow focus on IQ or cognitive skills, and establishing that the skills which influence earnings are multidimensional in nature. In particular, it has established the importance of socio-emotional skills, such as perseverance or motivation[1] in determining life outcomes such as career, income, marriage and health, beyond the effects of cognitive skills (Heckman and Rubinstein, 2001; Chiteji, 2010; Almlund et al., 2011; Heckman and Kautz, 2012).

Econometric research shows that multidimensional skills development can (and should) be modelled taking into account its dynamic nature (Heckman, 2006, 2007; Cunha and Heckman, 2007; Cunha et al., 2010). This literature has generated important insights into skill formation, including the role of parental investments, the existence of critical periods for skills development when investments are more productive, and the potential 'cross-productivity', between cognitive and socio-emotional skills, where higher skill in one dimension could increase skill in another dimension in future (Heckman et al., 2006). However, most of the evidence on the formation of socio-emotional skills comes from research on developed countries, arguably due to data availability. Understanding these processes and how skills themselves determine social and economic outcomes is equally, or perhaps even more important for developing countries (Roy et al., 2018).

This paper makes three contributions to the literature on skill formation: first, we provide the first evidence from a developing country on socio-emotional skill production throughout the whole childhood into early adulthood, capturing key aspects of the skill development process, building on Cunha et al. (2010); Attanasio et al. (2017, 2020a); Attanasio (2015); Agostinelli and Wiswall (2020). Using data from the Young Lives (YL) study and exploiting recent methodological results for estimating dynamic factor models (Agostinelli and Wiswall, 2020), we consider how socio-emotional skills and cognition develop as a function of parental background and measures of household investment between the age of 8, 12, 15, 19 and 22 years. Second, we exploit the careful design of our dataset in its most recent round (age 22) to disaggregate socio-emotional skill formation during early adulthood into two distinct latent skills which are important for future labour market outcomes; (1) 'social skills' - skills which enable individuals to work with others; and (2) 'task effectiveness'- skills incorporating aspects of conscientiousness, self-efficacy and persistence (or grit). Third, we consider the effect of these two distinct socio-emotional skills on risky behaviours at 22, which have been shown to be predictive of future success.

The literature on human capital production in developed countries has expanded a great deal over the past two decades (see Del Boca et al. (2013) and Almond et al. (2018) for reviews). Within this literature, socio-emotional skills have increasingly been show to play a key role in the developmental

[1]We use the term socio-emotional skills in this paper, though noncognitive is also in common usage in the economics literature. They have variously been referred to as soft, social, psychosocial skills in the economics literature to date, as well as personality traits or social-emotional competencies. We discuss the composition of the measures we use in detail in section 3.

process and later life social and economic outcomes. Heckman et al. (2013) document that the influential Perry pre-school program in the US improved later life outcomes mainly through its lasting effect on socio-emotional skills, and Cunha et al. (2010) find that whilst 16% of the variation in educational attainment among a sample of adults in the US is explained by adolescent cognition, 12% is due to adolescent socio-emotional traits (see also Duckworth et al. (2007); Almlund et al. (2011)).

Analysing how socio-emotional skills are shaped by early circumstances in developing countries is important for expanding the knowledge base to incorporate the majority of the global population, improving our understanding of how the current levels of inequality are generated and persist, as well as how and when inequality can be reduced. Our study context is Peru, a middle-income country with persistent levels of inequality according to World Bank estimates (monetary poverty: 20.2% in 2019; Gini coefficient: 0.44 in 2016). A recent survey of employers in Peru found that despite improvements in access to education, socio-emotional skills are those that employers have most difficulty finding in potential employees (Novella et al., 2019). Similarly, despite great progress in educational attainment in Latin America in recent decades, Cunningham et al. (2016) show that this has not translated into higher workplace productivity, arguing that increases in efficiency in the continent could be realised through improvements in socio-emotional skills. There is a small body of evidence on the effectiveness of interventions aimed at improving socio-emotional skills in low- and middle-income countries from small-scale experiments on older girls or young women (Krishnan and Krutikova, 2013; Ashraf et al., 2020; Edmonds et al., 2020). Relatedly, Alan and Ertac (2018) and Alan et al. (2019) have showed the effectiveness of a larger elementary school-based intervention on the socio-emotional skills of patience and grit (persistence) respectively in Turkey, though for younger children, around the age of ten.

Only three papers to our knowledge estimate the production function for both cognitive *and* socio-emotional skills in a developing country context, however all cover only the period during very early childhood.[2] Notably, two of these (Helmers and Patnam (2011) and Sánchez (2017)) also utilise data from earlier rounds of the YL study, which is one of the few available in developing countries that includes detailed longitudinal information on children and families through childhood. We extend this work by providing new evidence on the production of socio-emotional skills going beyond the period of very early childhood that has been studied previously. Relatedly, Glewwe et al. (2017) provide reduced-form evidence that a range of socio-emotional skills at age 9-12 are predictive of school to work transitions at age 17-21 after controlling for cognitive skills, using a cohort study in China. Our work builds on theirs by formalising the process of socio-emotional skill accumulation, and investigating how its dynamic nature gives way to such relationships.

Our model considers how initial conditions and measures of household investment, cognition and socio-emotional skills interact from the age of 8, and then through ages 12, 15, 19 to our 'final' (adult) outcomes at 22 years. We exploit the multiple measures of each of these dimensions available in the YL data to model skills and investments as latent variables. In turn, parameters of the production functions

[2] Attanasio et al. (2020a) investigate socio-emotional skill development in Colombia aged up to four years; Helmers and Patnam (2011) estimate the technology of cognitive and socio-emotional skill formation in India from ages 8 to 12; and Sánchez (2017) provides estimates for a similar model in Peru, but only from ages 1 to 8. There are a handful of studies which estimate production functions for human capital defined as cognitive skills and/or health in developing countries (e.g Attanasio et al. (2017); Attanasio (2015), Keane et al. (2022)).

are identified using instrumental variables, using assumptions that are standard in the literature (Cunha and Heckman, 2008) regarding the joint distribution of the unobservables and measurement error. Identification comes from the assumption that measurement errors are independent across latent skills and time, which is tantamount to assuming observable measures are only correlated to through latent variables. We also assume that measurement errors are independent of the production shocks. We employ a methodology developed by Agostinelli and Wiswall (2020) which allows us to estimate production functions which build on the current literature by also allowing for non-constant elasticity of substitution between inputs.

Our results show that cognitive skills are the most important determinant of overall (multidimensional) skill development across all stages between the ages of 8 and 19: cognition is not only highly, and increasingly, self-productive over childhood, it is also the driver of socio-emotional skill accumulation. At the same time, somewhat surprisingly, we find that socio-emotional skills do not affect cognitive development at any stage. Our results also suggest that socio-emotional skills are positively affected by investments at all ages. Similarly, cognitive development is affected by investments at all ages. As a result, a socioeconomic gradient in socio-emotional skill emerges between the ages of 8 and 12 and widens over adolescence. We illustrate this result using simulations which show that cash transfer programmes targeting poor families can be an effective tool to reduce these gaps. Interestingly, the largest impact of cash transfers on skills is observed during adolescence (at age 15), suggesting that investments beyond the first 1000 days of life can have large returns. Finally, in an extension of the model that allows for a dynamic relationship between investments and skills, we find that returns to investments differ significantly across the distribution of child skills - investments are most productive for children with low levels of cognitive skill.

We make a contribution to the literature by disaggregating which socio-emotional skills may be useful for future life success. Modelling socio-emotional skills as an aggregate 'bundle' (as we do by necessity between the ages of 8-19) has become commonplace in the economics literature on human capital development, primarily due to limitations in the type of data required to estimate dynamic models of skill accumulation (that we also face). Paired with developments in flexible econometric methods that take account of imperfectly observed skills, this literature has progressed almost independently of the discussion on the definition of socio-emotional skills. Lundberg (2017) notes "a lack of consensus about what non-cognitive (socio-emotional) skills are, and the absence of a consistent set of metrics that can be applied across studies" (p220). In Heckman et al. (2006)'s seminal paper establishing that a low-dimensional vector of latent skills was predictive of life outcomes, just two measures of socio-emotional skills were used: *Locus of Control* and *Self-Esteem*. Whilst this work has spawned a literature that tends to invoke a single factor approach to socio-emotional/non-cognitive skills, the authors note "Since there are many aspects of noncognitive skills – self control, time preference, sociability, and so forth – it is less likely that one trait captures all aspects of these behaviors" (p420). A recent review by Deming (2022) reviews the literature and finds a "lack of understanding about what these [soft] skills are and how to measure or develop them" (p90).

We make a step forward in terms of unpacking this single bundle using the latest wave of the YL study collected at the age of 22 which was designed (by the authors) to allow researchers to investigate a broad range of skills in early adulthood related to labour market readiness (Porter et al., 2020). In the 2016 wave, we expanded the questionnaire to include extra modules to measure socio-emotional skills, whilst building on information collected in previous rounds. Defining and measuring socio-emotional skills is challenging, particularly in developing countries (Laajaj and Macours, 2019; Laajaj et al., 2019). We drew on the most recent literature in both psychology and economics as well as policy (e.g. OECD (2017)), with carefully piloting of the proposed measures. In the earliest rounds YL had collected information on pride/shame, agency, and aspirations for the future. By 2013, the concepts of generalized self-efficacy (Bandura, 2010) and self-esteem (Rosenberg, 1965) as well as peer and parent relations were also included (Yorke and Ogando, 2018). In 2016 we included new measures for Grit (Duckworth et al., 2007), teamwork and leadership (Richards et al., 2002). We also included Conscientiousness and Emotional Stability (Neuroticism) from the "Big five" stable traits/factors of personality (Costa and MacCrae, 1992) given the evidence that several of the Big Five are strong predictors of economic outcomes such as job performance and wages (Borghans et al., 2008; Gensowski, 2018).[3]

From an exploratory factor analysis, we find that at age 22 the range of our measures of socio-emotional skills vary along two distinct dimensions that we label *social skills* and *task effectiveness*. The latent trait we call social skills is correlated with measures of young adults' ability to work in teams, form relationships with their peers and take on leadership roles. Task-effectiveness is measured by indexes of agency: aspects of the ability to act independently and make one's own life choices (Emirbayer and Mische, 1998); self-efficacy: belief in one's own ability to execute tasks that lead to the accomplishment of goals (Bandura, 2010); grit: a measure of perseverance and passion for long-term goals (Duckworth and Quinn, 2009); and conscientiousness, the "tendency to be organized, responsible, and hardworking" (VandenBos, 2007). Social skills, task effectiveness or the indices that contribute to our measures have been linked to a range of social and economic outcomes. For example, Duckworth et al. (2007), Duckworth and Quinn (2009) and recently Alan et al. (2019) have shown grit to be associated with attainment and employment outcomes; Borghans et al. (2008) have shown the predictive power of conscientiousness for outcomes like years of education and job performance; and the Perry Pre-School programme mentioned above (Heckman et al., 2013) targeted social skills such as working with others and resolving conflict. Task effectiveness and social skills relate quite closely to several existing frameworks in the literature. For example, the CASEL framework for Systemic Social and Emotional Learning (Durlak et al., 2015) defines "self-management"[4] and "relationship skills"[5].

We find that the bundles of *social skills* and *task effectiveness* develop differently over early adulthood (ages 19-22). Aggregate socio-emotional skill accumulated by the end of adolescence (age 19) strongly and positively affects both social skills and task effectiveness at 22, however cognitive

[3]YL piloted the Big Five survey prior to the fifth survey round, but found that only Conscientiousness and Neuroticism had construct validity (Porter et al., 2020).

[4]The ability to successfully regulate one's emotions, thoughts, and behaviors in different situations — effectively managing stress, controlling impulses, and motivating oneself. The ability to set and work toward personal and academic goals.

[5]The ability to establish and maintain healthy and rewarding relationships with diverse individuals and groups. The ability to communicate clearly, listen well, cooperate with others, resist inappropriate social pressure, negotiate conflict constructively, and seek and offer help when needed.

skill enters *negatively* into a production function of social skills, suggesting a substitution effect - those with lower cognitive skills may improve their social skills to compensate. We also examine how early interaction with the labour market or higher education might impact on the formation of socio-emotional skills over the same period by including a full vector of time use - time spent in paid and unpaid work, care, leisure, and time studying - as a factor affecting their overall skills, Similar to Keane et al. (2022) on cognition. As with cognition, we find that time use impacts the two domains differently: time spent studying is associated with higher levels of task-effectiveness but hours spent in home production, work or caring for family members has the opposite effect. In contrast, time use has no distinct effect on social skills. By then examining the relationship between skills and risky behaviours, we show that having higher levels of task effectiveness is associated with a reduced probability of having smoked, taken drugs or engaged in gang activity by age 22.

Together, our results suggest that early inequalities in cognitive skills and family background drive the emergence and widening of inequalities in socio-emotional skills, which are in turn important in determining behaviours predictive of future social and economic outcomes. They add to a growing body of evidence on the importance of early conditions in determining the development of human capital, and show that the impact of the family environment goes beyond its effect on cognition to influence young adults' social skills and sense of ability to control their life circumstances.

The remainder of this paper is structured as follows: Section 2 outlines our empirical model of human capital development; Section 3 describes the data we use to estimate this model and presents some descriptive evidence as to income gradients of cognitive and socio-emotional skills; Section 4 discusses the estimates of the model of human capital development between the ages of 8 and 19; Section 5 presents evidence on how socio-emotional skills accumulated over early adulthood and impact risky behaviour ate age 22; and Section 6 concludes with a discussion of our results.

2 An Empirical Model of Skill Development

Our model of skills development follows Agostinelli and Wiswall (2020). We assume that socio-emotional (s) skill is 'produced' over T discrete periods, where T marks the end of childhood and adolescence. Whilst socio-emotional skills are broad and complex, we focus on the evolution of a one-dimensional *aggregate* across the early periods, a simplification that is now the norm in the literature on human capital development (discussed above), and is relaxed in our final period. At the beginning of the period, $t = 0$, the set of initial conditions are a child's human capital, human capital of their parents, and the resources of their family. In subsequent periods $t = 1, .., T$, we assume that the developmental process has two main features: a function governing the development of human capital and another determining how families make investments. The latter of these determines how present (t) human capital of children and parents and family resources determines household investment behaviour, and the former how future ($t + 1$) human capital is determined by the same inputs (except resources) and investments. We assume an identical process for cognitive (c) skill development over the same period. In our data, initial conditions ($t = 0$) are observed at age 8, and the end of childhood and adolescence ($t = T$) at age 19.

In order to capture potential malleability in skills over early adulthood, we then extend this framework by assuming there is some function mapping skills accumulated by the end of adolescence (T) into socio-emotional skills in early adulthood ($T+1$). Given the relative breadth of data we have available in early adulthood, we disaggregate socio-emotional skills along two dimensions: social skills and task effectiveness. We do not model the evolution of cognitive skills over this period as the data we use in our empirical application does not measure cognition in early adulthood ($T+1$). In the data we use to estimate the model, early adulthood ($T+1$) corresponds to age 22.

Finally, as it is not possible to perfectly measure skills, parental human capital or investments, we follow the literature in assuming a measurement system which specifies a relationship between observable data and the underlying latent variables they measure. Throughout, we denote latent human capital of children and parents by $H_{j,t}$ and P_j for $j \in \{s, c\}$ and investments by I_t. Observable measures are denoted by Z_{θ_t} for $\theta_t \in \{H_{s,t}, H_{c,t}, P_s, P_c, I_t\}_{t=0}^{T+1}$. Specifying a measurement system in this way allows us to 'back out' the underlying latent variables to be used as inputs/outputs of the investment and human capital production functions, and has become standard in the literature on human capital development over the past decade (e.g Cunha and Heckman (2007), Cunha and Heckman (2008) Cunha et al. (2010), Attanasio et al. (2017, 2020a); Attanasio (2015)). Next we outline in more detail the five main components of our empirical model: the initial conditions; the production function of socio-emotional and cognitive skills and investment functions between $t = 0$ (age 8) and $t = T$ (19); the production function of socio-emotional skill between T and $T+1$ (22); and the measurement system.

2.1 Initial Conditions

The vector of initial conditions at t=0 - the beginning of a developmental stage - can be written as

$$\mathbf{\Omega} = (\ln H_{c,0}, \ln H_{s,0}, \ln P_c, \ln P_s, \ln Y_0)\,,$$

where $H_{k,0}$ and P_k for $k \in \{s, c\}$ are child and parental stocks of human capital component k respectively, and Y_0 is family income at $t = 0$. Parents' human capital is assumed to be time invariant and are captured by parental stocks of each component of human capital in the initial period. We assume that these initial conditions are jointly normally distributed:

$$\mathbf{\Omega} \sim N(\boldsymbol{\mu}_\Omega, \mathbf{\Sigma}_\Omega)\,,$$

with $\boldsymbol{\mu}_\Omega$ and $\mathbf{\Sigma}_\Omega$ being the mean vector and covariance matrix of the initial conditions respectively. This assumption of joint normality of the latent variables in the initial period does not restrict their subsequent joint distribution - a restriction Cunha et al. (2010) show would implicitly restrict the functional form of the human capital production function.

2.2 Investment

Using a reduced form approximation of a parental investment policy function, we specify investment at time t as

$$\ln I_t = \beta_{1,t} \ln H_{c,t} + \beta_{2,t} \ln H_{s,t} + \beta_{3,t} \ln P_c + \beta_{4,t} \ln P_s + \beta_{5,t} \ln Y_t + \pi_t \quad , \tag{1}$$

where Y_t, $H_{k,t}$ and P_k are as in the vector of initial conditions, and π_t is a shock to investment assumed to be mean zero with variance $\sigma^2_{\pi_t}$ but is not necessarily normally distributed. Using this approximation means abstracting from both parents' preferences and beliefs regarding the production technology and the returns to their investments in children. The cost of this flexibility is that the parameters of this investment function do not have a strict theoretical interpretation.

Considering this, the parental behaviour consistent with values of the parameters in Equation 1 is ambiguous. However, we interpret $\beta_{i,t} > 0$ for $i = 1, 2$ to indicate reinforcement of skills by parents, and $\beta_{i,t} < 0$ for $i = 1, 2$ to indicate skill compensation. Reinforcement is consistent with parents investing more in their child upon realising they have high stocks of human capital, and compensation with parents investing more upon realising the opposite.[6] The parameters $\beta_{i,t}$ for $i = 3, 4$, simply capture how parents' investment decisions are influenced by their own stocks of human capital. If, for example, $\beta_{4,t} < 0$, parents with higher levels of cognitive skill would invest less in their child's development.

We acknowledge that there are a vast range of possible investments that can be made in human capital, and that in the later stages of adolescence children themselves likely begin to play a role in investment decisions. In our estimation of this model, in line with similar studies (Attanasio, 2015; Attanasio et al., 2017) we use measures of investment between the ages of 8-19 that cover expenditure on school resources, nutrition and time spent studying. Although very different, all of these measures are positively associated with one another. Our focus across these ages is to capture some measure of the overall investment-related environment. We treat time use as part of this aggregate investment over these ages given that Peru is a middle-income country in which many families face a high opportunity cost between sending their child to school, encouraging them to spend time on study or needing them to work. In many respects this is similar to parental time-use investments used for example in Cunha et al. (2010) and Del Boca et al. (2013). When children reach age 19 and enter early adulthood, we exploit the added flexibility afforded to us by the data at this age to broaden time-use to incorporate a range of activities that may act as direct determinants of skill accumulation. We discuss the measures of investment in Section 3, and the skill technology we specify between 19-22 below.

2.3 Socio-emotional Capital Accumulation

In periods $t = 1, ..T$, we assume socio-emotional skill in $t + 1$ to be a function of three types of input: children's stocks of skill, parental human capital and investments. Assuming a flexible trans-log form for the production function and considering one general type of investment, I_t, the production function of socio-emotional skill can be written as:

$$\ln H_{s,t+1} = \rho^s_{1,t} \ln H_{s,t} + \rho^s_{2,t} \ln H_{c,t} + \alpha^s_{1,t} \ln P_s + \alpha^s_{2,t} \ln P_c + \gamma^s_t \ln I_t + \eta^s_t \quad , \tag{2}$$

where $H_{k,t}$ and P_k are as in Equation 1, and I_t and η^s_t parental investment and production shocks

[6] Again, a consequence of the reduced form nature of the investment function is that we cannot disentangle realisation from expectations - it might be that parents that perceive returns to investments to be higher in fact invest more.

respectively. The production shock is assumed to be mean zero with variance $\sigma^2_{\eta^s_t}$. This form of the production function allows for self- and cross-productivities in skills, represented by $\rho^s_{1,t} > 0$ and $\rho^s_{2,t} > 0$ respectively. In Appendix A we extend Equation 2 to include an interaction term $(\ln H_{j,t} \times \ln I_t)$ for $j \in \{s, c\}$ to capture complementarity between present stocks of skill and investment.

A key interest in estimating Equation 2 is the role of investments. Attanasio et al. (2020b) show by using YL data in India that investments are endogenous in the production of skills, and that this endogeneity leads to *understating* the role of investments in skill production. We do not explicitly account for this endogeneity here, and focus on the relative role of investments in the developmental process as opposed to specific point estimates of its importance. We also bear in mind when interpreting our results that they likely represent underestimates of the impact that investments might have.

2.4 Socio-emotional Skill and Cognitive Development

To examine how socio-emotional skill affects cognitive development over childhood and adolescence, we specify the same trans-log functional form as in Equation 2 for cognitive development:

$$\ln H_{c,t+1} = \rho^c_{1,t} \ln H_{c,t} + \rho^c_{2,t} \ln H_{s,t} + \alpha^c_{1,t} \ln P_c + \alpha^c_{2,t} \ln P_s + \gamma^c_t \ln I_t + \eta^c_t \quad (3)$$

In the above equation, all parameters have an identical interpretation to their analogues in Equation 2 and the production shock is again assumed to be mean zero with variance $\sigma^2_{\eta^c_t}$. Of particular interest is the level of cross-productivity between socio-emotional skill and cognition, indicated by the sign and size of $\rho^c_{2,t}$. A large, positive value for this coefficient would indicate that socio-emotional skills can have a large influence on cognition, whereas if this parameter close to zero then they have no impact on cognitive development. Given the evidence that cognitive skills are positively associated with a wide range of economic outcomes, estimates of these parameters show the extent to which they can be influenced indirectly through boosting children's socio-emotional skill. In Appendix A we also extend Equation 3 to include an interaction term to capture complementarity between present stocks of skill and investment.

2.5 Socio-emotional Skill Development in Early Adulthood

We extend our analysis of socio-emotional skill accumulation beyond adolescence and into early adulthood at $(T + 1)$. In our data, this corresponds to age 22. We treat this period differently to those between $t = 0, .., T$ - covering the ages of 8-19 - given the divergence of circumstances once individuals reach the age of 18. We extend the model laid out so far in two ways.

First, we depart from discussing socio-emotional skills in the aggregate and assume they develop along different dimensions. As discussed in the Introduction, the survey we are using has been designed precisely for this purpose. Guided by the literature and the data available, we group socio-emotional skills into two dimensions found to be important in determining a range of social and economic outcomes: social skills, and task effectiveness skills. The only study we know of which has attempted to disaggregate skills into multiple dimensions is Glewwe et al. (2017), which extracts two factors for cognitive skills, and three for socio-emotional skills. The measures used are quite different from ours and include internalising and externalising behaviour, self esteem, depression and resilience.

The benefit of this breakdown is threefold. It firstly allows us to understand how specific socio-emotional skills which have been shown as important in the labour market are formed over early adulthood. It also allows us to allow for even more flexibility in the production functions we estimate over this period. In addition, although we do not have complete data on labour market outcomes, it also enables us to analyse how these domains are correlated with intermediate outcomes at over the same period.[7] Doing so with an aggregate index of socio-emotional skill would not allow us to evaluate which of its domains matters and for what. We discuss how this disaggregation allows for additional flexibility when outlining the measurement system in the next subsection. The next section discusses in more detail the measures and framework used to arrive at this disaggregation.

Second, parents can no longer be expected to be the sole 'investors' in children, and experiences at this age diverge considerably - some individuals continue living at home and in full time education, others are working full time either in the world of paid work; are working without pay for their own family; have set up business for themselves; or they are at home either unemployed or raising a family. We therefore do not include an explicit investment input in to the production functions, but rather use their added flexibility at this stage to include aspects of home and labour market experience that might affect the productivity of skill development.

Formally, between T (the terminal period of 'childhood') and $T+1$ (a point in time in early adulthood), we assume that social skills and task effectiveness are formed as a function of both cognition and socio-emotional skill accumulated by the end of adolescence and Total Factor Productivity (TFP), denoted $\ln A_t$. That is, for socio-emotional skill $j \in \{s, t\}$, we assume that:

$$\ln H^{j}_{s,T+1} = \ln A_T + \rho^{s,j}_{1,T} \ln H_{s,T} + \rho^{s,j}_{2,T} \ln H_{c,T} + \eta^{s,j}_{T} \tag{4}$$

The coefficients of the above equation have an identical interpretation to those in Equation 2. The inclusion of the TFP term allows us to capture the productivity of socio-emotional skill accumulation over the period. We define TFP to include:

$$\ln A_T = \ln\left(e^{\alpha_T + \mathbf{x}'_T \boldsymbol{\beta}_\mathbf{T}}\right) = \alpha_T + \mathbf{x}'_T \boldsymbol{\beta}_\mathbf{T}\,, \tag{5}$$

where $\mathbf{x}_T$ is a vector of characteristics which affect the productivity of skill development over the period and α_T represents residual productivity - the extent to which skill production is unexplained by the inputs and characteristics in $\mathbf{x}_\mathbf{T}$. As we discussed in outlining the investment equation, we explicitly model time use as a determinant of skill accumulation here, and include the number hours spent studying, doing paid work, caring for household members and engaging in tasks related to home production in $\mathbf{x}_T$. It is difficult to specify investments between these ages as "children" have become young adults, and many have moved out of the family home or are financially independent. Keane et al. (2022) evaluate the impact of similar vector of time-use on cognitive development in Ethiopia, Peru, India and Vietnam, finding that, when they crowd out school or study time, time spent on domestic

[7] There are some measures of labour market outcomes at age 22, however many are either still in education or have not spent a meaningful amount of time in the labour market.

chores and home production negatively impact on cognition up until the age of 19. Given we are concerned with the evolution of "soft skills" of task-effectiveness and social skills, time-use is arguably even more relevant, as time spent working may arguably improve either of these skills.

2.6 A Measurement System for Unobservables

The inputs/outputs of the production and investment equations - $H_{k,t}$, P_k, and I_t - are unobservable. Often, and in the data we use in this paper, there are only various imperfect measures available with which to analyse how they combine in the process of human capital development. Parameter estimates using these raw measures in such an analysis will suffer from bias induced by their measurement error, however. To exploit the multiplicity of measures and circumvent the issue of measurement error, we assume that observable variables in the data are a linear combination of measurement parameters, the log of latent variables they aim to measure, and measurement error. This allows us to use covariances between observable measures to estimate the model laid out in this section using only variation in their respective latent variables.

2.6.1 The Measurement System Over Childhood and Adolescence

More precisely, for observable measure $Z_{\theta,m,t}$ and unobservable variable $\theta_t \in \{H_{c,t}, H_{s,t}, P_c, P_s, I_t\}_{t=0}^{T}$ we assume that

$$Z_{\theta,m,t} = \mu_{\theta,m,t} + \lambda_{\theta,m,t} \ln \theta_t + \varepsilon_{\theta,m,t} \qquad m = 1, ..., M_\theta \,, \tag{6}$$

where $\mu_{\theta,m,t}$ is an intercept, $\lambda_{\theta,m,t}$ a factor loading, and $\varepsilon_{\theta,m,t}$ a measurement error. The factor loading has a similar interpretation to a regression coefficient in that it indicates how movements in θ_t are observed in $Z_{\theta,m,t}$. Since the latent variables have no location or scale, we impose the normalisations $\lambda_{\theta,1,0} = 1$ and that $E(\ln \theta_0) = 0$ for each $\theta_0 \in \{H_{c,0}, H_{s,0}, P_c, P_s\}$.[8] This anchors its location and scale to that or the normalising measure in that a one unit increase in the latent variable is equivalent to a one unit increase in the normalising measure. Commonly, these restrictions are imposed on the measurement system in each period as oppose to only in the initial period (e.g Cunha et al. (2010), Attanasio et al. (2017)), however Agostinelli and Wiswall (2016) show that doing so can ex-ante restrict the flexibility of the production function and bias estimates of its parameters, and so recent studies have moved away from imposing such restrictions (Attanasio et al., 2020a; Attanasio, 2015).

Only normalising in the initial period also means that multiple measures are not required to identify the measurement parameters in subsequent periods, and that they can be directly estimated as part of the estimation algorithm (which we outline below). In our setting this result is particularly beneficial since we do not have consistent measures across periods. We therefore assume that our aggregate "bundle" of socio-emotional skill grows across periods but that its location and scale remains anchored

[8] For a given observable measure with known measurement mean and factor loading, there are an infinite number of latent distributions - mean and variance - consistent with observing the distribution of the observed measure. Agostinelli and Wiswall (2020) refer to this as a problem of *location and scale*.

to that of the initial normalising measure.[9] We can then directly estimate the extent to which the measures we have in each period capture this bundle of socio-emotional skills. It does mean, however, that we have to impose restrictions on the production functions in order to identify their parameters in each period. We discuss this in more detail below.

In addition to the normalizations on the initial period measurement system, we also assume full independence of the measurement errors:

(1) across alternative measures at a point in time, $Cov(\varepsilon_{\theta,m,t}, \varepsilon_{\theta,m',t}) = 0 \, \forall \, m' \neq m$;

(2) across all measures at all other points in time, $Cov(\varepsilon_{\theta,m,t}, \varepsilon_{\theta,m',t'}) = 0 \, \forall \, m'$ and $t' \neq t$; and

(3) across all latent skills at every point in time, $Cov(\varepsilon_{\theta,m,t}, \theta'_{t'}) = 0 \, \forall \, \theta'$ and t'.

These assumptions are stronger than those required to identify the joint distribution of initial conditions, but are exhaustive for consistent estimation of the investment and production function parameters using the methodology we employ, which we outline at the end of this section.

2.6.2 The Measurement System in Early Adulthood

At $T+1$ we disaggregate socio-emotional skill into two domains: social skills (s) and task effectiveness (t). We therefore specify a new measurement system for latent stocks of these skills. For each socio-emotional skill $H^j_{s,T+1}$ for $j \in \{s, t\}$, we again assume a linear-log relationship between observable measures and latent skill:

$$Z_{H^j_s,m,T+1} = \mu_{H^j_s,m,T+1} + \lambda_{H^j_s,m,T+1} \ln H^j_{s,T+1} + \varepsilon_{H^j_s,m,t} \qquad m = 1, \ldots, M_{H^j_s} \tag{7}$$

To save on notation, we omit the time subscript on stocks of socio-emotional skill j, $H^j_{s,T+1}$ when it is used as a subscript. To identify the measurement parameters of observables and the distributions of latent socio-emotional skills, we impose normalizations on this $T+1$ measurement system identical to those imposed on the measurement system in the initial period. For each $H^j_{s,T+1}$ we centre their distribution around zero and fix one factor loading to be equal to one. That is, for $j \in \{s, t\}$, we impose $E(\ln H^j_{s,T+1}) = 0$ and $\lambda_{H^j_s,1,T+1} = 1$. This again fixes the location and scale of each domain of socio-emotional skill to that of one of its measures. As we are departing from using an aggregate measure of socio-emotional skill as in the T periods of childhood, these restrictions are normalizations as opposed to *re*-normalizations that might bias estimates of the production functions (Agostinelli and Wiswall, 2016).

2.6.3 Measurement Signal and Noise

The form of the measurement system in Equation 6 allows us to straightforwardly decompose the variance of the observable measures in to the portions attributable to the unobservables - the *signal* -

[9]We use "anchoring" here in the standard, classical factor analysis sense that normalising ties the location and scale of the latent variable and normalising measure to one another. This is not the same as the practice of anchoring proposed by Cunha et al. (2010), which is intended to link parameter estimates to cardinal, economic outcomes.

and to measurement error - the *noise*. The signal, $s_{\theta,m,t}$, in each latent variable (θ_t) can be written in terms of the components of Equation 6 as:

$$s_{\theta,m,t} = \frac{\lambda^2_{\theta,m,t} V(\ln \theta_t)}{\lambda^2_{\theta,m,t} V(\ln \theta_t) + V(\varepsilon_{\theta,m,t})},$$

with the noise given by $(1 - s_{\theta,m,t})$. We can estimate both of these measures directly and evaluate how well the observables measure their latent counterparts.

2.7 Empirical Specification and Estimation

2.7.1 Production and Investment Function Restrictions

We estimate Equations 1, 2, 3 and the measurement system across 3 periods of childhood and adolescence. The starting point of the model, $t = 0$, is age 8, and the three period cover the ages of 8-12, 12-15, and 15-19 respectively. In each of these periods, we restrict both the investment and production functions to have constant returns to scale (CRS) which, in Equations 1-3 respectively, requires:

$$\sum_{i=1}^{5} \beta_{i,t} = 1$$

and

$$\rho^k_{1,t} + \rho^k_{2,t} + \alpha^k_{1,t} + \alpha^k_{2,t} + \gamma^k_t = 1 \quad \text{for} \quad k \in \{s, c\},$$

This restriction is, in part, imposed by the available data. Relaxing the CRS constraint would require that we either impose restrictions on the measurement parameters or re-normalise the latent variables in each period. The data we use do not contain any measures that satisfy the assumption of age-invariance which Agostinelli and Wiswall (2020) show is sufficient to relax the CRS assumption, however, and re-normalising in every period would mean repeatedly altering the location and scale of the latent variable.[10] Agostinelli and Wiswall (2016) show that this could unnecessarily restrict the production functions and limit our ability to make comparisons over time: our assumption - as outlined in our description of the measurement system - is that an initial bundle of socio-emotional (and cognitive) skill as measured and normalised in the initial period is propagated through the model, and captured by the measures we subsequently have available.

Agostinelli and Wiswall (2020) are able to relax the CRS assumption due to the presence of an *age-invariant* measure in their data and find that there returns to scale of cognitive production are different from one only between the ages of 5 and 8. Between 8 and 12, however, they are unable to reject that it is constant. Attanasio (2015) use YL data from India in which they also have available an age invariant measure and do not find any evidence that the production functions of health and cognition

[10]Formally, Agostinelli and Wiswall (2020) define a measure as age-invariant between two points in time if, $\mu_{\theta,m,t} = \mu_{\theta,m,t+1}$ and $\lambda_{\theta,m,t} = \lambda_{\theta,m,t+1}$

are not CRS.[11] If the data we use contained a similar measure of, for example, socio-emotional skill then it would be possible to test whether or not the technology is in fact CRS. Faced with trade-off between imposing re-normalisations on the measurement system or restricting the production functions, and due to our interest in the dynamic relationships between the inputs of the developmental process, we choose the latter.

We then estimate the socio-emotional skill measurement system and Equation 4 in period $T+1$, between the ages of 19-22. Here, as a consequence of the normalizations imposed on latent socio-emotional skills, we do not impose the restriction of CRS on the production function and allow its returns to scale to be freely estimated. That is, we only assume:

$$\text{RTS} = \rho^{s,j}_{1,T} + \rho^{s,j}_{2,T} = k > 0 \tag{8}$$

Given the normalizations on the measurement system in this period, we are able to estimate this more general function shown in Equation 4, which also includes a free TFP term. The next subsection provides a simple example of our estimation algorithm and the restrictions we impose on the production functions and/or measurement system, and Appendix A outlines in detail its full application.

2.7.2 Estimating the Model

We estimate the model from 8 until 22 using an algorithm developed by Agostinelli and Wiswall (2020), which, in our application, has three main steps:

(1) Estimating the initial period measurement parameters, and the joint distribution of the initial conditions by exploiting the normalisations and covariances in observable measures.

(2) Estimating the first period investment measurement and structural parameters using instrumental variables (IV), with measures of the initial conditions acting as instruments for one another.

(3) Estimating the first period skill measurement and structural parameters using IV, with measures of initial conditions (except resources) again acting as instruments for one another, and measurements of investments also used as instruments for one another.

We then repeat (2) and (3) for periods 2 and 3, and use the same IV-based method to estimate the functions describing the development of social skills and task effectiveness between 19-22. To see how the algorithm works, consider a simplified model with only child and parental stocks of socio-emotional skill, $H_{s,t}$ and P_s respectively. With three measures of each, and the normalisations that $E(\ln H_{s,0}) = 0$, $\lambda_{H_{s,0},1,0} = 1$, and $E(\ln P_s) = 0$, $\lambda_{P_s,1,0} = 1$ the factor loadings can be recovered as:

$$\lambda_{\theta,m,0} = \frac{\text{Cov}(Z_{\theta,m,0}, Z_{\theta,m',0})}{\text{Cov}(Z_{\theta,1,0}, Z_{\theta,m',0})} = \frac{\lambda_{\theta,m,0}\lambda_{\theta,m',0}Var(\theta)}{\lambda_{\theta,m',0}Var(\theta)} \qquad \text{for } \theta \in \{H_{s,0}, P_s\}$$

[11] They do find that the returns to scale of the cognitive production function was less than one, but conclude that jointly they cannot reject that the process governing the development of health and cognition has CRS. The Indian YL cohort contains the Peabody Picture Vocabulary Test, which Attanasio (2015) use as age-invariant - at all ages, whereas the older Peruvian cohort only has this measure at ages 12 an 15.

With the factor loadings identified and the scale and location of the latent variables fixed, their joint distribution is identified. We then construct the following residual measures:

$$\frac{Z_{\theta,m,0} - \mu_{\theta,m,0}}{\lambda_{\theta,m,0}} - \frac{\varepsilon_{\theta,m,0}}{\lambda_{\theta,m,0}} = \tilde{Z}_{\theta,m,0} - \tilde{\varepsilon}_{\theta,m,0} = \ln\theta_0 \qquad \text{for } \theta \in \{H_{s,0}, P_s\}$$

Substituting the investment function into one investment measurement equation, using the above definition of $\ln\theta_0$, and re-arranging gives a simple reduced form investment equation:

$$Z_{I,m,0} = \mu_{I,m,0} + \lambda_{I,m,0}\big(\beta_{1,0}\ln H_{s,t} + \beta_{2,0}P_s + \pi_0\big) + \varepsilon_{I,m,0}$$

$$Z_{I,m,0} = \mu_{I,m,0} + \lambda_{I,m,0}\big(\beta_{1,0}(\tilde{Z}_{H_s,m,0} - \tilde{\varepsilon}_{H_s,m,0}) + \beta_{2,0}(\tilde{Z}_{P_s,m,0} - \tilde{\varepsilon}_{P_s,m,0}) + \pi_t\big) + \varepsilon_{I,m,0}$$

$$Z_{I,m,0} = \delta_{0,0} + \delta_{1,0}\tilde{Z}_{H_s,m,0} + \delta_{2,t}\tilde{Z}_{P_s,m,0} + \delta_{3,t}\ln Y_t + \nu_0 \quad , \tag{9}$$

where the coefficients $\delta_{i,0}$, $i = 1, 2, 3$ are a mixture of the structural investment and measurement parameters, and ν_0 a mixture of the measurement errors and investment shocks:

$$\tilde{Z}_{\theta,m,0} = \frac{Z_{\theta,m,0} - \mu_{\theta,m,0}}{\lambda_{\theta,m,0}} \quad \text{for} \quad \theta \in \{H_{s,0}, P_s\}$$

$$\delta_{0,0} = \mu_{I,m,0}$$

$$\delta_{i,0} = \lambda_{I,m,0}\beta_{i,0} \quad \text{for} \quad i = 1, 2, 3$$

$$\nu_0 = \varepsilon_{I,m,0} + \lambda_{I,m,0}\big(\pi_0 - \beta_{1,0}\tilde{\varepsilon}_{H_s,m,0} - \beta_{2,0}\tilde{\varepsilon}_{P_s,m,0}\big)$$

Given that the residual measures ($\tilde{Z}$s) are not independent of ν_0, we estimate the parameters of Equation 9 using the alternative measures of socio emotional skills for children and parents as instruments. Under the assumptions that measurement errors are independent of one another and of latent variables, these are valid instruments. The structural parameters can then be recovered using the CRS restriction:

$$\beta_{i,0} = \frac{\delta_{i,0}}{\sum_i \delta_{i,0}} = \frac{\lambda_{I,m,0}\beta_{i,0}}{\lambda_{I,m,0}}$$

Residual investment measures can then be constructed, and the production function of next periods socio-emotional skill estimated in an identical manner. Using a Cobb-Douglas functional form, its analogous reduced form representation is:

$$Z_{H_s,m,1} = \tau_{0,0} + \tau_{1,0}\tilde{Z}_{H_s,m,0} + \tau_{2,t}\tilde{Z}_{P_s,m,0} + \tau_{3,t}\tilde{Z}_{I,m,0} + \upsilon_0 \quad , \tag{10}$$

with

$$
\begin{aligned}
\tau_{0,0} &= \mu_{H_s,m,1} \\
\tau_{1,0} &= \lambda_{H_s,m,1}\rho_0^s \\
\tau_{2,0} &= \lambda_{H_s,m,1}\alpha_0^s \\
\tau_{3,0} &= \lambda_{H_s,m,1}\gamma_0^s \\
\upsilon_0 &= \varepsilon_{H_s,m,1} + \lambda_{H_s,m,1}\left(\eta_0^s - \rho_0^s\tilde{\varepsilon}_{H_s,m,0} - \alpha_0^s\tilde{\varepsilon}_{P_s,m,0} - \gamma_0^s\tilde{\varepsilon}_{I,m,0}\right)
\end{aligned}
$$

Again, we estimate the reduced form parameters in Equation 10 using alternative measures of socio-emotional skill and investment, their validity being based on the assumption that measurement errors are fully independent. The structural parameters can again be backed out by using the assumption of CRS:

$$
\begin{aligned}
\rho_0^s &= \frac{\tau_{2,0}}{\sum\limits_i \tau_{i,0}} = \frac{\lambda_{H_1,m,1}\rho_0^s}{\lambda_{H_1,m,1}} \\
\alpha_0^s &= \frac{\tau_{2,0}}{\sum\limits_i \tau_{i,0}} = \frac{\lambda_{H_1,m,1}\alpha_0^s}{\lambda_{H_1,m,1}} \\
\gamma_0^s &= \frac{\tau_{3,0}}{\sum\limits_i \tau_{i,0}} = \frac{\lambda_{H_1,m,1}\gamma_0^s}{\lambda_{H_1,m,1}}
\end{aligned}
$$

This gives an intuition as to how imposing CRS - and the methodology more generally - facilitates comparisons over time when measures are not consistent and not age-invariant. Intuitively, the restriction scales each of the reduced form parameters by the factor loading of the left-hand-side measure. It is this re-scaling that "adjusts" the reduced form coefficient to remove the effect of having a different scale than the latent variable (which in this first period is defined by the normalising measures). If, however, we had one measure of socio-emotional skill for which we could assume $\mu_{H_s,m,0} = \mu_{H_s,m,t}$ and $\lambda_{H_s,m,0} = \lambda_{H_s,m,t}$ for all $t > 0$, then we could allow the RTS of the socio-emotional skill production function to be free, recovering its structural parameters as, for example,:

$$
\rho_0^s = \frac{\tau_{1,0}}{\lambda_{H_s,m,0}} = \frac{\lambda_{H_1,m,1}\rho_0^s}{\lambda_{H_s,m,0}}
$$

This would also allows us to augment the production functions with a TFP term, recovering it as:

$$
\ln A_t = \tau_{0,0} - \mu_{H_1,m,0} = (\mu_{H_s,m,1} + \ln A_t) - \mu_{H_1,m,0}
$$

In this case, both the nature of the measure and its presence over time would mean this re-scaling does not require direct estimation of the factor loading and measurement mean, and so no restriction must be made on the parameters of the production function.

In estimating the investment and human capital production functions, a choice must be made as to which measures should be used as *lead* measures, i.e as outputs and inputs, and which should be used as instruments. We choose to use the measure that shares the the most variation with the unobserved bundle of skills in each period as a lead measure, and instrument it with others. Appendix A provides a full description of the estimation algorithm, and the next section describes the data and measures we use in more detail.

3 Data and Measures

In our estimations we use data from the Young Lives (YL) longitudinal survey in Peru. The survey was first administered in 2002 to two cohorts of children: 2,052 aged 1 (the younger cohort) and 714 aged 8 (the older cohort).[12] Follow-up surveys have been conducted at ages 5, 8, 12, and 15 for the younger cohort, and 12, 15, 19, and 22 for the older cohort. Although the sample is smaller, we use the older cohort due to the fact it covers adolescence and early adulthood and because there are measures of socio-emotional skills available at all ages.

To select the children, a multi-stage sampling procedure was used. First, 20 clusters (districts) were selected within the country at random, then, within each cluster, a village/town (or a group of villages/towns) and a group of eligible households within each village/town was chosen at random respectively. The sample is representative of all but those in the top 5% of the income distribution (Escobal and Flores, 2008).[13]

The survey provides information on a variety of aspects related to child development, including child and maternal indicators of perceptions, attitudes and aspirations, cognitive test scores, child and maternal anthropometric measures, as well as a wide array of information on child, family and other contextual characteristics.

Attrition in the older cohort sample (14.1% over 15 years, equivalent to an annual rate of 0.9%) is relatively low compared to other longitudinal studies in developing countries. There is evidence that the attrition from the YL survey is not random, with those that remain in the sample more likely to be males, from wealthier households and from urban areas. There is very little evidence, however, that this should induce any bias once household characteristics from the first visit are controlled for (Sánchez and Escobal, 2020).

3.1 Sample Characteristics

Table 1 shows the characteristics of the older Peruvian cohort in the baseline survey and in each sample we use to estimate our model. For example, comparing the age 12 to the age 8 column shows how the estimation sample in our first period differs to the baseline sample. Given the samples in columns

[12]The survey has also been carried out in Ethiopia, India, and Vietnam. As in Peru the younger cohort samples are 2000 in each country, however with 1000 participants the older cohort is slightly larger than in Peru.

[13]There were around 1,818 districts in Peru in 2002. From them, the wealthiest 5% was excluded using information from the Peru Map of Poverty from year 2000.

(2)-(5) are our *estimation* samples, they exclude children with any missing values for the measures we use in these estimations. As mentioned above, attrition is very low in the YL sample so the vast majority of differences in sample sizes across columns comes from missing answers to questions we use in our analysis. One thing to note in the baseline sample (column (1)) is the large mean and standard deviation of household income. This is due to the presence of one large, outlying value. Given that we use monetary measures as proxies for investments, we exclude this one observation from our main analysis so it does not skew our results. For this reason, columns (2) -(5) of Table 1, which contains descriptive statistics on the samples used in our estimations, have significantly lower mean incomes which are much closer to the median. In practice, our results are not change qualitatively by this exclusion.

3.2 Specifying the Measurement System for Unobservables

In each of its waves, the Young Lives survey has detailed information on the developmental, economic, and family circumstances of children. An important feature of the measurement system laid out in Section 2 is that it is *dedicated* - it assumes that observables measure only one latent variable. Given the multi-dimensional nature of socio-emotional skills, and the different measures of its constituents in the YL data, we first verify this structure by using an Exploratory Factor Analysis and drawing on measures that satisfy the properties of Core Self Evaluation (CSE).

In the case of socio-emotional skill measures, we first excluded those which could be viewed as measuring some dimension of socio-emotional skill, but that relied on the evaluation of external circumstances or other people as opposed to the children/adolescents themselves. For example, the data contains a measure of trust, however the items of which it comprises ask children about whether or not "*Most people in the community are honest*", or whether they "*believe the government does what is right for people like me*". We then ensured the remaining observables shared enough variation with which to back out the latent variables. Finally, we grouped measures into those of children's human capital, endowments, and investments and excluded those that loaded heavily on more than on factor, or on the "wrong" factor based on our ex-ante belief about the measure. For example, if a socio-emotional measure loaded heavily on latent cognition it was excluded from our analysis. Below we list the measures of socio-emotional skill, cognition, investments, and endowments we use to estimate the model outlined in Section 2. Appendix B describes the YL socio-emotional measures in full, and Appendix C shows the results of the EFA and discusses in more detail how we narrowed measures to the subset used in our analysis.

Socio-emotional skills: In the initial period, $t = 0$, we use five measures on children's conduct, emotional regulation, hyperactivity, peer relationships and their social skills. The questions are administered to the children's caregiver, and are centered on discerning the number of symptoms of, for example, hyperactivity they display. Similar behavioural indices to these have often been used to identify bundles of early socio-emotional skill (e.g Cunha et al. (2010), Attanasio et al. (2020a)). Thereafter, we use some combination of measures of children's agency, pride, self-efficacy and self-esteem. All of these measures are calculated from children's responses to questions regarding their degree of agreement or disagreement to a number of statements using Likert scales. Prior to its administration, these instruments were piloted and, where necessary, adapted to the local context to

Table 1: Sample characteristics in the age 8 baseline and estimation samples

	(1) *Age 8*	(2) *Age 12*	(3) *Age 15*	(4) *Age 19*	(5) *Age 22*
Wealth index	0.47	0.52	0.58	0.64	0.67
	(0.23)	(0.22)	(0.18)	(0.16)	(0.14)
Household income (USD)	434	284	344		
s.d	(4,937)	(290)	(507)		
Median	160	220	239		
Female caregiver	0.97	0.98	0.96	.	.
Female cohort member	0.46	0.46	0.47	0.47	0.48
Caregiver's education					
None	0.13	0.12	0.11	.	.
Primary	0.38	0.38	0.37	.	.
Secondary	0.37	0.38	0.38	.	.
Technical/Vocational	0.09	0.09	0.10	.	.
University	0.02	0.03	0.03	.	.
Adult literacy	0.00	0.00	0.01	.	.
Dependent children					
None	0.09	0.12	0.18	0.26	0.30
One	0.32	0.33	0.31	0.35	0.39
Between 2 and 4	0.51	0.50	0.47	0.37	0.30
More than 5	0.08	0.04	0.03	0.02	0.01
Language					
Spanish	0.88	0.90	0.88	0.90	0.90
Quechua	0.10	0.08	0.10	0.09	0.09
Other	0.00	0.00	0.00	0.00	0.00
N	714	606	607	571	550

Notes: All numbers are proportions. The sex, education, and age of the caregiver were not recorded at age 19 or 22, nor was the income of the cohort member's household. *Dependent children* refers to the number of children aged between 0 and 17 years in the household of the cohort member. Standard errors for the mean wealth index and household income are in parentheses. For household income, the median value is also shown below the mean and its standard deviation.

they were understood by children (Yorke and Ogando, 2018).

Treating socio-emotional skill as an aggregate in periods 1-3, covering the ages of 8-19, is a constraint imposed mainly by the data as opposed to representing an explicit assumption regarding the dimensionality of socio-emotional skills over this period. This is very similar to many papers in the literature. The majority of the socio-emotional assessments in the YL data are not administered in the initial wave of the YL survey, nor are there multiple measures of particular domains until age 22. As a result, we cannot disaggregate socio-emotional skills until the final period of our model at age 22. At this age we use three measures of each of children's social skills, two of which are sub-scales of the ROPELOC self-evaluation (Richards et al., 2002) scale measuring leadership and teamwork, and one from the Marsh Self-Description Questionnaire Yorke and Ogando (2018) assessing relationships with peers. Task effectiveness skills comprise agency, grit, conscientiousness, emotional stability.

Cognitive skills: For cognitive skill in the initial period we use children's score on a series of Ravens progressive matrices alongside measures of the child's general writing and reading level as assessed through various other assessments. In the periods thereafter, we use combinations of scores on maths and language tests administered as part of the YL survey, and the Peabody Picture Vocabulary Test (PPVT) to measure cognitive skill. Appendix B provides detailed information on the cognitive assessments administered as part of the the Young Lives survey that we use.

Investments: As measures of latent investment, we use caregivers' responses to a number of questions about the material and time investments made in children's development. We use measures of expenditure on books, uniforms and food per child in the household alongside those of the time children spend in school and studying. In using hours of schooling and study we assume that caregivers have an important role in determining how time is allocated to these activities. Again, Appendix B describes all the measures considered and Appendix C describes how they were reduced to a subset for analysis.

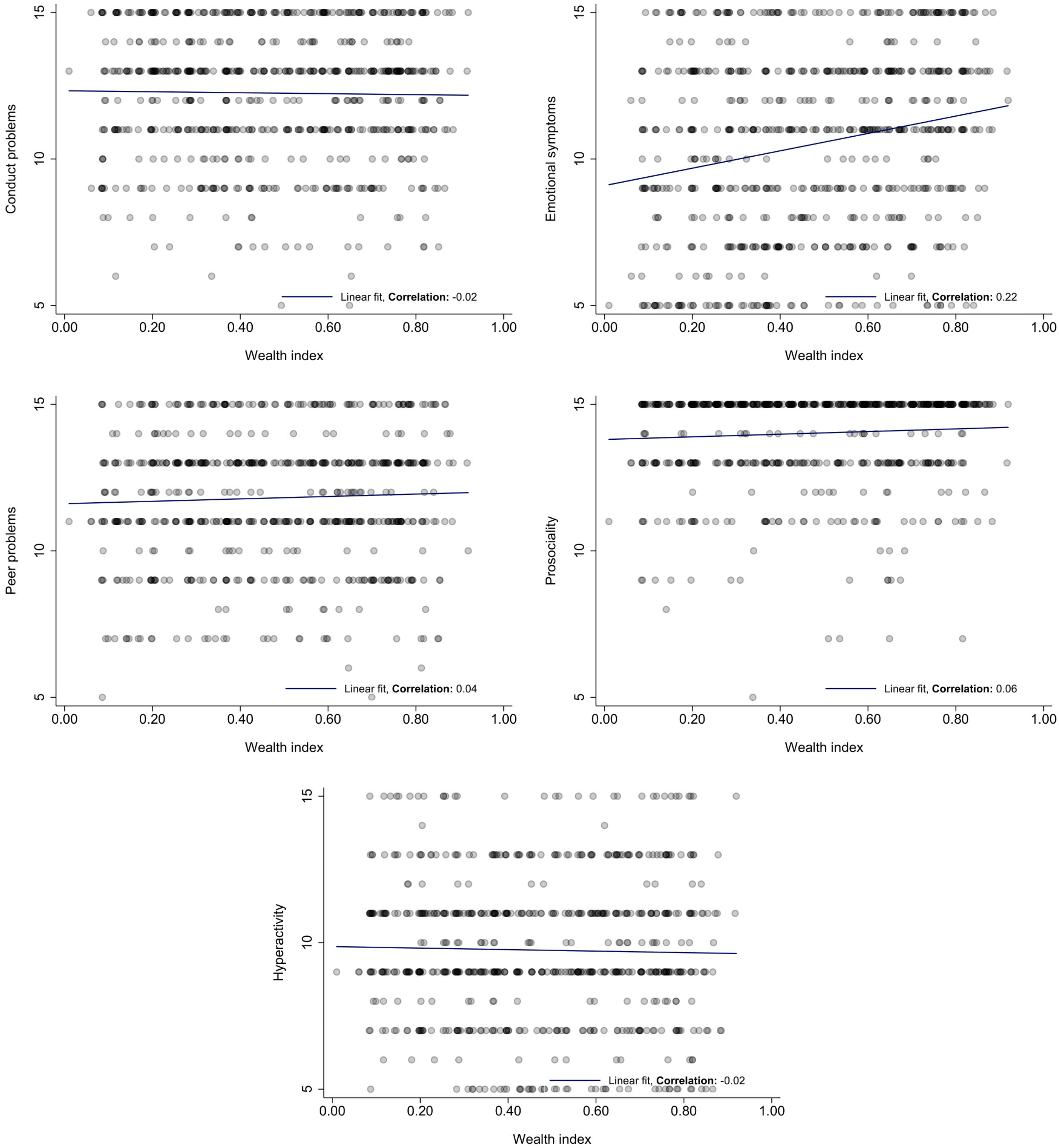
Parental human capital: As measures of cognitive endowments, we use the level of education of the caregiver, an assessment of their ability to understand text written in their native language, and a measure of the degree of difficulty they have reading in general. For socio-emotional skill of the caregiver, we use their responses to questions about their agency, pride and a subjective evaluation of their life circumstances. We use the caregiver as opposed to the mother's and/or father's information for two reasons. Firstly, doing so allows to make use of as much of the sample as possible - for 5% of children their caregiver is not a biological parent. Secondly, measures of socio-emotional skill are available only for the household member recorded as the caregiver, not the parents separately.

Family resources: The YL survey contains household income information for the older Peruvian cohort up until age 15. We use family income as a measure of family resources up until this age. Given there is no information on household income available at age 19, we use the YL wealth index as a measure of family resources at that age. This is a measure of the material resources of the family which ranges from 0 to 1, and is constructed as the average of three sub-indices measuring housing quality, access to services and ownership of a range of durable goods. Briones (2017) describes the construction of the YL wealth index in detail.

3.3 Observable Skill Gradients

Our main interest is the process of human capital development as it relates to the emergence of skill inequalities and the intergenerational transmission of disadvantage. To first look at this question descriptively, we correlate observable measures of socio-emotional skill with the available measures of the economic wellbeing of the YL children. Figure 1 shows the raw correlation between the five available measures of socio-emotional skill at the baseline survey - the measures of conduct issues,

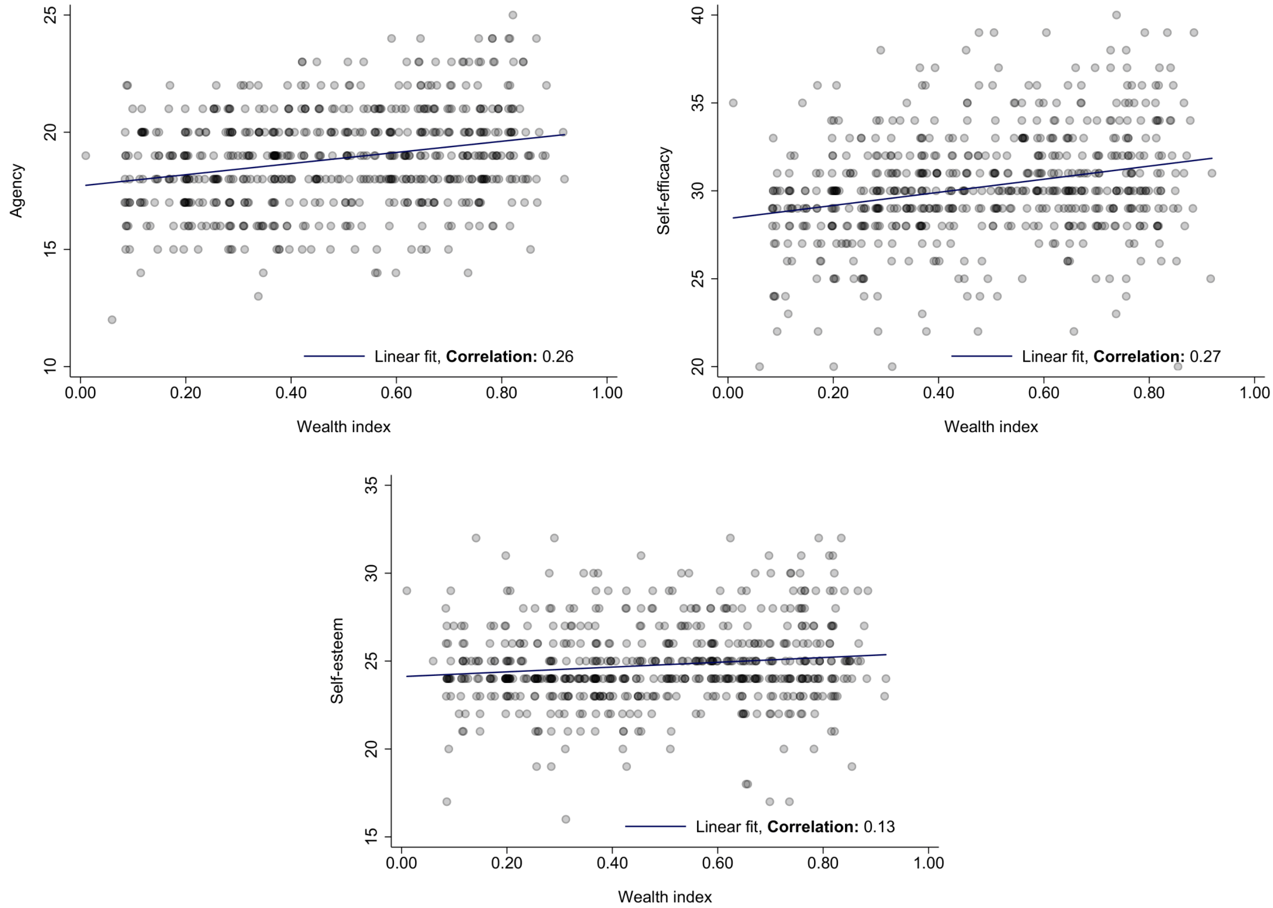
Figure 1: Socio-emotional skill measures and household wealth at baseline (Age 8)



Note: The measures used are described in Subsection 3.2 and Appendix B. The scale of all measures except prosociality have been reversed so a higher value indicates more "skill". The wealth index is constructed to range between 0 and 1 and is an average of three subindices: housing quality, access to services, and ownership of certain consumer durables. See Briones (2017) for further details.

emotional instability, difficulty with peers, prosociality, and hyperactivity - and household wealth. The scale of all of these measures except for prosociality (which is already, in theory, a positive measure) have been reversed to be positive so a higher value means more "skill". Of the five measures, there only appears to be a somewhat moderate positive relationship between the number of symptoms of emotional instability a child displays and wealth. For the other measures their correlation with wealth is very close to zero. As proxied by these measures then, it appears as though there is only a small gradient in children's socio-emotional skill across the distribution of wealth at age 8.

Figure 2: The correlation between socio-emotional skill measures at 19 and initial (age 8) household wealth



Note: The measures of, clockwise from top left, agency, self-efficacy and self-esteem are described in detail in Appendix B. The wealth index is constructed to range between 0 and 1 and is an average of three subindices: housing quality, access to services, and ownership of certain consumer durables. See Briones (2017) for further details.

Figure 2 shows analogous plots, correlating the socio-emotional skill measures we use at age 19 - agency, self-efficacy and self-esteem - with wealth at age 8.[14] Across the measures there is evidence of a moderate, positive relationship with family wealth. The measure of self-esteem has the smallest correlation with wealth at 0.13, whereas both agency and self-efficacy have a correlation of around 0.25. The consistent positive correlation across measures suggests that a wealth gradient in socio-emotional

[14]We use wealth at age 8 for comparability and to focus on the correlation between earlier conditions and later skills skills. Using wealth at age 19 does not in fact alter the results as wealth is persistent across rounds of the YL survey.

skill exists at the end of adolescence. Given that the relationship appears to be stronger than at age 8, there is - at least descriptively - evidence that small gradients apparent in childhood widen over time. The gradients in measures of socio-emotional skills ate age 22 show similar correlations with wealth at age 8 (Appendix Figures C1 and C2).

One of the drawbacks in a descriptive analysis of this nature is that it relies on comparing different measures of aggregate socio-emotional skill over time. From a survey design perspective, this is mainly due to the fact it is often deemed unsuitable to assess certain socio-emotional skills in children at particular ages. For example, it would perhaps make little sense to try and assess the (self-reported) generalised self-efficacy of an 8 year old, or to ascertain the strength of the relationships with their peers. Likewise, it might not be suitable to continue to ask parents about the conduct and hyperactivity of their children when they are aged 19.

Over and above the problems in comparing mis-measured proxies, this adds another complication in descriptively interpreting how socio-emotional skill develops over time. Here, we interpret the descriptive results at a high-level, and, in estimating the model laid out in Section 2, we aim to understand in more detail if and how skill gradients emerge. The availability of different measures across periods is much less of a concern in this analysis given the normalisations on the measurement system, the estimation method we use, and our focus on the development of a composite (or aggregate) measure of socio-emotional skill over childhood.

In Appendix Figure C3 we also show that there is a moderate, positive correlation between the baseline measures of cognitive skill and family resources. Children's level of writing and reading as well as their score in the Ravens math test at age 8 all appear to be increasing with the level of household wealth as measured in the YL. It also appears that the relationship between the cognitive measures and wealth is stronger than in the case of baseline socio-emotional skill measures.

4 Results Over Childhood and Adolescence

4.1 Measurement System

Table 2 shows the estimated socio-emotional skill measurement parameters and the proportion of variance in each measure attributable to signal and noise. It shows that there is heterogeneity in the extent to which observable measures capture variation in latent aggregate socio-emotional skill, both across and within the four periods. For example, in the initial period, at age 8, a reasonable portion of the variance in all five measures is explained by variation in latent socio-emotional skill: three measures are estimated to have roughly a third of their variance attributable to latent skill, and all more than 10%. In the next period, however, the measure of pride has a signal of 87%, compared with a signal of 1.3% in agency. Both social skills and task effectiveness appear to be well measured by observables in period 4, with no measure sharing less than roughly a fifth of its variance with its respective unobservable. This highlights the importance of using a latent factor structure to estimate the skill production functions: using raw measures as inputs/outputs of the production (and investment) functions would mean estimating their parameters without adjusting for bias induced by measurement error.

Table 2: Measurement parameters associated with observable socio-emotional skill

	$\mu_{\theta,m,t}$	$\lambda_{\theta,m,t}$	$s_{\theta,m,t}$	$1 - s_{\theta,m,t}$
Initial (age 8) socio-emotional skill				
Conduct problems*	12.263	1.000	0.363	0.637
Emotional issues*	10.513	1.326	0.329	0.671
Hyperactivity*	9.752	1.070	0.333	0.667
Peer problems*	11.815	0.788	0.225	0.775
Peer pro-sociality	14.013	0.387	0.105	0.895
Period 1 (age 12)				
Agency	6.991	0.032	0.013	0.987
Pride & self-esteem	11.906	1.244	0.865	0.135
Period 2 (age 15)				
Agency	17.920	0.316	0.212	0.788
Pride & self-esteem	22.112	0.280	0.263	0.737
Period 3 (age 19)				
Agency	18.357	1.160	0.479	0.521
Self-esteem	30.342	1.243	0.193	0.807
Self-efficacy	24.841	0.234	0.042	0.958
Period 4 (age 22) social skills				
Leader	9.586	1.000	0.374	0.626
Peers	9.228	1.340	0.562	0.438
Teamwork	22.921	2.427	0.310	0.690
Period 4 (age 22) task effectiveness				
Agency	16.181	1.000	0.189	0.811
Grit	27.393	2.095	0.640	0.360
Conscientiousness	25.428	1.517	0.292	0.708
Emotional stability	33.064	1.504	0.416	0.584

Note:* indicates negative measures that were reversed so a higher value represented a higher level of skill. The initial and periods 1-4 represent ages 8, 12, 15, 19, and 22 respectively. From left to right the columns represent the observable measure and its estimated mean, factor loading, signal, and noise respectively. All parameters are estimated as outline in Appendix A.

Section 2 highlighted that the estimation algorithm we use requires selecting "lead" measures of skill to be used as inputs/outputs of the investment and production equations, while others are used as instruments. Although this was partly determined by our EFA of the measures (outlined in Appendix C, Table C4) Table 2 confirms our selections - in periods 1 and 2 we used pride & self esteem as lead measures and in period 3 agency. In estimating the investment production functions we exploit only the signal in each observable measure, however there would be efficiency gains if measures consistently shared, for example, two thirds of their variance with latent skill. This has direct implications for the precision of our parameter estimates during periods in which measures are noisy - if observable measures have little shared variation attributable to latent socio-emotional skill, our estimates of the production and investment parameters will imprecise. Given that we use an IV strategy to estimate the production and investment functions, measures having little shared variation - and so being weak instruments - also has implications for consistency. In period 2, for example, the measure of children's agency is used as an instrument, and shares only 1% of its variation with latent skill. In all other periods, the relationship between latent skills and measures appears sufficiently strong.

Table 3 shows the measurement parameters and signal/noise proportions associated with measures of cognitive skill, parental human capital and investments. Again, the Table shows the extent to which observable measures share variance with their respective latent variable varies both within and across periods. Measures of cognitive skill - for both the child and caregiver - tend to have relatively large portions of their variance explained by latent cognition. There are larger differences in signal across measures for investments parental socio-emotional skill, however, again highlighting the importance of accounting for measurement error in observable measures.

Table 3: Measurement parameters associated with observable cognitive skill, parental human capital and investment

	$\mu_{\theta,m,t}$	$\lambda_{\theta,m,t}$	$s_{\theta,m,t}$	$1 - s_{\theta,m,t}$
Initial (age 8) cognitive skill				
Ravens test score	20.822	1.000	0.135	0.865
Writing level	2.418	0.190	0.631	0.369
Reading level	3.582	0.236	0.521	0.479
Period 1 (age 12)				
PPVT score	72.729	9.026	0.583	0.417
Writing level	2.840	0.132	0.251	0.749
Reading level	3.938	0.098	0.167	0.833
Maths test score	5.742	1.062	0.620	0.380
Period 2 (age 15)				
PPVT score	97.137	16.289	0.656	0.344
Cloze language test score	14.749	4.282	0.562	0.438
Maths test score	13.764	4.658	0.490	0.510
Period 3 (age 19)				
Language test score	67.531	15.351	0.751	0.249
Maths test score	59.656	17.959	0.659	0.341
Parental socio-emotional skill				
Agency	12.974	1.000	0.079	0.921
Pride	8.297	1.214	0.375	0.625
Subjective wellbeing	4.848	0.961	0.072	0.928
Parental cognitive skill				
Caregiver's education	7.251	1.000	0.533	0.467
Literacy (first language)	2.502	0.198	0.693	0.307
Understands paper	2.604	0.163	0.571	0.429
Period 1 (age 12) investment				
No. food groups consumed	21.569	2.702	0.433	0.567
School uniform expenditure	62.311	66.103	0.150	0.850
Hours at school	4.741	0.597	0.168	0.832
Hours studying	2.857	0.197	0.032	0.968
Book expenditure	127.540	98.787	0.117	0.883
Period 2 (age 15)				
No. food groups consumed	24.000	3.465	0.332	0.668
School uniform expenditure	186.408	84.414	0.209	0.791
Hours at school	6.514	1.233	0.199	0.801
Hours studying	2.523	0.946	0.278	0.722
Book expenditure	216.107	129.214	0.227	0.773
Period 3 (age 19)				
Hours at school	3.587	1.507	0.323	0.677
Hours studying	1.403	0.754	0.236	0.764
No. food groups consumed	8.496	-0.237	0.015	0.985
Non-food expenditure	616.067	250.154	0.026	0.974
Education expenditure	728.966	615.501	0.239	0.761

Note: Parental human capital is assumed to be time invariant so are measured at only one point in time. From left to right the columns represent the observable measure and its estimated mean, factor loading, signal, and noise respectively. All parameters are estimated as outlined in Appendix A. All expenditure variables are per dependent child in the household.

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4.2 The Determinants of Investment

Table 4 shows the estimates of our investment function parameters through childhood and adolescence. There is no strong evidence of reinforcement or compensation at any stage. Although there is a compensatory effect with respect to cognition in the first period, its 90% confidence interval marginally covers zero and so we fail to reject that it is equal to zero. The elasticities of investment with respect to cognitive and socio-emotional skill are small and are not statistically different from zero in any other period. It therefore appears that in our sample, parents do not invest in response to revealed human capital. This is broadly in line with findings in studies in similar settings, where there is limited evidence of household investment responding to child stocks of human capital. Attanasio et al. (2017, 2020a); Attanasio (2015) find some evidence of investments' responsiveness to cognitive skill in childhood, but very little of any parental response to revealed health or socio-emotional capital. Whilst Attanasio et al. (2020a); Attanasio (2015) focus mostly on earlier periods of childhood (until 12 and 4 years respectively), the results of Attanasio et al. (2017), who estimate investment functions up until the age of 15, overlap with the analysis in our earlier periods.

We do find that parental socio-emotional skill has a large impact on parental investment behaviours, particularly between the ages of 8-12 and 12-15. Their effect is similarly large but not statistically different from zero between the ages of 15-19. Although using data from the US, Agostinelli and Wiswall (2020) find similarly large impacts on investment of parents' socio-emotional relative to cognitive skill, whereas Attanasio et al. (2020a) find the reverse in Colombia albeit at much younger ages. Family resources are estimated to strongly determine investments to an increasing degree in each period.[15] We also find that the variance of the production shock is decreasing over time, suggesting that in later adolescence, there are fewer external factors over and above income (and the other inputs) that explain household investments.

4.3 Skill Production in Childhood and Adolescence

We first present estimates of restricted Cobb-Douglas production functions for both socio-emotional and cognitive skill. In terms of Equations 2 and 3, this means estimating the production functions excluding the interaction of investments with human capital. We then estimate versions of the production function with interactions between skills and investment in order to test whether or not any complementarities exist between them.

Socio-emotional skill

In table 5 we show estimates of the Cobb-Douglas production function for socio-emotional skill up to age 19. First focusing on the role of lagged human capital, we find some evidence of self-productivity in late childhood, between 15-19, but not in the earliest stage. We also find evidence of cross-productivity between cognitive skill and socio-emotional skill in all periods, however in period two, when it is at its

[15] In the last period we use a wealth index, not family income, as a proxy for family resources. This is because Family income is not available for age 19 in the YL survey. We use income in the first two rounds due to its ease with which its elasticity can be interpreted. Using the wealth index in each period does not change the results of Table 4 qualitatively.

Table 4: Estimates of investment function parameters

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Human capital			
$\ln H_{s,t}$	-0.023	0.028	-0.017
	(0.097)	(0.193)	(0.026)
	[-0.183,0.137]	[-0.290,0.345]	[-0.061,0.026]
$\ln H_{c,t}$	0.110	0.027	-0.021
	(0.077)	(0.132)	(0.275)
	[-0.017,0.238]	[-0.190,0.245]	[-0.474,0.432]
Parental human capital (fixed over time)			
$\ln P_s$	0.563**	0.398*	-0.022
	(0.241)	(0.220)	(0.212)
	[0.166,0.960]	[0.035,0.761]	[-0.371,0.327]
$\ln P_c$	-0.019	0.002	0.069
	(0.064)	(0.039)	(0.067)
	[-0.124,0.087]	[-0.061,0.066]	[-0.041,0.180]
Resources			
$\ln Y_t$	0.368***	0.545***	0.991***
	(0.130)	(0.199)	(0.341)
	[0.154,0.582]	[0.217,0.872]	[0.430,1.552]
$\sigma^2_{\pi_c}$	2.34	3.33	.0183
N	603	596	579

Notes: Standard errors are in parentheses and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, and 19 for the three columns respectively. The output in each column is investment. The inputs in the left column are are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and family income, respectively. In period 3 (ages 15-19) the we use the YL wealth index as a proxy for family income as this information is not available. The wealth index is a measure of the material resources of the family which ranges from 0 to 1, and is constructed as the average of three sub-indices measuring housing quality, access to services and ownership of a range of durable goods. See Briones (2017) for detail. All inputs except of family income are treated as unobservable. The observables used as measures of each and their associated measurement parameters estimated from the measurement system outlined in Section 3 are provided in Appendix B.

largest, then it is estimated imprecisely. Although smaller in magnitude in the first period, cognition plays an important role on the development of socio-emotional skill given there is no evidence of self-productivity in this period. Together, these results suggest that cognition is a key actor in the development of socio-emotional skill across childhood. These findings are similar to those of Helmers and Patnam (2011), who use YL data from India for ages 8 to 12 and find that cognitive skills influence socio-emotional skill accumulation to a greater extent than lagged stocks of themselves. However, they contrast slightly with Cunha et al. (2010), who use data from the US and find socio-emotional skill to be unaffected by cognitive skill in both early and late childhood, and to be increasingly self-productive over time between the birth and the age of 14.

It should be noted that Cunha et al. (2010) study human capital development in a sample of children in the US, whereas our sample is from Peru, a developing country. Given that, to our knowledge, there are no other studies that estimate socio-emotional production functions over an extended period similar to our study (Helmers and Patnam (2011) analysis overlaps only with period 1 in our model), it is conceivable that the developmental process differs in these two settings due to country and/or sample specific factors. It should also be considered throughout this section that Cunha et al. (2010), and indeed all other similar studies, do not necessarily use measures that identify an identical composite socio-emotional skill as here.

Moving to the role of parental human capital, there is not consistent evidence of their influence on socio-emotional development other than in the first period, between the ages of 8-12. We estimate that parents' cognitive skill has little effect on on the production of socio-emotional skill except in the last period, between 15-19, where it is estimated they have a small negative impact on skills. In the first period, between 8-12, children's skill is highly malleable with respect to parental socio-emotional skill - its corresponding elasticity is estimated to be 0.58. The results in Table 5 also show that investments strongly, positively affect socio-emotional skill in all periods to roughly the same extent - the estimated elasticities are 0.21, 0.24, and 0.2 respectively. Only in the first period, however, is this effect estimated with real precision - the same period in which skills are being influenced by parents' socio-emotional skill and early cognition. In the second period, the estimated 90% confidence interval comfortably straddles zero, and in the last it does so marginally. We note here that throughout this section we do not necessarily interpret the estimates of large confidence intervals as strong evidence of absence of an effect for any input. Our sample size is relatively small in comparison with other similar studies, and, as Table 2 shows, our measures of socio-emotional skill are sometimes noisy. These two features of our data might then manifest in noisy parameter estimates.

To explore whether or not these effects differ across the distribution of cognitive and socio-emotional skill, Appendix Tables C9 and C10 show the estimated production function parameters when an interaction of cognitive and socio-emotional with investment is included respectively.[16] We include the interactions separately rather than in the same equation due to the small size of our sample and the high-degree of collinearity between inputs induced by their inclusion, a common problem when estimating trans-log production functions.[17] We estimate that investments in the initial period are

[16]See equation A1 in Appendix A.

[17]Collinearity is also a concern due to the estimation method we use, which relies on instrumental variables. The estimation algorithm is outlined in detail in Appendix A

Table 5: Estimates of Cobb-Douglas socio-emotional production function parameters

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	-0.062	0.028	0.073***
	(0.084)	(0.844)	(0.024)
	[-0.200,0.077]	[-1.360,1.415]	[0.034,0.112]
$\ln H_{c,t-1}$	0.233**	0.818	0.705***
	(0.114)	(0.745)	(0.207)
	[0.046,0.421]	[-0.407,2.044]	[0.365,1.046]
Parental human capital (fixed over time)			
$\ln P_s$	0.577***	-0.187	0.091
	(0.147)	(1.041)	(0.193)
	[0.335,0.820]	[-1.900,1.525]	[-0.226,0.408]
$\ln P_c$	0.039	0.104	-0.068*
	(0.076)	(0.201)	(0.041)
	[-0.086,0.164]	[-0.226,0.434]	[-0.136,-0.001]
Investments			
$\ln I_{t-1}$	0.212***	0.237	0.199
	(0.076)	(0.379)	(0.129)
	[0.087,0.338]	[-0.386,0.861]	[-0.013,0.410]
$\sigma^2_{\eta_n}$	1.5	13.9	.833
N	601	600	565

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, 15, and 19 for the three columns respectively. The output in each column is socio-emotional skill. The inputs in the left column are are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment. All inputs are treated as unobservable. The observables used as measures of each and their associated measurement parameters estimated from the measurement system outlined in Section 3 are provided in Appendix B.

decreasing in children's cognitive skill in Table C9, but there is no evidence of any complementarity in any other period. There is a large negative interaction effect in the last period, however we cannot reject that it is equal to zero. From Table C10, we infer that there are no strong interaction effects with respect to socio-emotional skill. This is in spite of there a being statistically significant interaction effect in the first period, as the point estimates and precision of the skill elasticities are sensitive to the inclusion of the interaction terms. This is unsurprising given the the noise with which self-productivities were estimated, and the relatively low level of variation in socio-emotional measures relative to cognitive measures which leaves them more likely to introduce collinearities when used as interactions. We therefore do not draw any conclusions from Table C10.[18]

Turning finally to the estimated role of shocks to production, we find that their variance increases between the first two periods and then decreases significantly in late adolescence. This suggests that factors other than the inputs in Table C10 impact the socio-emotional development most between the ages of 12-15 and that by the final period, between 15-19, there is relatively less external factors influencing socio-emotional development. In the middle period covering ages 12-15, however, the variance of the shocks increases substantially. Given the imprecision of the estimates between these ages, this is perhaps unsurprising. It is likely that socio-emotional skill development across this period is somewhat more malleable to external factors.

Cognitive skill

Table 6 shows analogous estimates to those in 5 for the production function of cognitive skill. In line with the much of the skill development literature, we find strong self-productivity in cognitive skill that is increasing over time (e.g Cunha et al. (2010), Helmers and Patnam (2011),Agostinelli and Wiswall (2020),Attanasio et al. (2017, 2020a); Attanasio (2015)). We cannot reject zero cross-productivity in any period, however. Again, these results are comparable with studies that find little or small effects of socio-emotional skills on cognition (e.g Cunha et al. (2010), Helmers and Patnam (2011) and Attanasio et al. (2020a)).

For parental human capital, we find a strong positive effect on socio-emotional skills in the initial period. The elasticity is estimated to be of roughly the same magnitude as in the production of socio-emotional skills, suggesting that parental socio-emotional skill plays a larger role in the early development of both skills in our sample. We do not estimate any large role for parental cognitive skill, however. We also find that investments influence cognitive development in all periods to a similar extent. The variance of production shocks is largest in the last period, however it is small and broadly similar in all periods, suggesting that cognitive production is influenced by little other than the inputs at any stage.

In Tables C11 and C12 we provide estimates of the production function with interactions of investment with cognition and socio-emotional skill respectively.[19] There is a large, negative interaction effect between cognition and investments in the first and last periods in Table C11 , meaning that

[18]It is also caused by features of the estimation method that, in its present application, mean calculating the non-linear combinations of coefficients that have 1) been affected by the inclusion of the interaction and 2) are already estimated imprecisely.

[19]See equation A2 in Appendix A.

Table 6: Estimates of Cobb-Douglas cognitive production function parameters

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	0.048	-0.033	0.016
	(0.075)	(0.114)	(0.012)
	[-0.075,0.172]	[-0.220,0.154]	[-0.005,0.036]
$\ln H_{c,t-1}$	0.361***	0.595***	0.927***
	(0.089)	(0.079)	(0.095)
	[0.214,0.508]	[0.466,0.724]	[0.770,1.084]
Parental human capital (fixed over time)			
$\ln P_s$	0.366***	0.205	-0.039
	(0.133)	(0.143)	(0.079)
	[0.147,0.585]	[-0.031,0.440]	[-0.169,0.092]
$\ln P_c$	0.048	-0.016	-0.018
	(0.050)	(0.026)	(0.021)
	[-0.034,0.130]	[-0.058,0.026]	[-0.052,0.016]
Investments			
$\ln I_{t-1}$	0.177***	0.249***	0.114***
	(0.051)	(0.085)	(0.043)
	[0.093,0.260]	[0.109,0.390]	[0.043,0.185]
$\sigma^2_{\eta_c}$	.058	.0771	.142
N	597	594	551

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, 15, and 19 for the three columns respectively. The output in each column is cognitive skill. The inputs in the left column are are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment. All inputs are treated as unobservable. The observables used as measures of each and their associated measurement parameters estimated from the measurement system outlined in Section 3 are provided in Appendix B.

investments are more productive in children with low stocks of cognitive skill. In the last period, however, this effect is not statistically different from zero. In Table C12 there is a large positive interaction effect between investments and socio-emotional skill in the second period, which would suggest that across the period investments have higher returns in high-skilled children. The 90% confidence interval of this interaction contains zero, however.

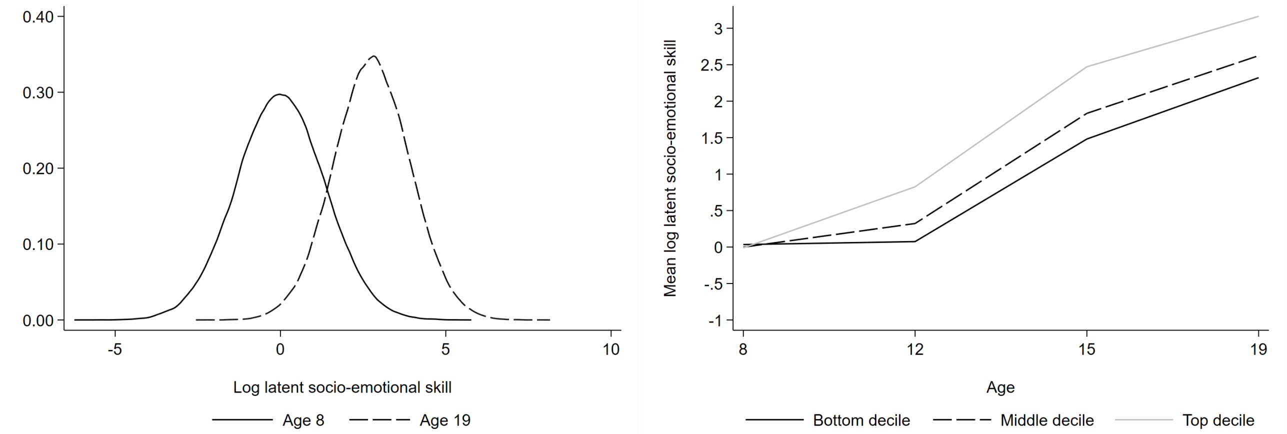
4.4 The Implications of the Estimated Model

Together, the results of this section suggest that inequality in socio-emotional skill arises through i) the impact of family investments and ii) its cross-productivity with cognition. To understand the implications of our results more concisely, we simulate the distribution of socio-emotional skills over time to analyse how they develop across the income distribution. To do so we first draw 100,000 synthetic observations from the estimated joint distribution of initial conditions, estimates of which are shown in Appendix Tables C7 and C8. From the estimated investment parameters we then forward simulate household investment in the initial period and, subsequently, socio-emotional (and cognitive) skills in period 2. Repeating this process for periods 2 and 3 then simulates the full developmental path of skills between the ages of 8 and 19.

Figure 3 shows this simulated distribution of socio-emotional skill over time from two perspectives. Panel (a) plots its marginal distribution at the age of 8 and 19. Over time, the distribution becomes slightly narrower, suggesting the the overall dispersion of of socio-emotional skill declines with age. Panel (b) plots the mean level of log latent socio-emotional skill at each age, and shows that the relationship between income and and skills strengthens over time, however. At age 8, the mean level of skill is approximately zero among those in the bottom, middle and top deciles of the income distribution, suggesting little-to-no relationship between income and skills. This is in line with the low correlations between the two presented in Figure 1. By age 12, however, a small gap opens up and those in the top decile of the income distribution have a higher level of skill on average than those in the bottom (or middle) decile. This then persists and widens slightly over time, and results in a clear income gradient in socio-emotional skills at age 19. Figure 3 makes it clear that whilst the overall dispersion of skills reduces over time in the sample, by age 19 they are strongly tied to income as a result of the estimated developmental process.

To assess the implications of our results for policy we also simulate the impact of an anti-poverty programme on socio-emotional skills. In our model, cash transfers affect skills through parental investments. We calibrate the size of the transfer to replicate the impact of JUNTOS, the national cash transfer programme for poor families in Peru, and consider the impact of a one-shot cash transfer to families. Figure 4 (left) shows the distribution of socio-emotional skills at age 8 and 19, also obtained from 100,000 synthetic observations from the estimated joint distribution of initial conditions. We also show the impact of a one-shot transfer to poor families at age 15 (the age period in which household income has the largest impact on parental investments) on socio-emotional skills. As expected, the transfer shifts the skills distribution for poor families to the right, though the push is not sufficient to reach the level of skills in the average family. Figure 4 (right) confirms that a one-shot cash transfer has its largest impact on socio-emotional skills when made at age 15, however this is not the case for cognitive skills, which are more sensitive to cash transfers made at age 12.

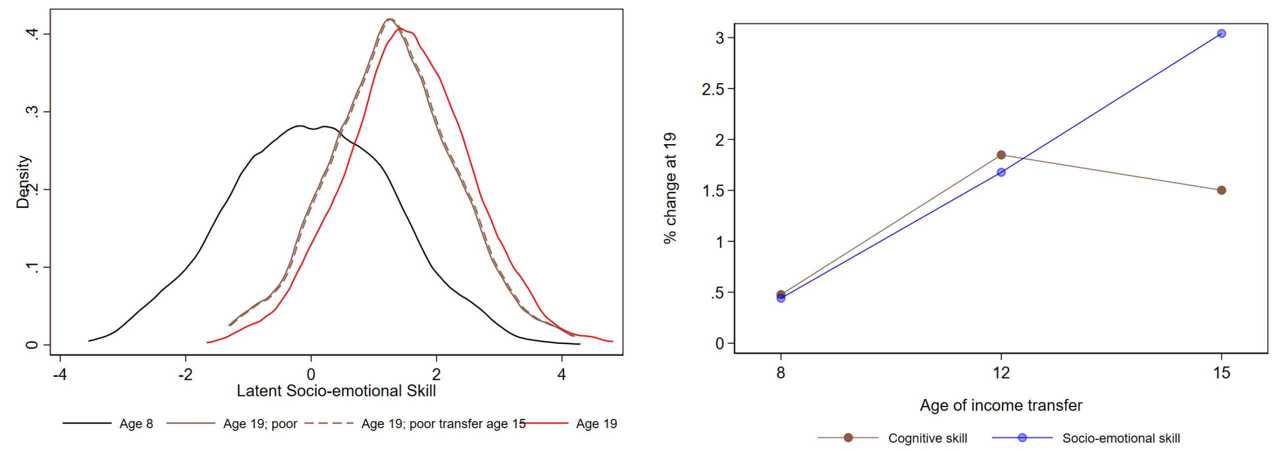
Figure 3: The Simulated Distribution of Socio-emotional Skill Over Childhood



(a) Marginal distribution of socio-emotional skill at age 8 and 19 **(b)** Mean stocks of socio-emotional skill over time across the income distribution

Note: Panel (a) the simulated distribution of socio-emotional skill at age 8 and 19, and panel (b) shows the simulated evolution of mean latent socio-emotional skill in the bottom, middle and top deciles of the income distribution. Both were estimated by simulating the developmental path of 100,000 observations randomly drawn from the estimated initial conditions.

Figure 4: The Simulated Impact of a Cash Transfer Programme on Socio-emotional Skill



(a) Marginal distribution of socio-emotional skill at age 8 and 19 **(b)** Effect on skills based on time of transfer

Note: Panel (a) shows the simulated distribution of socio-emotional skill at age 19 with and without a cash transfer for poor families at age 15, equivalent to 25% of household income, similar to the size of JUNTOS transfer. Panel (b) shows the simulated overall impact of the same cash transfer made at ages 8, 12 and 15 on skills.

5 Results Over Early Adulthood

With the results of the previous section in mind, we now move to estimates of how socio-emotional skills develop across early adulthood, and how they affect the likelihood of engagement in risky behaviour.

5.1 Production Function Estimates for Socio-emotional Skills

Table 7 shows estimates of the production functions of two disaggregated domains of socio-emotional skill between the ages of 19 and 22: social skills (column 1) and task effectiveness (column 2). The production functions estimated here - shown in Equation 4 - include TFP and allow the RTS to be freely estimated.

The estimates show that over early adulthood, the stock of socio-emotional skill accumulated by the end of adolescence has a strong, positive impact on both social skills and task effectiveness, to a similar extent. Cognition is cross-productive in the development of task effectiveness, however the opposite is true for social skills: over the period, a 1% increase in cognition associated with roughly a 0.41% *increase* in task effectiveness, but a 0.47% *decrease* in social skills. This suggests a level substitution for low cognition - individuals with lower levels of cognitive skills may develop higher social skills to compensate.

Moving to the vector of time-use included in TFP, we estimate that no allocation of time has an impact on the accumulation of social skills over early adulthood. However, in the case of task effectiveness, the coefficients on all of the time-use factors are are estimated to be significantly different from zero, although in different directions. Specifically, the number of hours in paid work, caring for household members, and carrying out tasks related to home production negatively affects task effectiveness, whereas time spent studying outside of any formal education has a strong positive impact on its development over and above the effect of cognitive skill. The varying effect of skills and time-use highlights the importance of disaggregating skills along different domains. When aggregating measures of different facets of socio-emotional skills into one composite index, the effects of inputs will be either averaged across domains, or skewed to the the sign and size of one domain that has a disproportionate signal. This would mean overlooking differences in the in the ways different domains of skill develop, such as those we find in Table 7.

There are also differences in the returns to scale of the skill production functions. For social skills, the technology is estimated as having decreasing returns to scale, suggesting, for example, that doubling socio-emotional skills and cognition at the end of adolescence would result in only around a 50% increase in social skills. The technology for task effectiveness, however is estimated to have a RTS of roughly 1.3, and its corresponding 90% confidence interval only marginally contains 1. This would suggest that that the same doubling of inputs would lead to a 130% increase in task effectiveness at age 22. The variance of the shocks is also larger for task effectiveness suggesting there are more external factors influencing its development relative to social skills and that task effectiveness is more malleable than social skills over early adulthood.

As an illustration to understand the implications of the model on skills at age 22, in Figure 5

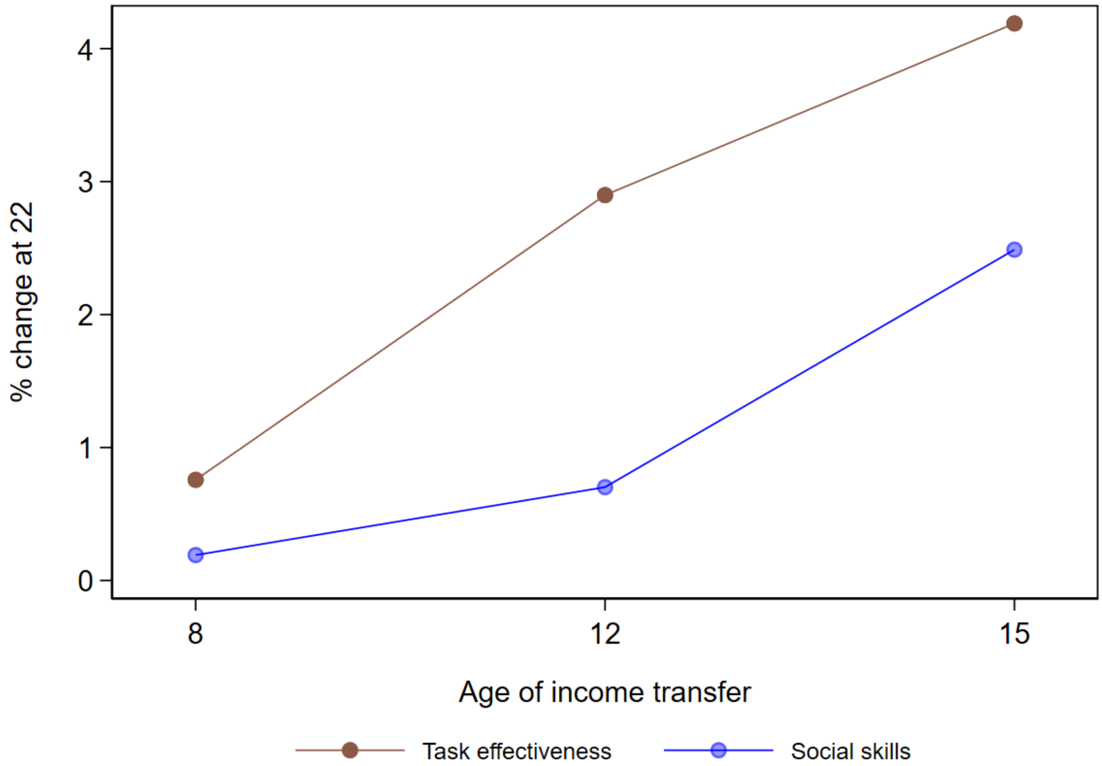
Table 7: Estimates of socio-emotional production functions in adulthood

	(1) *Social skills*	(2) *Task effectiveness*
Lagged human capital		
$\ln H_{s,t-1}$	0.933***	0.892***
	(0.136)	(0.199)
	[0.709,1.157]	[0.565,1.219]
$\ln H_{c,t-1}$	-0.473***	0.413**
	(0.123)	(0.196)
	[-0.675,-0.271]	[0.091,0.735]
Total Factor Productivity ($\ln A_T$)		
Hours studying	-0.070	0.707***
	(0.112)	(0.132)
	[-0.255,0.115]	[0.490,0.923]
Hours working	-0.015	-0.078**
	(0.028)	(0.032)
	[-0.061,0.031]	[-0.130,-0.026]
Hours caring	-0.019	-0.122***
	(0.030)	(0.044)
	[-0.068,0.031]	[-0.194,-0.049]
Hours home production	-0.009	-0.100***
	(0.036)	(0.030)
	[-0.069,0.051]	[-0.149,-0.051]
α_T	-0.095	-1.311***
	(0.477)	(0.470)
	[-0.879,0.690]	[-2.084,-0.538]
Returns to scale	0.460***	1.305***
	(0.143)	(0.185)
	[0.224,0.696]	[1.000,1.610]
$\sigma^2_{\eta^j_s}$	.555	1.2
N	550	550

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. T = age 19 in each column. The left column contains lagged child socio-emotional skill and cognitive skill; the variables included in $\ln A_T$; residual productivity α_T; and the estimates Returns to Scale (RTS). Lagged human capital is treated as unobservable. The observables used as measures for each are described in Appendix B. Appendix A outlines the method used to obtain all estimates in the table.

we revisit the impact of a one-shot cash transfer similar in magnitude to the national cash transfer programme in Peru at ages 8, 12, and 15 (respectively) on social skills and task effectiveness at age 22. Similar to the results shown in Figure 4, in both cases the largest gains are obtained from cash transfers at age 15. The transfer has a larger impact on task effectiveness due to its positive cross-productivity with cognitive skills at age 19.

Figure 5: The Simulated Impact of a Cash Transfer Programme on Social Skills and Task Effectiveness



Note: Results show the simulated overall impact of the same cash transfer made at ages 8, 12 and 15 on skills. Estimated by simulating the developmental path of 100,000 observations randomly drawn from the estimated initial conditions.

5.2 Socio-emotional Skills and Risky Behaviour

The discussion of the estimated parameters of the investment and production functions to this point has necessarily been centred on relating the stocks of latent variables to one another over time. Even with the measurement system and normalizations, this discussion remains somewhat abstract. In order to provide a more socially or economically meaningful measure of the importance of human capital, we investigate the effect of skills on risky behaviours in early adulthood, given that many young people have not yet fully completed their education and begun earning. Risky behaviours are both predictive of future economic success, and may also reduce life-expectancy (Cawley and Ruhm, 2011). We define adult outcome O_{T+1} to be a function of our two $T+1$ socio-emotional domains (social skills and task effectiveness), cognitive skill at T and a vector of individual characteristics $\mathbf{x}_{T+1}$:

$$O_{T+1} = \mu_o + \gamma_1^o H_{s,T+1}^t + \gamma_2^o H_{s,T+1}^s + \gamma_3^o H_{c,T} + \mathbf{x}_{T+1}'\delta + \eta_{T+1}^o \quad \text{for} \quad j \in \{t, s\} \tag{11}$$

We assume the error term, η_{T+1}^o is independent of the inputs, and that the outcome is measured without error. As outcomes, we use six indicators of risky behaviour collected as part of the YLS (in a self-administered questionnaire for sensitive items): smoked at least once a month; ever been drunk; ever taken illegal drugs; ever had unprotected sex; carried a weapon in the last month; been arrested for being part of a gang or carrying a weapon in the last month; or has a child or is pregnant (or has a partner who is pregnant) at age 22. As controls, included in $\mathbf{x}_{T+1}$, we use individuals' gender and wealth. Using cognitive skill as captured by measures at T is somewhat analogous to assuming that cognitive skill is fixed from age 18 onward. Given our estimates of the increasing self-productivity of cognitive skill, and the evidence that cognition is much less malleable than socio-emotional skills over the lifecourse, this assumption is not overly restrictive.[20]

Table 8: Estimates of the impact of age 22 socio-emotional skills on risky behaviours

	(1) Smoked	(2) Drank	(3) Drugs	(4) Unprotected sex	(5) Carried weapon	(6) Gang	(1) Child
$\ln H_{s,T+1}^t$	-0.084*	-0.007	-0.096*	-0.022	-0.019	-0.067*	-0.041
	(0.049)	(0.068)	(0.053)	(0.059)	(0.024)	(0.038)	(0.053)
$\ln H_{s,T+1}^s$	0.015	-0.050	0.016	-0.023	0.022	0.044	0.018
	(0.058)	(0.074)	(0.057)	(0.067)	(0.033)	(0.045)	(0.066)
$\ln H_{c,T}$	0.144	0.099	0.166*	0.046	0.021	0.081	-0.067
	(0.098)	(0.124)	(0.100)	(0.120)	(0.045)	(0.073)	(0.100)
Female	-0.253***	-0.293***	-0.106**	0.181***	-0.019	-0.082**	0.252***
	(0.050)	(0.063)	(0.044)	(0.059)	(0.020)	(0.037)	(0.047)
Wealth index	0.024	0.026	0.305	-0.267	-0.060	-0.033	-0.031
	(0.173)	(0.202)	(0.199)	(0.184)	(0.103)	(0.136)	(0.147)
Outcome mean	0.23	0.51	0.15	0.30	0.05	0.12	0.30
N	531	523	441	499	535	534	551

Note: *, ** and *** denote statistical significance it 10%, 5% and 1% respectively. Standard errors in parentheses are calculated from 1,000 bootstrap replications. The outcomes in each column are whether not an individual has: smoked least once a month (1); ever been drunk (2); ever taken illegal drugs (3); ever had unprotected sex (4); carried a weapon in the last month (5); been arrested for being part of a gang or carrying a weapon in the last month (6); or has a child or is pregnant at age 22 (7). *Female* is a dummy indicating whether or not an individual is female, and the *wealth index* a measure of the material resources of the family which ranges from 0 to 1, constructed as the average of three sub-indices measuring housing quality, access to services and ownership of a range of durable goods. See Briones (2017) for detail. The number of observations differs in across columns due to missing responses.

All of the outcomes we use to estimate Equation 11 are binary. There are several possible ways to estimate its parameters for each outcome, however we use an IV linear probability model as it does not require us to make additional assumptions about the distribution of the measurement error, given the

[20] Kautz et al. (2014) discuss in detail how the development of socio-emotional and cognitive skills differs. Walsh and Walsh (2014) discuss how the slow-development of the pre-frontal cortex means personality traits are unstable over adolescence and later life stages.

findings of Laajaj and Macours (2019), and it is robust to miss-specification of the first stage. Appendix A discusses the estimation of Equation 11 in more detail. Table 8 reports the estimated marginal effects for each outcome. The marginal effect of task effectiveness is negative for every risky behaviour, and statistically different from zero for the likelihood of having smoked once a month (column 1), taken illegal drugs (column 3) and having been arrested for being part of a gang (column 6).

The pattern is not as clear for social skills, and none of these effects are estimated with precision; we cannot reject that they are zero for every outcome. The marginal effects of cognition are positive and significant for having taken illegal drugs (column 3). Wealth also has a large, positive marginal effect on this outcome - a relationship that is perhaps unsurprising considering that illegal drugs include those that might be considered "recreational" - for example marijuana. These results are slightly different from those of Heckman et al. (2006), who find cognitive skills also decrease the probability of risky behaviour. Further, in their analysis, they measure latent socio-emotional skills by self esteem and locus of control, which is a subset of our task effectiveness skill. Our results show that social skills do not have the same effect, highlighting that the definition of socio-emotional skills is important when drawing policy conclusions regarding skills and behaviour. The higher risk of drug taking for individuals with higher cognitive skills may also be related to the difference in context between US and Peru - but our results suggest that it is even more important to cultivate task effectiveness skills, if improved cognition does not reduce risky behaviour in this context.

The results in Table 8 highlight the complexity of the relationship between skills and outcomes. Firstly, they show again the importance if disaggregating socio-emotional skills along distinct domains. Not doing so, and treating socio-emotional skills as an aggregate, would mean overlooking how they affect outcomes differently - a key question for policy given the abstractness of aggregate "bundles" of skills. Secondly, the results show the potential interplay of skills in determining outcomes - even though being smarter is considered to be an improvement, it is likely that socio-emotional skills like task-effectiveness drive individuals to make life choices commensurate with social and economic success. Of course, we cannot know from this analysis the extent to which these skills are related to future social and economic outcomes, however evidence suggests risky behaviours are driven by the same factors that correlate with wages, employment and schooling attainment (Heckman et al., 2006).

6 Conclusion

In this paper we examined the accumulation of socio-emotional skills between the ages of 8 and 22 in Peru. We also estimate the developmental path of cognitive skill between 8-19, and the role it plays in this process (and vice-versa). To do so, we estimate a dynamic latent factor model of household investment and skill production using a framework developed by Agostinelli and Wiswall (2020) that captures key aspects of the skill accumulation process.

We find that household investments are largely determined by family resources and parents' socio-emotional skills, and no evidence that parents invest in response to their children's revealed human capital. Our estimates of human capital production functions suggest that these investments positively affect socio-emotional skill accumulation in the early periods of our model, and that the impact varies across the distribution of skills. Our results also show that socio-emotional skills' self-productivity is increasing with age and that cognition is highly self-productive across all of adolescence. We also find that socio-emotional skills are determined by stocks of cognitive skills to a far greater extent than past socio-emotional skills at all stages. The result is the emergence of a socioeconomic gradient in socio-emotional skill between the ages of 8-12 that then persists over adolescence.

In early adulthood between the ages of 19-22, we disaggregate socio-emotional skills along two domains: social skills and task-effectiveness, and relax some of the functional form restrictions required to estimate the technology of skill formation between 8-19. This portion of our analysis provides evidence that socio-emotional skills accumulated by the end of adolescence are important in building both these two domains in early adulthood, but there is a negative relationship between cognitive skill and the development of social skills, perhaps suggesting that individuals substitute low cognition with social skills. Over this period, we find that time spent studying positively affects the accumulation of task effectiveness, whereas the reverse is true for time in home production or caring for household members. Finally, we estimate the returns to scaling up the inputs of the socio-emotional skill functions are far greater for task effectiveness than for social skills. At age 22, we also find that task-effectiveness has a negative effect on the probability of individuals engaging in a range of risky behaviours, in particular smoking, taking drugs and engaging in gang related behaviour. Social skills on the other hand have no effect on these intermediate outcomes.

Together, these results suggest that gaps in socio-emotional skills arise and persist through differences in household investments and the cross-productivity of cognition in socio-emotional skill production. Certain socio-emotional skills are then highly self-productive across early adulthood, and lead to differences in engagement with a range of risk behaviours, this being predictive of likely lower economic success in future years. Gaining knowledge as to how human capital develops over childhood and adolescence is crucial in understanding the transmission of poverty and inequality across generations. The results of this paper offer several additions to the growing evidence base that has come from the literature on the economics of early skill accumulation over the past decade.

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A Identification and Estimation

For our main results we estimate equations 2, 3 (for socio-emotional and cognitive skills, respectively) and 1 (for investments) in between the ages of 8-12, 12-15, and 15-19 following Agostinelli and Wiswall (2020). In this Appendix, we show how this is done for the more general case that allows for dynamic complementarity in the production functions of skills by including the term $\ln H_{j,t} \times \ln I_t$ for $j \in \{s, c\}$, as follows:[21]

$$\ln H_{s,t+1} = \rho^s_{1,t} \ln H_{s,t} + \rho^s_{2,t} \ln H_{c,t} + \alpha^s_{1,t} \ln P_s + \alpha^s_{2,t} \ln P_c + \gamma^s_t \ln I_t + \kappa^s_t (\ln H_{j,t} \times \ln I_t) + \eta^s_t \quad \text{(A1)}$$

$$\ln H_{c,t+1} = \rho^c_{1,t} \ln H_{c,t} + \rho^c_{2,t} \ln H_{s,t} + \alpha^c_{1,t} \ln P_c + \alpha^c_{2,t} \ln P_s + \gamma^c_t \ln I_t + \kappa^c_t (\ln H_{j,t} \times \ln I_t) + \eta^c_t \quad \text{(A2)}$$

Assuming that $\kappa^s_t = 0$, is equivalent to assuming the production function of socio-emotional skills is Cobb-Douglas, as in equations 2, 3 (main text). If, however, $\kappa^s_t \neq 0$, investments can be more ($\kappa^s_t > 0$) or less ($\kappa^s_t < 0$) productive in children with higher stocks of skill. Put differently, $\kappa^s_t \neq 0$, captures any dynamic complementarities between already accumulated human capital and investments - the dynamic relationship between skills and investments that could result in the opening and widening of inequalities in human capital (Cunha et al., 2010).

The starting point in estimating this system is the identification of the initial period measurement parameters and the joint distribution of the initial conditions. Given that we have three measures of each of the latent variables in the initial period and have assumed full independence of the measurement errors, we are able to identify and estimate both. With the initial period measurement parameters and the joint distribution of the initial conditions recovered, Agostinelli and Wiswall (2020) show that the technologies in Equations A1, A2 and 1 (main text) can be sequentially identified in each subsequent period.

Estimation of the model of human capital accumulation between the ages of 8 and 19 laid out in Section 2 consists of four main steps:

1. First, we estimate the joint distribution of the initial conditions.
2. We then estimate the investment function of Equation 1 and recover the investment measurement parameters in the first period.
3. Next, we estimate the production function and measurement parameters for socio-emotional and cognitive skill in period 1.
4. We then repeat steps 2 and 3 for periods 2 and 3.

We then estimate the measurement system of two domains of socio-emotional skill at age 22: task

[21] It is possible to include both $(\ln H_{s,t} \times \ln I_t)$ and $(\ln H_{c,t} \times \ln I_t)$ simultaneously. However, for estimation purposes we only include one interaction at a time due to the collinearity between the interaction terms.

effectiveness and social skills. We impose normalisations on this measurement system that allow us to identify and estimate the flexible production functions - shown in Equation 4 - of these skills between the ages of 19 and 22.

A.1 The Joint Distribution Of Initial Conditions

The factor loadings of the measures of the initial conditions are retrieved by taking the ratio of the covariances of the observed measures. For example:

$$\lambda_{\theta,m,0} = \frac{\text{Cov}(Z_{\theta,m,0}, Z_{\theta,m',0})}{\text{Cov}(Z_{\theta,1,0}, Z_{\theta,m',})} \quad \forall m' \neq m \tag{A3}$$

Imposing the normalisation that the initial period latent variables all have a mean of zero, the measurement intercepts $\mu_{\theta,m,0}$, can be estimated by $\mathbb{E}(Z_{\theta,m,0})$. We then residualise measures as follows:

$$\tilde{Z}_{\theta,m,0} = \frac{Z_{\theta,m,0} - \mu_{\theta,m,0}}{\lambda_{\theta,m,0}} = \ln\theta_0 + \tilde{\varepsilon}_{\theta,m,0} = \ln\theta_0 + \frac{\varepsilon_{\theta,m,0}}{\lambda_{\theta,m,0}} \quad \forall m \tag{A4}$$

The latent variables are then equivalent to:

$$\tilde{Z}^*_{\theta,m,0} = \tilde{Z}_{\theta,m,0} - \tilde{\varepsilon}_{\theta,m,0} = \ln\theta_0 \tag{A5}$$

Having identified and estimated the factor loadings, the theorem of Kotlarski (1967) can be applied to the set of residual measures, $\{\tilde{Z}_{\theta,m,0}\}_{m=1}^{M_{\theta,0}}$, to identify the distributions of $\ln\theta_0$ and $\varepsilon_{\theta,m,0}$ conditional on $\mathbf{I}_0$. This then allows identification of the joint distribution of the initial conditions and investments at t= 0. Agostinelli and Wiswall (2020) show that the production technologies are sequentially identified in each of the following periods $t = 0, ..., T$.

The diagonal and off- diagonal elements of the covariance matrix of the initial conditions can be estimated by

$$\frac{\text{Cov}(Z_{\theta,1,0}, Z_{\theta,2,0})\text{Cov}(Z_{\theta,1,0}, Z_{\theta,3,0})}{\text{Cov}(Z_{\theta,2,0}, Z_{\theta,2,0})} = \frac{\lambda_{\theta,2,0}\lambda_{\theta,3,0}\text{Var}(\ln\theta_0)^2}{\lambda_{\theta,2,0}\lambda_{\theta,3,0}\text{Var}(\ln\theta_0)} = \text{Var}(\ln\theta_0) \tag{A6}$$

and

$$\text{Cov}(Z_{\theta,1,0}, Z_{\theta',1,0}) = \text{Cov}(\ln\theta_0, \ln\theta'_0) \tag{A7}$$

respectively. Since $\ln Y_0$ and $\ln Z_0$ are measured without error, their respective variance is easily computed, and their covariance with a given unobservable initial condition, θ_0, are:

$$\text{Cov}(\ln Y_0, \ln\theta_0) = \text{Cov}(\ln Y_0, Z_{\theta,1,0})$$

Given the assumption that unobservables are mean zero in the initial period, the mean vector is

$$\mu_\Omega = (0,0,0,0,0,0,\mu_{Y,0})$$

A.2 Investment Functions

Substituting Equation 1 in to one measurement equation for investment in the first period gives the following expression:

$$\begin{aligned} Z_{I_0,m,0} = \mu_{I_0,m,0} + \lambda_{I_0,m,0}(\beta_{1,0}\ln H_{s,0} + &\beta_{2,0}\ln H_{c,0} + \beta_{3,0}\ln P_s \\ &+\beta_{4,0}\ln P_c + \beta_{5,0}\ln Y_0 + \pi_0) + \varepsilon_{I_0,m,0} \end{aligned} \tag{A8}$$

Substituting the corresponding proxies of latent inputs in to the investment equations - $\tilde{Z}^*_{\theta,m,0}$ for each $\theta_0 \in \{H_{s,0}, H_{c,0}, P_s, P_c\}$ - in to Equation A8 in place of the unobservables this can be re-written as

$$\begin{aligned} Z_{I_0,m,0} = \mu_{I_0,m,0} + \lambda_{I_0,m,0}(\beta_{1,0}\tilde{Z}^*_{H_s,m,0} + &\beta_{2,0}\tilde{Z}^*_{H_c,m,0} + \beta_{3,0}\tilde{Z}^*_{P_s,m} \\ &+\beta_{4,0}\tilde{Z}^*_{P_c,m} + \beta_{5,0}\ln Y_0 + \pi_0) + \varepsilon_{I_0,m,0} \end{aligned} \tag{A9}$$

and so

$$\begin{aligned} Z_{I_0,m,0} = \mu_{I_0,m,0} + \delta_{1,0}\tilde{Z}_{H_s,m,0} + \delta_{2,0}&\tilde{Z}_{H_c,m,0} + \delta_{3,0}\tilde{Z}_{P_s,m} \\ &+ \delta^j_{4,0}\tilde{Z}_{P_c,m} + \delta_{5,0}\ln Y_0 + \nu_0 \end{aligned} \tag{A10}$$

where

$$\begin{aligned} \delta_{i,0} =& \lambda_{I_0,m,0}\beta_{i,0} \quad \text{for} \quad i = 1,..,5 \\ \nu_0 = \varepsilon_{I_0,m,0} + \lambda_{I_0,m,0}(\pi_0 - &\beta_{1,0}\tilde{\varepsilon}_{H_s,m,0} - \beta_{2,0}\tilde{\varepsilon}_{H_c,m,0} - \beta^j_{3,0}\tilde{\varepsilon}_{P_s,m,0} - \beta^j_{4,0}\tilde{\varepsilon}_{P_c,m,0}) \end{aligned}$$

Since we are using error contaminated proxies for the latent inputs of Equation A10, $\mathbb{E}(\tilde{Z}_{\theta,m,0}\nu_{j,0}) \neq 0$. We therefore use all other measures of each latent variable as instruments to estimate the reduced form parameters in Equation A10. Given the assumptions on the measurement errors, $\mathbb{E}(Z_{\theta,m',0}\nu_{j,0}) = 0 \quad \forall\, \theta_0$ and $m' \neq m$ and so these alternative measures are valid instruments. With the CRS assumption we can recover the measurement and structural parameters of the investment equation as:

$$\beta_{i,0} = \frac{\delta_{i,0}}{\sum_{i=1}^{6} \delta_{i,0}} = \frac{\lambda_{I_0,m,0}\beta_{i,0}}{\sum_{i=1}^{6} \lambda_{I_0,m,0}\beta^{j}_{i,0}} \quad \text{for} \quad i = 1, .., 5$$

We then construct residual investment measures as:

$$\tilde{Z}_{I,m,0} = \frac{Z_{I,m,0} - \mu_{I,m,0}}{\lambda_{I,m,0}} = \ln I_0 + \tilde{\varepsilon}_{I,m,0}$$

and investment is equal to:

$$\tilde{Z}^{*}_{I_j,m,0} = \tilde{Z}_{I_0,m,0} - \tilde{\varepsilon}_{I,m0} = \ln I_0 \tag{A11}$$

A.3 Production Functions

The parameters of equations A1 and A2 are estimated in an identical manner. We show how this is done for Equation A1. We start by substituting Equation A1 in to that of an observable measurement of period 1 stock of socio-emotional skill, giving:

$$\begin{aligned} Z_{H_s,m,1} = \mu_{H_s,m,1} + \lambda_{H_s,m,1}\big(&\rho^{s}_{1,0} \ln H_{s,0} + \rho^{s}_{2,0} \ln H_{c,0} + \alpha^{s}_{1,0} \ln P_s + \alpha^{s}_{2,0} \ln P_c \\ &+ \gamma^{s}_{0} \ln I_0 + \kappa^{s}_{0}(\ln H_{s,0} \ln I_0) + \eta^{s}_{0}\big) + \varepsilon_{H_s,m,1} \end{aligned} \tag{A12}$$

Once again using the fact that, based on the measurement system laid out in Equation 6, $\tilde{Z}^{*}_{\theta,m,0} = \ln \theta_0$ for $\theta_0 \in \{H_{s,0}, H_{c,0}, P_s, P_c, I_0\}$, Equation A12 can be written as

$$\begin{aligned} Z_{H_s,m,1} = \mu_{H_s,m,1} + \lambda_{H_s,m,1}\big(&\rho^{s}_{1,0}\tilde{Z}^{*}_{H_{s,0},m,0} + \rho^{s}_{2,0}\tilde{Z}^{*}_{H_{c,0},m,0} + \alpha^{s}_{1,0}\tilde{Z}^{*}_{P_s,m,0} + \alpha^{s}_{2,0}\tilde{Z}^{*}_{H_c,m,0} \\ &+ \gamma^{s}_{0}\tilde{Z}^{*}_{I_0,m,0} + \kappa^{s}_{0}\big(\tilde{Z}^{*}_{H_{s,0},m,0}\tilde{Z}^{*}_{I_0,m,0}\big) + \eta^{s}_{0}\big) + \varepsilon_{H_s,m,1}\, , \end{aligned} \tag{A13}$$

which can be re-arranged as:

$$\begin{aligned} Z_{H_s,m,1} = \mu_{H_s,m,1} + \phi^{s}_{1,0}\tilde{Z}_{H_{s,0},m,0} + \phi^{s}_{2,0}\tilde{Z}_{H_{c,0},m,0} + \chi^{s}_{1,0}\tilde{Z}_{P_s,m,0} + \chi^{s}_{2,0}\tilde{Z}_{H_c,m,0} \\ + \tau^{s}_{0}\tilde{Z}_{I_0,m,0} + \psi^{s}_{0}\big(\tilde{Z}_{H_{s,0},m,0}\tilde{Z}_{I_0,m,0}\big) + \upsilon^{s}_{1} \end{aligned} \tag{A14}$$

where

$$
\begin{aligned}
\phi^s_{i,0} &= \lambda_{H_s,m,1}\rho^s_{i,0} \quad \text{for} \quad i = 1, 2 \\
\chi^s_{i,0} &= \lambda_{H_s,m,1}\alpha^s_{i,0} \quad \text{for} \quad i = 3, 4 \\
\tau^s_0 &= \lambda_{H_s,m,1}\gamma^s_0 \\
\psi^s_0 &= \lambda_{H_s,m,1}\kappa^s_0
\end{aligned}
$$

and

$$
\begin{aligned}
\upsilon^j_1 = \varepsilon_{H_s,m,1} + \lambda_{H_j,m,1}\Big[&\eta^s_0 - \rho^s_{1,0}\tilde{\varepsilon}_{H_{s,0},m,0} - \rho^s_{2,0}\tilde{\varepsilon}_{H_{c,0},m,0} - \alpha^s_{1,0}\tilde{\varepsilon}_{P_s,m,0} - \alpha^s_{2,0}\tilde{\varepsilon}_{P_c,m,0} - \gamma^s_0\tilde{\varepsilon}_{I_0,m,0} \\
&- \kappa^s_0(\tilde{Z}_{H_{s,0},m,0}\tilde{\varepsilon}_{I_0,m,0} + \tilde{Z}_{I_0,m,0}\tilde{\varepsilon}_{H_{s,0},m,0} + \tilde{\varepsilon}_{H_{s,0},m,0}\tilde{\varepsilon}_{I_0,m,0})\Big]
\end{aligned} \tag{A15}
$$

As in estimation of the production functions, all alternative measures of the inputs are used as instrumental variables with their validity implied by assumptions regarding the joint distribution of the unobservables and measurement errors. The assumption of CRS again allows the structural parameters of Equation A1 to be calculated as

$$
\begin{aligned}
\rho^s_{i,0} &= \frac{\phi^s_{i,0}}{\phi^s_{1,0} + \phi^s_{2,0} + \chi^s_{1,0} + \chi^s_{2,0} + \tau^s_0 + \psi^s_0} \quad \text{for} \quad i = 1, 2 \\
\alpha^s_{i,0} &= \frac{\chi^s_{i,0}}{\phi^s_{1,0} + \phi^s_{2,0} + \chi^s_{1,0} + \chi^s_{2,0} + \tau^s_0 + \psi^s_0} \quad \text{for} \quad i = 3, 4 \\
\gamma^s_0 &= \frac{\tau^s_0}{\phi^s_{1,0} + \phi^s_{2,0} + \chi^s_{1,0} + \chi^s_{2,0} + \tau^s_0 + \psi^s_0} \\
\kappa^s_0 &= \frac{\psi^s_0}{\phi^s_{1,0} + \phi^s_{2,0} + \chi^s_{1,0} + \chi^s_{2,0} + \tau^s_0 + \psi^s_0}
\end{aligned}
$$

The denominator in each of the above equations gives the factor loading relating period 1 stock of socio-emotional skill to the observable measure $Z_{H_s,m,1}$. That is,

$$
\lambda_{H_s,m,1} = \phi^s_{1,0} + \phi^s_{2,0} + \chi^s_{1,0} + \chi^s_{2,0} + \tau^s_0 + \psi^s_0
$$

Again, a residual measure of socio-emotional skill in period 1 can than be constructed as:

$$
\tilde{Z}_{H_s,m,1} = \frac{Z_{H_s,m,1} - \mu_{H_s,m,1}}{\lambda_{H_s,m,1}} = \ln H_{s,1} + \tilde{\varepsilon}_{H_s,m,1}\,,
$$

and latent socio-emotional skill can be defined as being equal to:

$$\tilde{Z}^*_{H_j,m,1} = \tilde{Z}_{H_j,m,1} - \tilde{\varepsilon}_{H_j,m,1} = \ln H_{j,1}$$

The parameters of the cognitive production function and measurement system are estimated, and a residual measure of cognitive skill constructed, in the same way. An identical process for estimating the investment and production functions is then used in each subsequent period.

A.4 Variance of Investment and Production Shocks

The variance of shocks to investment and production are estimated by as the covariance between the residual from equations A10 and A14 with an alternative measure of their output respectively. Alternative residual measures are constructed by estimating equations A10 and A14 using $Z_{H_j,m',0}$ for $j \in \{s, c\}$ and $Z_{I_s,m',0}$ as outcomes and retrieving their measurement parameters. Given the assumptions on the measurement errors the variance of shocks can be estimated in each t as:

$$\text{Cov}\left(\frac{\nu_t}{\lambda_{I,m,t}}, \tilde{Z}_{I,m',t}\right) = Var(\pi_t) = \sigma^2_{\pi,t},$$

and

$$\text{Cov}\left(\frac{\upsilon^j_t}{\lambda_{H_j,m,t}}, \tilde{Z}_{H_j,m',t}\right) = Var(\eta^j_t) = \sigma^2_{H_j,t}$$

A.5 Signal to Noise Ratios

The proportion of the variance in an observable measure attributable to the latent variable it proxies as opposed to measurement error is estimated as a function of its measurement parameters and the variance of the unobservable. In the initial period, these are calculated as in Section A.1. In subsequent periods, they are recovered by estimating Equations A10 and A14 using each measure of investment and human capital as the dependent variable. The signal in, for example, a measure of socio-emotional skill at time t is then given by

$$s_{H_{s,1},m,t} = \frac{\lambda^2_{H_{s,1},m,t} V(\ln H_{s,1})}{\lambda^2_{H_{s,1},m,t} V(H_{s,1}) + V(\varepsilon_{H_{s,1},m,t})} = \frac{\lambda^2_{H_{s,1},m,t} \text{Cov}\left(\tilde{Z}_{H_{s,1},m,t}, \tilde{Z}_{H_{s,1},m',t}\right)}{V(Z_{H_{s,1},m,t})} \tag{A16}$$

A.6 Socio-emotional Skills in Early Adulthood

For the measures of three domains of socio-emotional skill - task-effectiveness (t) and social skills (s) - at age 22 ($T + 1$), we estimate the measurement system laid out in Equation 6 imposing the following normalizations for $j \in \{t, s\}$:

$$E(\ln H^j_{s,T+1}) = 0$$
$$\lambda_{H^j_{s,1,T+1}} = 1$$

These normalisations fix the location and scale of each of these latent socio-emotional skills to one of their observable measures. They also allow us to estimate the measurement means as $E(Z_{H_s,m,T+1}) = \mu_{H_s,m,T+1}$. Given these measurement parameters, we take one measurement equation for socio-emotional skill $Z_{H^j_s,m,+T+1}$ and substitute in to it Equation 4, giving:

$$Z_{H^j_s,m,T+1} = \mu_{H^j_s,m,T+1} + \lambda_{H^j_{s,m,T+1}}(\ln A_T + \rho^{s,j}_{1,T} \ln H_{s,T} + \rho^{s,j}_{2,T} \ln H_{c,T} + \eta^{s,j}_T) + \varepsilon_{H^j_s,m,T+1}$$

After substituting in to this equation residual measures of period T socio-emotional and cognitive skill and rearranging, we arrive at an expression similar to Equations A10 and A14:

$$Z_{H^j_s,m,T+1} = \mu_{H_s,m,T+1} + \phi^{s,j}_{1,T+1}\tilde{Z}^*_{H_s,m,T} + \phi^{s,j}_{2,T+1}\tilde{Z}^*_{H_c,m,T} + \lambda_{H^j_{s,m,T+1}} \ln A_T + \upsilon^{s,j}_{T+1} \tag{A17}$$

Substituting in our expression of $\ln A_T$, this can be re-written as:

$$Z_{H^j_s,m,T+1} = \phi^{s,j}_{0,T+1} + \phi^{s,j}_{1,T+1}\tilde{Z}_{H^s,m,T} + \phi^{s,j}_{2,T+1}\tilde{Z}_{H_c,m,T} + \mathbf{x}'_T\omega^{s,j}_{T+1} + \upsilon^{s,j}_{T+1} \tag{A18}$$

Where:

$$\phi^{s,j}_{0,T+1} = \mu_{H_s,m,T+1} + \lambda_{H^j_{s,m,T+1}}\alpha_T$$
$$\phi^{s,j}_{i,T+1} = \lambda_{H^j_{s,m,T+1}}\rho^{s,j}_{i,T} \qquad \text{for} \quad i = 1,2$$
$$\omega^{s,j}_{T+1} = \lambda_{H^j_{s,m,T+1}}\boldsymbol{\beta}$$
$$\upsilon^{s,j}_{T+1} = \varepsilon_{H^j_s,m,T+1} + \lambda_{H^j_{s,m,T+1}}(\eta^{s,j}_T - \rho^{s,j}_{1,T}\tilde{\varepsilon}_{H_s,m,T} - \rho^{s,j}_{2,T}\tilde{\varepsilon}_{H_c,m,T})$$

Given the normalisations on the period T measurement system, both $\mu_{H_s,m,T+1}$ and $\lambda_{H^j_{s,m,T+1}}$ are known, and the location and scale of socio-emotional skill j is anchored in one of its measures. Using the same instrumental variables strategy as om estimating the investment and production functions of periods 1-3, we can then recover α_T, $\boldsymbol{\beta}$ and $\rho^{s,j}_{i,T}$, for $i = 1,2$ without the restriction of CRS. We estimate the returns to scale (RTS) as:

$$\frac{\phi^{s,j}_{2,T+1} + \phi^{s,j}_{1,T+1}}{\lambda_{H^j_{s,m,T+1}}} = \frac{\lambda_{H^j_{s,m,T+1}}(\rho^{s,j}_{1,T} + \rho^{s,j}_{2,T})}{\lambda_{H^j_{s,m,T+1}}}$$

A.7 The Parameters of the Adult Outcome Equation

Substituting a residual measure of $T+1$ task effectiveness and and social skills, and a time T measure of cognition in to equation 11 gives:

$$O_{T+1} = \mu_o + \gamma_1^o \tilde{Z}^*_{H_s^t,m,T+1} + \gamma_2^o \tilde{Z}^*_{H_s^s,m,T+1} + \gamma_3^o \tilde{Z}^*_{H_c,m,T} + \mathbf{x}'_{T+1}\boldsymbol{\delta} + \eta^o_{T+1} \tag{A19}$$

As in estimating the production and investment equations across period 1-4, this can be rearranged as:

$$O_{T+1} = \mu_o + \gamma_1^o \tilde{Z}_{H_s^t,m,T+1} + \gamma_2^o \tilde{Z}_{H_s^s,m,T+1} + \gamma_3^o \tilde{Z}_{H_c,m,T} + \mathbf{x}'_{T+1}\boldsymbol{\delta} + \nu^o_{T+1} \qquad , \tag{A20}$$

where

$$\nu^o_{T+1} = \eta^o_{T+1} + \gamma_1^o \varepsilon_{H_s^p,m,T+1} + \gamma_2^o \varepsilon_{H_s^l,m,T+1} + \gamma_3^o \varepsilon_{H_c,m,T} \tag{A21}$$

Although we do not have to disentangle the factor loadings from the parameters of the outcome equation, we have an identical measurement error problem as in estimating Equations A10, A14 and A18.

Given we use indicators of risky behaviours as outcomes, we use a similar instrumental variable strategy and estimate a linear probability model using alternative measures of the two socio-emotional skill domains and cognition as instruments - but for binary outcomes with endogenous, continuous independent variables. We favor this method over maximum likelihood or control function methods for two main reasons. Firstly, consistency estimators based on these methods relies on full specification of the first stage equations and having continuously distributed endogenous variables (Blundell and Powell, 2004). The variables we use as proxies are not truly continuous (although we assume that the latent variables are), and we know we do not have a complete set of relevant instruments on the latent variables, so these assumptions are not satisfied. An estimator of a LPM using 2SLS will not be inconsistent, however, and only on standard IV assumptions i.e that $\mathbb{E}(Z_{H_s^k,m',T+1}\nu_{j,0}) = 0 \quad \forall H_s^k$ and $m' \neq m$.

Secondly, an IV LPM makes no assumptions about the distribution of the measurement error, wheres ML/control function methods rely on joint normality of ν^o_{T+1} and in the error term in the first stage regressions. Given ν^o_{T+1} is an additive function of the measurement error and outcome equation error, this amounts to assuming that the measurement errors, outcome equation errors, and the errors in the first stage regressions are jointly normally distributed. As alluded to in the main body of this study, the methodology we use to estimate the investment and human capital production functions is robust to non-normal measurement errors (Agostinelli and Wiswall, 2020), an added benefit given Laajaj and Macours (2019) find evidence that measurement error in socio-emotional skill measures is non-classical among samples in Kenya and Colombia.

B Additional description of child assessments

The observable measures of child and parental human capital and investment in the Young Lives data are derived from both caregivers' and children's responses to survey questions across waves. In the case of cognitive skill, all measures are scores on tests administered as part of the survey. Below, we provide more detail on the types of measures used for each of the inputs in to and outputs of the human capital development process.

Socio-emotional Skill Measures

We do not use all of the socio-emotional measures available in the YL survey. Instead, where possible, we focus on those that can be described as reflecting children's Core Self-Evaluation (CSE) - those that predominantly ask questions about the children themselves, and their evaluation of aspects of their personality. For example, we excluded commonly used measures of subjective wellbeing such as Cantril's ladder (Cantril et al., 1965), and measures of children's trust in others or their social networks. We also use measures in some rounds but not in others because their sub-items changed over time. This is the case, for example, with measures of pride and self-esteem, which change substantially after age 15.

Early socio-emotional skills

In the initial period at age 8, the children are not directly asked questions so we used caregivers' responses to 25 questions designed to measure 5 aspects of the children's socio-emotional skills: emotional symptoms, conduct issues, inattention, peer/relationship problems, and pro-social behaviour. Each of these sub-scales contains 5 questions about whether a child exhibits certain behaviours. In the survey, the possible responses caregivers could provide were *yes*, *sometimes*, and *no*. We assign numerical responses and sum within the 5 sub-scales, giving us 5 measures of socio-emotional skill.

Young Lives Psychosocial Scales

Across its rounds, the Young Lives survey has adapted several commonly used scales designed to measure specific psychosocial characteristics. At ages 12, 15, 19, and 22 we use a measure of *pride and self-esteem*, based on Rosenberg (1965) scale. This scale poses statements to children about their self-confidence as it relates to their belongings, home, abilities, work, and achievements. For example, the following statements are contained in the scale:

- *I feel proud the show my friends or other visitors where I live*;
- *I am often proud because I do have the right books, pencils, and other equipment for school*;
- *I am proud of my achievement at school*; and
- *The job I do makes me feel proud.*

The children are then asked to what degree these statements represent their beliefs. At age 12, possible responses are on a 3-point scale of *no*, *yes*, or *more or less* respectively. At ages 15, 19, and 22 possible responses were on a 5-point scale from *strongly agree* to *strongly disagree*. After being assigned a numeric value, responses were summed to give each child a pride/self-esteem "score".

We also use a scale measuring agency at ages 12, 15, 19, and 22. This scale is based on Rotter (1966) and Bandura (1993), and poses a number of statements to children about the degree of control they have over their life. For example, the scales includes statements such as:

- *If I try hard I can improve my situation in life*;
- *I like to make plans for my future studies and work*; and
- *If I study hard at school I will be rewarded by a better job in the future.* .

The possible responses across ages are the same as in the case of the pride and self-esteem scale. Again, once assigned a numeric value, these responses are summed to give each child a agency/self-efficacy score. More information on the selection, construction, and validity of all of these scales can be found in Yorke and Ogando (2018).

General Self-efficacy

At ages 19 and 22 we utilise a newly added self-efficacy measure from the Young Lives data. This measure is based on the *general self-efficacy* scale of Jerusalem and Schwarzer (1979), which is designed to measure individuals' belief in their self-determination and ability to cope with adversity. Again, the scale consists of statements that children are asked to agree/disagree with. It contains statements such as:

- *I can always manage to solve difficult problems if I try hard enough*;
- *It is easy for me to stick to my aims and accomplish my goals*; and
- *I can solve most problems if I invest the necessary effort*.

Responses to these statements are on a 4-point scale from *strongly agree* to *strongly disagree*. These responses are assigned numeric values and then summed to prove a general self-efficacy "score" which we use as a measure of socio-emotional skill. Yorke and Ogando (2018) provides more detailed information on the selection and construction of this scale in the Young Lives data.

Marsh Self Description

At ages 19 and 22 we also use sub-scales of the Marsh Self-description Questionnaires measuring general self-esteem, peer relations, and parent relations. Each sub-scale is comprised of eight statements about self-concept in the respective domain. They sub-scales are based heavily on the proposed multi-dimensional structure of self-concept of Shavelson et al. (1976). These statements are presented to children, who are then asked to what extent they agree or disagree with them. As examples, the general self-esteem scale includes the statement *a lot of things about me are good*; the peer relations scale a statement that *I get along with other kids easily*; and the parent relations scale that *my parents understand me*. Once again, the possible responses to these statements range from *strongly agree* to *strongly disagree*, which we assign numeric values and sum within sub-scales to derive scores for each.

Yorke and Ogando (2018) provides more detailed information on theoretical concepts underpinning the Marsh Self-description questionnaires and the validity of their structure.

Duckworth and Quinn Grit Scale

At age 22, we use measures of two aspects of "grit" as designed by Duckworth and Quinn (2009). These sub-scales are shortened versions of those first proposed in Duckworth et al. (2007) and are designed to measure what they define as *consistency of interest* and *perseverance of effort*. As with the vast majority of the psychometric measures we use, these assessments involve presenting children with several statements - in this case four - about the relevant aspect of grit, then asking them the extent to which they agree the statements describe themselves. Respectively, the consistency of interest and perseverance of effort scales contain statements such as *I often set a goal but choose to pursue a different one*, and *I finish whatever I begin*. Responses to the statements are on a 5-point scale, from *not like me at all* to *very much like me*. We sum responses within each group to construct scores for each aspect of grit.

Review of Personal Effectiveness with Locus of Control (ROPELOC)

At age 22 we also make use of two, three-question sub-scales from the ROPELOC measuring their leadership and cooperative teamwork abilities (Richards et al., 2002). The two scales contain questions statements such as *I am seen as a capable leader* and *I am good at cooperating with team members* respectively. Children are asked to what extent they agree these statements describe themselves, with possible responses being on a 4-point scale from *strongly agree* to *strongly disagree*. After being assigned numeric values, we use the sum of responses within each sub-scale as measure of their ability in each domain.

Big Five Inventory

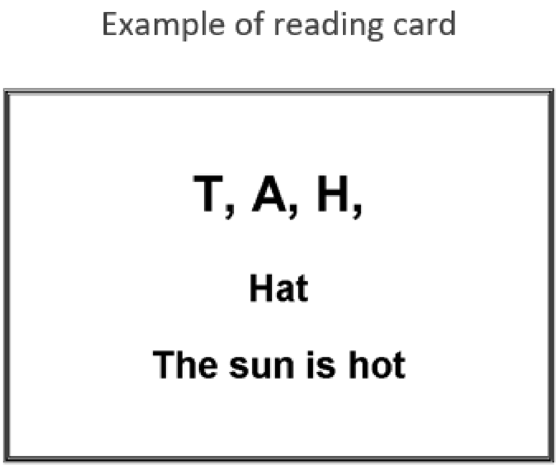
Also at age 22, we use two components of the Big Five Inventory - conscientiousness and neuroticism. The sub-scales are part of the larger inventory which also seeks to measures openness, agreeableness, and extraversion. They contain eight and nine statements respectively and respondents are asked the extent to which they agree that these statements describe them. For example, the statements representing conscientiousness include:

- *I am someone who does a thorough job*;
- *I am someone who tends to be organised*; and
- *I am someone who makes plans and follows through with them.*.

Similarly, the statements indicating neuroticism include:

- *I am someone who is relaxed, handles stress well*;
- *I am someone who is emotionally stable, not easily upset*; and
- *I am someone who gets nervous easily*.

Figure B1: Example of a YL reading card used to asses children's reading level at ages 8 and 12



Source: Revollo and Scott (2022)

Responses are on a 5-point scale from *strongly agree* to *strongly disagree* and are assigned a numeric value. The responses are summed within each of the two components to give children a score for conscientiousness and neuroticism.

B.1 Cognitive Skill

The YL data survey contains cognitive assessments at every age except 22. As with the socio-eomtional skill measures, the assessments administered differ across ages based on suitability, however the measures cover the same three broad domains of cognitive skills: language ability and fluid intelligence, or reasoning.

Reading and Writing Levels

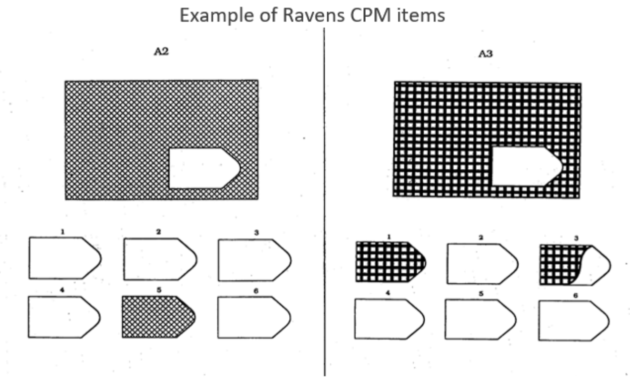
At ages 8 and 12, the writing level of children in the older cohort was assessed by asking them to read from aloud from cards containing three lines, the first containing individual letters, the second a word, and the third a simple sentence. Figure B1 shows what one of these cards looks like. The children were give a score of 1 if they could read the sentence, 0.66 if they could read the word, and 0.33 if they could read the letters, and 0 if they could not read anything.

For the writing assessment, interviewers read aloud a sentence which children were asked to transcribe. For example, children might have been asked to write down the sentence "*the sun is hot*". Sentences were adapted based on the country in which the test was administered to ensure comprehension. If children could write the sentence down easily they were awarded 1 point, and were awarded 0.5 or 0 points respectively if they wrote it down with errors or could not write it at all.

Raven's Coloured Progressive Matrices

At age 8 children are administered the the Raven's coloured progressive matrices test Raven (1958). This assessment involves showing children patterns with missing blocks, and asking them to identify which block from a choice of six completes it. The test as administered in the YL survey has 36 items, asked in order of difficulty. A child's raw score in the test is calculated as the total number of correct responses.

Figure B2: Examples of straightforward Raven's matrices at age 8



Source: Revollo and Scott (2022)

Peabody Picture Vocabulary Test (PPVT)

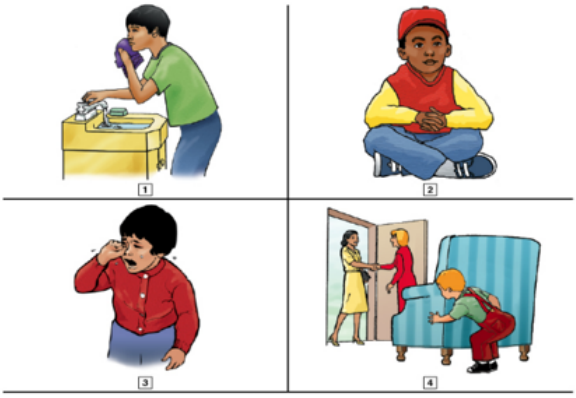
The PPVT was administered to children in age ages 12 and 15, and is designed to measure receptive vocabulary in children as young as 2.5 years old. The test involves presenting children with cards depicting four different scenarios, and asking them which picture best shows a sentence or word read aloud by the examiner. For example, an examiner might say "point to the picture that shows crying" whilst showing them the card in Figure B3. The questions become increasingly difficult, with the starting point of the test determined by the child's age.

YL Maths Test

The YL also contains a maths test to measure "mathematical achievement". For the older Peruvian cohort, this test was administered at ages 12, 15, and 19. At age 12 it consisted of 10 mathematics questions from the International Association for the Evaluation of Educational Achievement's (IEA) 2003 Trends in International Mathematics and Science Study Reddy et al. (2003). Children's raw score were simply the total number of correct answers.

At age 15 the test was expanded to include 30 questions in two sections, one with 20 questions on mathematics (addtion, division etc.) and another with 10 problem solving questions. At age 19 the test was further altered to account for differences in competencies across countries. Questions were grouped into three "booklets" of increasing difficulty, and children started on the second, intermediate booklet. If they performed well on intermediate skills they then answered questions on advanced skills, whereas if they performed poorly they moved on to answer questions on basic skills. **?** describes the

Figure B3: Example of a PPVT picture card at ages 12 and 15



Source: Revollo and Scott (2022)

tests and their internal and external validity in detail.

YL Reading Comprehension/Language Test

At age 19, children's reading comprehension was tested in a similar manner to their mathematical achievement ate the same age, described above. Comprehension questions were grouped into three booklets: (1) basic comprehension, (2) intermediate comprehension and (3) advanced comprehension. Children started with questions in booklet 2, and progressed to booklets 1 or 3 depending on their performance. The items administered were country specific in that they described or asked about day-to-day activities or situations that commonly occur in Peru. Revollo and Scott (2022) describes the design of the reading comprehension test in detail.

Cloze Language Test

At age 15, the children were administered the Cloze reading comprehension test, developed by the Development Analysis Group in Peru (GRADE - Grupo de Análisis para el Desarrollo). It was made up of 24 items, of increasing difficulty that asked children to fill in missing words in a sentence. Figure B4 shows an example of an item on the test. Ra scores were the total correct answers.

Figure B4: Example of a Cloze test card at age 15

SENTENCES

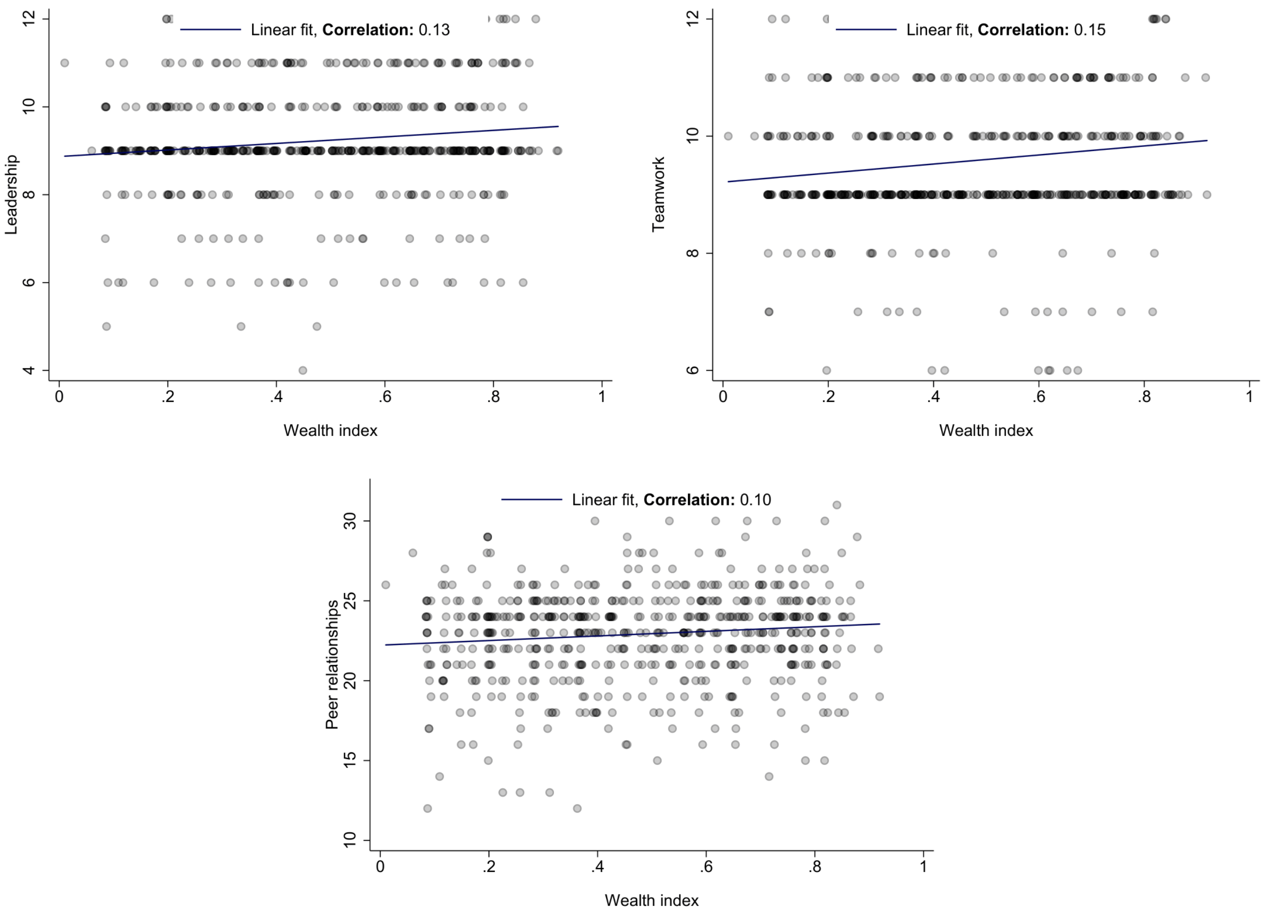
1. The main ____________ was blocked so we had to find another way to get inside the school.
2. Eliza plays with Ismael the most because he is her ___________ friend.
3. The sun was shining brightly in the sky so we sought __________ under a tree.

Source: Revollo and Scott (2022)

C Additional Tables and Digures

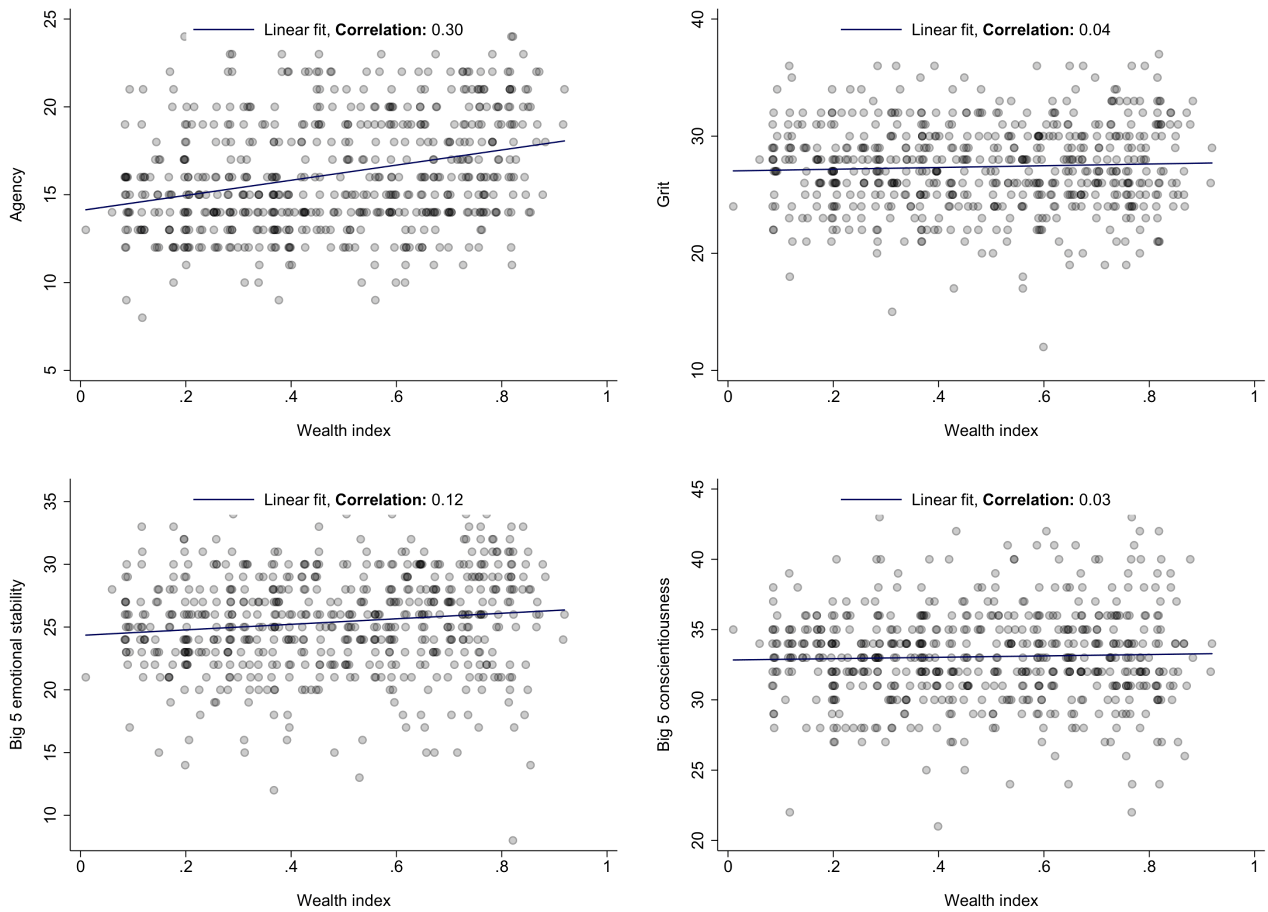
C.1 Additional Descriptive Figures and Tables

Figure C1: The correlation between measures of social skills at age 22 and household wealth at age 8



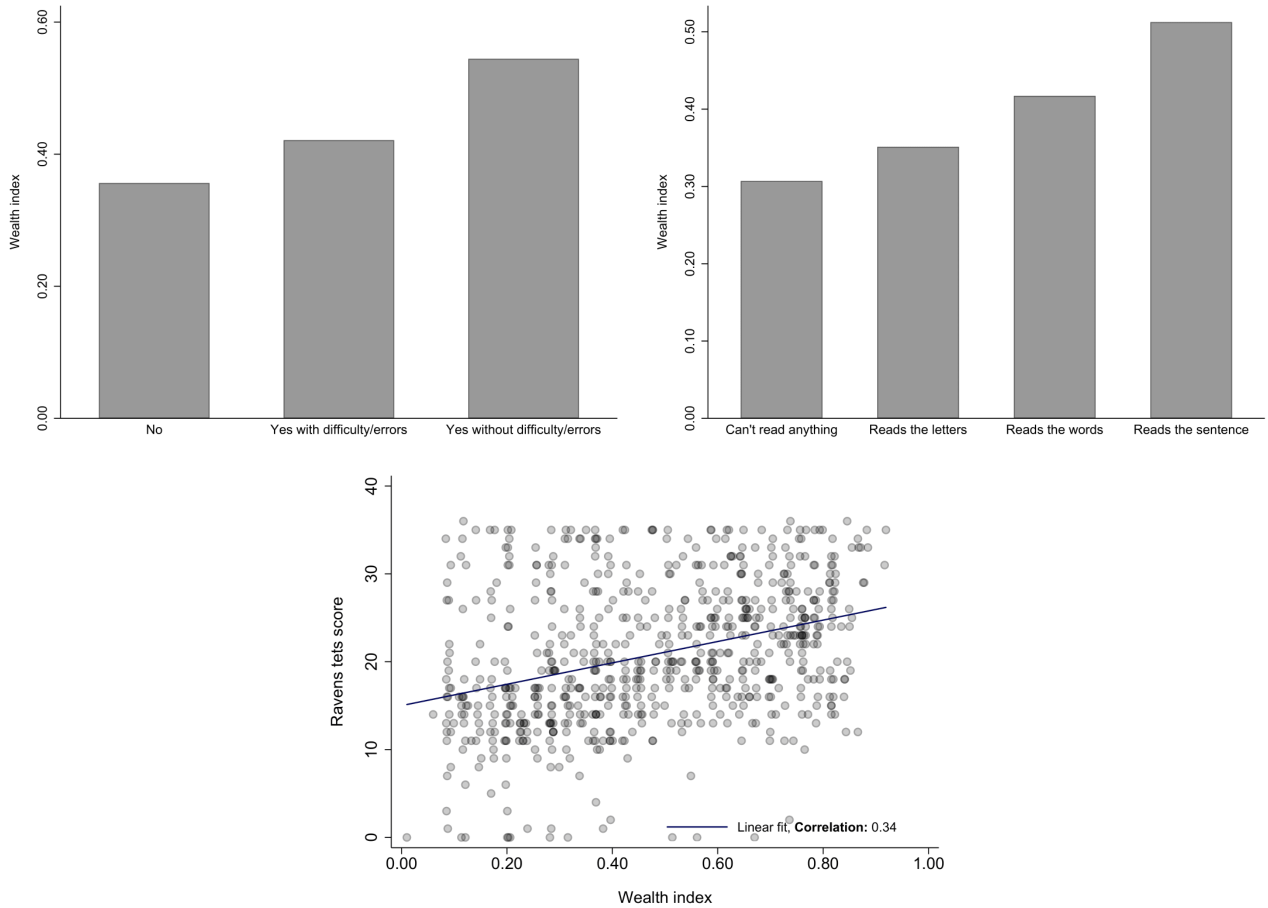
Note: The measures, clockwise from top left, are of leadership qualities, ability to work in a team, and quality of relationships with peers, and are are described in detail in Appendix B. The wealth index is constructed to range between 0 and 1 and is an average of three subindices: housing quality, access to services, and ownership of certain consumer durables. See Briones (2017) for further details.

Figure C2: The correlation between measures of Task Effectiveness skills at age 22 and household wealth at age 8



Note: The measures, clockwise from top left, are of agency, grit, emotional stability, and conscientiousness, and are are described in detail in Appendix B. The wealth index is constructed to range between 0 and 1 and is an average of three subindices: housing quality, access to services, and ownership of certain consumer durables. See Briones (2017) for further details.

Figure C3: The correlation between cognitive skill measures and household wealth at Age 8



Note: The measures, clockwise from top left, are of the child's writing ability, reading ability, and score on the Ravens progressive matrices test, and are described in detail in Appendix B. The wealth index is constructed to range between 0 and 1 and is an average of three subindices: housing quality, access to services, and ownership of certain consumer durables. See Briones (2017) for further details.

C.2 Summaries of Observable Measures Used in Estimations

Table C1: summary statistics of observable socio-emotional skill measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
Age 8					
Conduct issues*	12.263	2.210	15	5	11
Hyperactivity*	9.752	2.469	15	5	11
Pro-sociality	14.013	1.587	15	5	10
Emotional regulation*	10.513	3.080	15	5	11
Peer problems*	11.815	2.212	15	5	11
Age 12			11		
Pride & self-esteem	12.415	2.646	16	2	14
Agency	6.911	1.364	10	2	9
Age 15					
Pride & self-esteem	22.936	2.905	30	14	17
Agency	18.168	2.054	25	11	14
Age 19					
Agency	18.865	2.088	25	12	14
Self-esteem	24.778	2.335	32	16	17
Self-efficacy	30.205	3.274	40	8	21
Peer relationships	22.748	3.255	32	10	21
Age 22: task effectiveness					
Agency	16.181	3.275	25	8	18
Grit	27.393	3.730	40	12	25
Big 5 emotional stability	25.428	4.002	36	8	26
Big 5 conscientiousness	33.064	3.323	44	21	23
Age 22: social skills					
Leadership	9.228	1.281	12	4	9
Teamwork	9.586	1.172	12	6	7
Peer relationships	22.921	3.124	32	12	21

Note: The measures in this table are those of socio-emotional skill used to estimate the human capital production and investment functions. From left to right, the columns contain the aspect of socio-emotional skill the measures capture, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample. A * indicates a the order of a measure was reversed from negative to positive so that a higher value indicates more skill.

Table C2: summary statistics of observable cognitive skill measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
Age 8					
Ravens score	20.822	8.062	36	0	37
Writing level	2.418	0.709	3	1	3
Reading level	3.582	0.968	4	1	4
Age 12					
Math score	5.754	1.774	8	0	9
PPVT score	72.025	15.554	106	10	71
Writing level	2.845	0.394	3	1	3
Reading level	3.934	0.387	4	1	4
Age 15					
Math score	13.139	5.722	29	0	29
PPVT score	96.924	17.300	125	13	72
Cloze score	14.706	5.658	24	0	25
Age 19					
Math score	16.960	5.611	28	1	28
Language score	15.926	3.718	24	3	20

Note: The measures in this table are those of cognitive skill used to estimate the human capital production and investment functions. From left to right, the columns contain either the name of the test through which skill was measured of the aspect of cognition the test captured, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample.

Table C3: summary statistics of observable investment and parental skill measures used in estimating investment and production functions

	Mean	sd	Max.	Min.	Unique values
Age 12					
Per-child expenditure on books	1.341	2.822	65	0	.
Per-child expenditure on unforms	1.028	3.135	76	0	.
Hours studying	2.950	1.282	8	0	9
Hours in school	4.776	1.585	12	0	10
Age 15					
Per-child expenditure on books	1.670	1.821	20	0	,
Per-child expenditure on uniforms	1.302	1.841	27	0	.
Food groups	22.436	4.038	32	3	27
Hours studying	2.079	1.168	7	0	8
Hours in school	5.908	1.966	11	0	10
Age 19					
Educational expenditure	0.537	1.729	36	0	.
Per-child non-food expenditure	4.502	6.517	55	0	.
Food groups	8.914	1.923	14	3	12
Hours in school	3.565	3.645	15	0	16
Hours studying	1.473	1.852	12	0	11
Parental socio-emotional skill					
Agency	12.974	2.030	15	7	9
Pride & self-esteem	14.458	1.154	15	8	8
Cantril's ladder	4.848	2.044	9	1	9
Parental cognitive skill					
Education	7.251	4.539	18	0	17
Can read newspaper	2.604	0.713	3	1	3
Can understand things written in Spanish	2.502	0.787	3	1	3

Note: The measures in this table are those of investment and parental human capital used to estimate the human capital production and investment functions. From left to right, the columns contain a descriptions of the investment or human capital measures, their sample mean and standard deviation (sd), and the maximum, minimum and number of unique values in the sample. Variables with missing number of unique values are continuous.

C.3 Results of Initial Exploratory Factor Analysis (EFA) Across Ages 8-19

As part of our EFA, we first examine whether our observable measures have enough variation to capture sufficient variation in the latent variables we use as inputs/outputs of the production and investment functions. To do so, we first analyse the extent of the shared variation in the observable measures, and retain/discard their underlying factors based on their eigenvalues and a parallel analysis as proposed by Horn (1965). The measures we use in this EFA at each age described in the previous Section of this Appendix, and were those that best met the principal of Core Self-Evaluation (CSE).

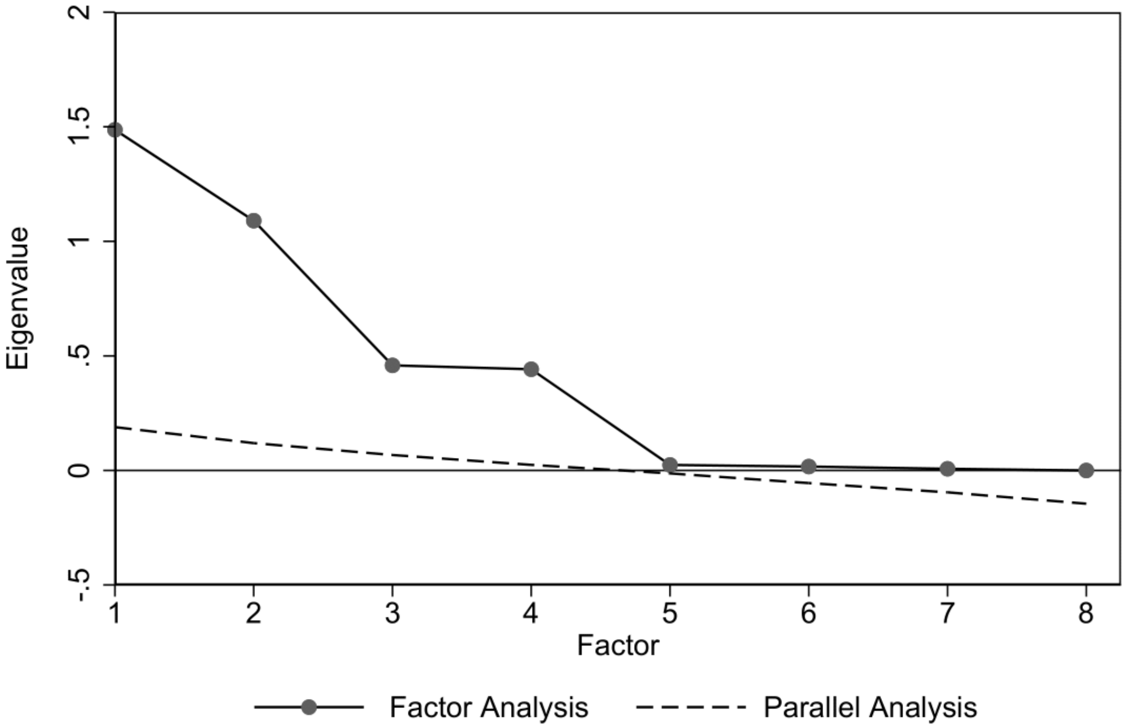
The parallel analysis first involves randomly simulating data of the same dimension as that being analysed. For example, if preforming an EFA on 6 variables measuring characteristics of N individuals, the resulting simulated dataset would be $N \times 6$. The eigenvalues of the correlation matrix among the randomly simulated data are the calculated and compared with those from the factors underlying the the actual data. Horn (1965) suggests retaining factors from the actual data as long as their eigenvalues are larger than those from the randomly generated correlation matrix. To complement this we generate scree plots as proposed by Cattell (1966), plotting the eigenvalues of factors in order of magnitude.[22]

Figure C4 shows one of these plots for initial cognitive and socio-emotional skill. Using Horn (1965)'s rule-of-thumb, the figure would suggest these measures have enough variation to retain at most 4 factors. Cattell (1966) suggests retaining only the factors whose eigenvalues are larger than that of the factor at which the first large drop in eigenvalue occurs. In Figure C4 the first major drop in eigenvalue occurs at factor 3. Additionally, Kaiser (1960) suggests keeping only a number of factors greater or equal to the number of eigenvalues greater than 1, which is true for only 2 latent factors in Figure C4. Together, these criteria suggest that these measures are rich enough to capture at least the two underlying factors we ex-ante believe to be underlying the measures. We repeat this analysis in each round, grouping observables as those measuring child human capital, investments, or parental skills.

Having verified the measures share meaningful variation with which to capture their underlying factor, we then establish the relationship between each measure and retained factor by estimating their factor loadings. Tables C4 and C5 show the rotated factor loadings and unique variance associated with each measure of human capital and investment respectively in each period. We rotate the factor loadings obtained from an EFA using the *oblique quartimin* rotation, which enables us to obtain a vector of factor loadings allowing for underlying factors to be correlated and so the loadings accurately capture the extent to which observables group around factors. For children's human capital (Table C4) there is a clear divide between those the we ex-ante believe to measure socio-emotional versus cognitive skill. For example, in the initial period the emotional conduct measures do load heavily on Factor 2 - which we define as the socio-emotional factor - whereas the cognitive assessments load heavily on Factor 1 - the cognitive factor. There are a couple of slight exceptions to this, however. Agency appears to load on both factors in periods 2 and 3, albeit to a much larger extent on the socio-emotional factors. The same is true for self-efficacy in period 3. This is perhaps unsurprising given the relationship between measures of this type an cognitive skill. We retain these measures given that they are highly correlated with cognition, and are measures of particular interest to the questions of this paper.

[22] To conduct this analysis we use Philip B. Ender's *-fapra-* package in Stata.

Figure C4: Eigenvalues from EFA and parallel analysis of initial (Age 8) child socio-emotional and cognitive skill measures



Note: The solid line connects the eigenvalues of the factors underlying 8 measures of socio-emotional (5 measures) and cognitive skill (3) at age 8 in the YL survey. The dotted line connects the eigenvalues of the 8 factors underlying randomly simulated data of the same dimension (i.e $N \times 8$). This figure was generated using Philip B. Ender's *-fapra-* package in Stata.

Although, informed by the data, we only retain one factor for investments, Table C5 shows the estimated rotated factor loadings and unique variance associated with each measure of investment across periods. These are useful in that they provide an ex-ante approximation to the extent of signal in each measure.

Table C4: Factor loadings and unique variance of observable cognitive and socio-emotional skill measures

	Factor 1	Factor 2	Uniqueness
Age 8			
Conduct issues	0.019	0.605	0.630
Emotional symptoms	0.055	0.450	0.788
Hyperactivity	-0.035	0.620	0.621
Peer problems	-0.007	0.274	0.925
Prosociality	0.026	0.185	0.964
Ravens test score	0.389	-0.063	0.852
Writing level	0.790	-0.048	0.385
Reading level	0.750	0.067	0.418
N	606		
Age 12			
Agency	-0.011	0.316	0.904
Pride	0.002	0.853	0.270
Current position on ladder	0.023	0.096	0.988
Maths test score	0.618	0.068	0.568
PPVT score	0.904	-0.020	0.202
N	630		
Age 15			
Agency	0.106	0.326	0.875
Pride	-0.002	1.201	-0.442
Cantril's ladder	0.100	0.114	0.975
Emotional problems	0.279	0.078	0.911
Maths test score	0.711	-0.048	0.499
PPVT score	0.821	0.025	0.321
Cloze test score	0.875	0.002	0.233
N	614		
Age 19			
Agency	0.197	0.325	0.830
Self-efficacy	0.683	0.148	0.473
Self-esteem	0.788	-0.057	0.393
Peer relationships	0.667	-0.061	0.567
Cantril's ladder	0.304	-0.030	0.910
Emotional problems	0.205	0.124	0.933
Maths test score	-0.006	0.821	0.327
Language test score	-0.004	0.839	0.297
N	584		

Note: The table contains rotated factor loadings and the proportion of variance in each cognitive and socio-emotional skill measure not shared with all others after retaining two factors from an initial exploratory factor analysis. Two factors were retained based on the assumption the measures proxy two latent concepts, socio-emotional and cognitive skill and the rules-of-thumb for factor retention proposed by Kaiser (1960), Horn (1965), and Cattell (1966). Factor loadings were obtained through an oblique quartimin rotation.

Table C5: Factor loadings and unique variance of observable investment measures

	Factor 1	Uniqueness
Age 12		
Per child book expenditure	0.584	0.659
Per child uniform expenditure	0.285	0.919
Per child non-food expenditure	0.332	0.890
Hours studying	0.155	0.976
Hours in school	0.327	0.893
Food groups	0.543	0.705
N	593	
Age 15		
Per child book expenditure	0.734	0.462
Per child uniform expenditure	0.419	0.824
Per child non-food expenditure	0.338	0.886
Hours studying	0.405	0.836
Hours in school	0.416	0.827
Food groups	0.427	0.818
N	526	
Age 19		
Education expenditure	0.319	0.898
Non-food expenditure (soles)	0.051	0.997
Hours studying	0.626	0.609
Hours in school	0.881	0.223
Food groups	0.080	0.994
N	618	

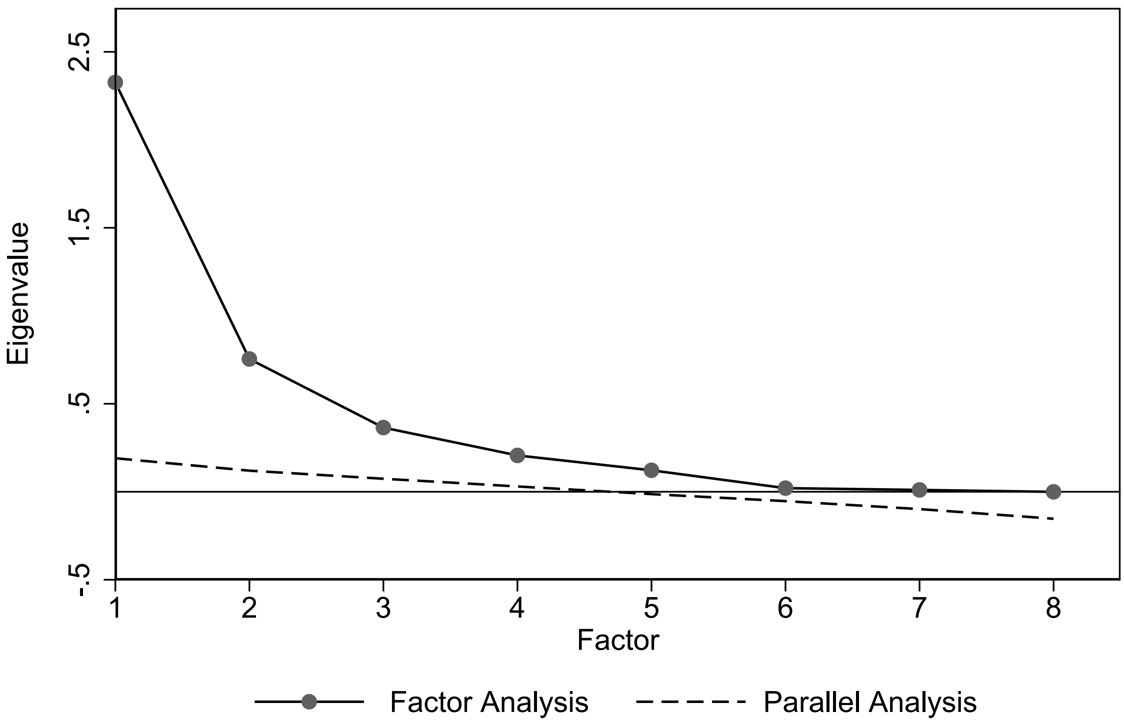
Note: The table contains rotated factor loadings and the proportion of variance in each investment measure not shared with all others after retaining one factors from an initial exploratory factor analysis. One factor was retained based on the assumption the measures proxy one latent investment and the rules-of-thumb for factor retention proposed by Kaiser (1960), Horn (1965), and Cattell (1966). Factor loadings were obtained through an oblique quartimin rotation.

C.4 Results of EFA on Age 22 Socio-emotional Skill Measures

At age 22, as was the case between ages 8-19, we again first used the principal of CSE to select measures, excluding those that were measuring subjective wellbeing or relied on assessments of their feelings/reactions to the behaviour of others. This meant, for example, excluding Cantril's ladder (Cantril et al., 1965) and measures of trust and respondents' relationship with their parents, as well as measures of pride and self-esteem that had changed substantially from earlier rounds.

We were then left with 8 measures of leadership qualities, quality of relationships with peers, ability to work in a team, self-efficacy, agency, grit, and the Big 5 emotional stability and conscientiousness scales. Ex-ante, we divided these into two groups, with the former 3 seemingly best representing social skills, and the latter 5 task effectiveness. With these measures we first confirmed they shared sufficient variation to extract as in the preceding periods - Figure C5 plots the eigenvalues of the factors underlying the measures alongside those from a parallel analysis as outlined in the previous subsection. It shows that, using the same rules-of-thumb as in the EFA of measures at previous ages the data supports extracting either 1 or 2 factors. Although the eigenvalue of the second factor is below 1 - another commonly used threshold to decide upon extraction (Kaiser, 1960) - we chose to extract 2 factors in order to disaggregate socio-emotional skills into 2 domains.

Figure C5: Eigenvalues from EFA and parallel analysis of age 22 socio-emotional skill measures



Note: The solid line connects the eigenvalues of the factors underlying 8 measures of socio-emotional skill at age 22 in the YL survey. The dotted line connects the eigenvalues of the 8 factors underlying randomly simulated data of the same dimension (i.e $N \times 8$). This figure was generated using Philip B. Ender's *-fapra-* package in Stata.

Table C6 then shows the estimated rotated factor loadings and unique variance that correspond to each retained measure and factor at age 22. It shows that, with the exception of self-efficacy, our ex-ante beliefs about the groupings of the skill measures is borned out in the data - leadership qualities, quality of relationships with peers and ability to work in a team load heavily on the first factor, whereas gency, grit, and the Big 5 emotional stability and conscientiousness scales load heavily on the second.

Table C6: Factor loadings and unique variance of observable socio-emotional skill measures at age 22

	Factor 1	Factor 2	Factor 3	Uniqueness
Social skills				
Leadership	0.668	0.004		0.551
Peer relationships	0.648	-0.091		0.648
Teamwork	0.583	0.062		0.609
Task effectiveness				
Agency	0.106	0.364		0.807
Self-efficacy	0.703	0.054		0.454
Grit	-0.040	0.643		0.617
Big 5 neuroticism	-0.047	0.498		0.780
Big 5 conscientiousness	0.161	0.512		0.607
N	596			

C.5 Additional Production Function Estimates

Table C7: Variance covariance matrix of the initial conditions

	$\ln H_{s,0}$	$\ln H_{c,0}$	$\ln P_s$	$\ln P_c$	$\ln Y_0$
$\ln H_{s,0}$	1.774				
$\ln H_{c,0}$	0.663	8.762			
$\ln P_s$	0.135	2.737	0.037		
$\ln P_c$	-0.373	9.500	1.930	12.870	
$\ln Y_0$	-0.0188	0.621	0.114	0.590	1.141

Table C8: Mean vector of the initial conditions

$\ln H_{s,0}$	$\ln H_{c,0}$	$\ln P_s$	$\ln P_c$	$\ln Y_0$
0	0	0	0	6.25

Table C9: Estimates of socio-emotional production function parameters with interacted investment and cognitive skill

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	-0.006	0.175	0.173***
	(0.057)	(0.682)	(0.063)
	[-0.100,0.087]	[-0.946,1.296]	[0.069,0.277]
$\ln H_{c,t-1}$	0.534***	0.683	0.508*
	(0.107)	(0.599)	(0.272)
	[0.358,0.711]	[-0.302,1.668]	[0.060,0.955]
Parental human capital (fixed over time)			
$\ln P_s$	0.190	0.023	0.124
	(0.154)	(0.652)	(0.273)
	[-0.063,0.443]	[-1.049,1.095]	[-0.325,0.572]
$\ln P_c$	0.012	0.092	-0.050
	(0.025)	(0.151)	(0.034)
	[-0.030,0.054]	[-0.157,0.340]	[-0.106,0.005]
Investments			
$\ln I_{t-1}$	0.481***	0.058	0.382
	(0.085)	(0.378)	(0.233)
	[0.340,0.621]	[-0.564,0.680]	[-0.001,0.764]
$\ln I_{t-1} \times \ln H_{c,t-1}$	-0.210***	-0.030	-0.135
	(0.064)	(0.343)	(0.171)
	[-0.315,-0.106]	[-0.595,0.534]	[-0.417,0.147]
$\sigma^2_{\eta_n}$	3.75	5.22	.893
N	602	601	565

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, 15, and 19 for the three columns respectively. The output in each column is socio-emotional skill. The inputs in the left column are are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment and its interaction with lagged human capital. All inputs are treated as unobservable. The observables used as measures of each are discussed in Appendix Tables B. Appendix A outlines the method used to obtain all estimates in the table.

Table C10: Estimates of socio-emotional production function parameters with interacted investment and socio-emotional skill

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	-0.394**	0.524	0.162***
	(0.194)	(0.841)	(0.062)
	[-0.713,-0.074]	[-0.858,1.907]	[0.059,0.265]
$\ln H_{c,t-1}$	0.198*	0.416	0.452**
	(0.102)	(0.862)	(0.194)
	[0.031,0.366]	[-1.002,1.835]	[0.134,0.770]
Parental human capital (fixed over time)			
$\ln P_s$	0.397***	-0.069	0.195
	(0.134)	(0.492)	(0.198)
	[0.176,0.618]	[-0.878,0.740]	[-0.131,0.521]
$\ln P_c$	-0.043	0.074	-0.039
	(0.028)	(0.128)	(0.027)
	[-0.088,0.003]	[-0.137,0.285]	[-0.084,0.005]
Investments			
$\ln I_{t-1}$	0.683***	0.145	0.219
	(0.207)	(0.536)	(0.138)
	[0.343,1.023]	[-0.736,1.027]	[-0.008,0.446]
$\ln I_{t-1} \times \ln H_{n,t-1}$	0.158**	-0.091	0.012
	(0.076)	(0.213)	(0.075)
	[0.034,0.283]	[-0.442,0.260]	[-0.111,0.135]
$\sigma^2_{\eta_n}$	2.4	11.4	.902
N	602	601	565

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, 15, and 19 for the three columns respectively. The output in each column is socio-emotional skill. The inputs in the left column are are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment and its interaction with lagged human capital. All inputs are treated as unobservable. The observables used as measures of each are discussed in Appendix Tables B. Appendix A outlines the method used to obtain all estimates in the table.

Table C11: Estimates of cognitive production function parameters with interacted investment and cognitive skill

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	0.048	-0.039	0.048*
	(0.039)	(0.166)	(0.029)
	[-0.016,0.113]	[-0.312,0.234]	[0.001,0.095]
$\ln H_{c,t-1}$	0.572***	0.623***	0.874***
	(0.080)	(0.120)	(0.207)
	[0.440,0.703]	[0.425,0.821]	[0.533,1.215]
Parental human capital (fixed over time)			
$\ln P_s$	0.121	0.210	-0.026
	(0.108)	(0.159)	(0.159)
	[-0.057,0.299]	[-0.051,0.471]	[-0.287,0.236]
$\ln P_c$	0.011	-0.002	-0.043**
	(0.019)	(0.014)	(0.020)
	[-0.020,0.042]	[-0.025,0.022]	[-0.076,-0.010]
Investments			
$\ln I_{t-1}$	0.437***	0.196**	0.312*
	(0.065)	(0.078)	(0.189)
	[0.330,0.544]	[0.068,0.324]	[0.001,0.624]
$\ln I_{t-1} \times \ln H_{c,t-1}$	-0.189***	0.012	-0.166
	(0.051)	(0.083)	(0.128)
	[-0.272,-0.105]	[-0.125,0.149]	[-0.377,0.045]
$\sigma^2_{\eta_c}$	.105	.681	.843
N	598	595	551

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, and 15 for the three columns respectively. The output in each column is cognitive skill. The inputs in the left column are are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment and its interaction with lagged human capital. All inputs are treated as unobservable. The observables used as measures of each are discussed in Appendix B. Appendix A outlines the method used to obtain all estimates in the table.

Table C12: Estimates of cognitive production function parameters with interacted investment and socio-emotional skill

	Period 1 *Ages 8-12*	Period 2 *Ages 12-15*	Period 3 *Ages 15-19*
Lagged human capital			
$\ln H_{s,t-1}$	0.043	-0.518	0.028
	(0.152)	(0.854)	(0.027)
	[-0.208,0.293]	[-1.922,0.887]	[-0.016,0.072]
$\ln H_{c,t-1}$	0.356***	1.047	0.882***
	(0.080)	(0.695)	(0.169)
	[0.224,0.488]	[-0.096,2.191]	[0.604,1.160]
Parental human capital (fixed over time)			
$\ln P_s$	0.404***	0.277	-0.042
	(0.139)	(0.271)	(0.144)
	[0.174,0.633]	[-0.169,0.724]	[-0.279,0.195]
$\ln P_c$	-0.023	-0.001	-0.030*
	(0.023)	(0.021)	(0.018)
	[-0.061,0.015]	[-0.036,0.034]	[-0.059,-0.001]
Investments			
$\ln I_{t-1}$	0.219	0.072	0.189**
	(0.163)	(0.240)	(0.093)
	[-0.049,0.487]	[-0.323,0.466]	[0.035,0.342]
$\ln I_{t-1} \times \ln H_{n,t-1}$	0.002	0.122	-0.028
	(0.061)	(0.207)	(0.044)
	[-0.099,0.102]	[-0.219,0.463]	[-0.100,0.044]
$\sigma^2_{\eta_c}$	.0619	.494	.878
N	598	595	551

Notes: Standard errors are in parentheses, and 90% confidence intervals are in square brackets. Both are calculated using the delta method. $t-1$ = ages 8, 12, and 15 for the three columns respectively. The output in each column is cognitive skill. The inputs in the left column are are lagged child socio-emotional skill and cognitive skill; parental socio-emotional and cognitive skill; and investment and its interaction with lagged human capital. All inputs are treated as unobservable. The observables used as measures of each are discussed in Appendix B. Appendix A outlines the method used to obtain all estimates in the table.