The Formation and Evolution of Childhood Skill Acquisition: Evidence From India[*]

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ABSTRACT

Building on recent advances in the literature and using a rich data set for two cohorts of children aged between one and twelve for Andhra Pradesh, India, we investigate the determinants of children's cognitive as well as non-cognitive skills. We find evidence of self-productivity for cognitive skills and cross-productivity effects from cognitive on non-cognitive skills. Moreover, we demonstrate that parental investment has contemporaneously positive effects on skill levels for all age groups. Investigating other determinants of these skills, we find child health at age one to influence cognitive abilities at age five, whilst child health at age one is influenced by parental care already during pregnancy and earliest childhood. Understanding the determinants which account explicitly for the effect of a large number of child, caregiver and household characteristics provides insights with regard to possible policy interventions to improve the chances of children in poor environments of developing cognitive and non-cognitive skills crucial for success in many spheres of life.

KEYWORDS: Children, cognitive skills, non-cognitive skills

JEL Classification: J13, O15

1   Introduction

The investigation of the determinants of a child's socio-economic success in later life has traditionally focused on schooling. A large body of literature in psychology and more recently also in economics, however, argues that the true determinants of a child's success in life are formed already during early childhood. Heckman et al. (2006) have shown that for this reason, school quality and resources devoted to students are only effective in as much as they remedy (to a limited extent) deficits in ability caused in earlier childhood. In explaining school and professional success much emphasis has been put on the analysis of the importance of cognitive skills (Heckman, 1995). The psychometric literature (e.g., Heckman and Rubinstein, 2001; Cunha and Heckman, 2008), however, has shown that non-cognitive abilities, such as motivation, perseverance, risk aversion, self-control etc., also play an important role in setting the course for a successful later life beyond childhood.

The early economic analysis of child development (Becker and Tomes, 1986) assumed that childhood consisted of a single homogeneous phase. Psychological research (e.g., Thompson and Nelson, 2001) demonstrated that child development is comprised of multiple stages. A child develops cognitive and non-cognitive skills through different stages during childhood. She acquires cognitive skills very early in life, beginning already in the womb. The development of cognitive skills, for example IQ, is mostly completed by age eight to ten. While the development of non-cognitive skills also starts early in life and is equally affected by a child's environment, these skills remain malleable later in life (Carneiro et al., 2003). Importantly, these cognitive and non-cognitive skills interact and reinforce each other, characteristics termed *self-* and *cross-productivity* (Carneiro et al., 2003).

There are two main influences shaping a child's abilities during this multistage development process: a child's genetic endowment as well as inputs received from the outside world, including family and the wider environment children are born into. Many studies highlight the importance of genetic variance in determining child development. By examining behavioural patterns of adopted children vis-à-vis their siblings (Scarr and Richard, 1983; Teasdale and Owen, 1985), as well as those between a pair of monozygotic and dizygotic twins (Wilson, 1983), the research has focused on establishing that siblings with uncorrelated genetic structure do not resemble each other in any measured talents. Thus while family and home environment contexts may have common influences in fostering child development, these environments can be construed in different ways by children based on their genome structure. Nonetheless, these studies highlight how family and environment play a crucial role in child development over

the child's early periods. Scarr and Weinberg (1983) find, from a sample of transracial families, that young siblings (black/interracial adoptees compared to their natural brothers/sisters) are intellectually similar, hence concluding that younger children are more influenced by differences within their family environment.[1] More fundamentally, emerging research by geneticists shows that environmental factors may cause genes to express themselves differently. This effect, traditionally termed as 'epigentics', reveals that many behaviour patterns of genes can be altered by life cycle experiences (Hunter, 2008). Regarding inputs from outside, Carneiro and Heckman (2003) have shown that the principal source of influence are a child's parents. Hence, a child's abilities can be produced and modified through outside influences over the different stages of childhood and even to some extent in later adult life. This implies that inputs and environmental factors have different effects during these different development stages. In addition, inputs are cumulative in nature, a characteristic labeled dynamic complementarity (Carneiro et al., 2003). This, in turn, implies that early investments must be followed up by investments during later stages in life to render early investments more effective (Currie and Thomas, 1995). It also means that deficiencies, above all in cognitive skills, caused early in life are hard to remedy and the later remediation occurs, the less effective it is (O'Conner et al., 2004). Hence, while for some skills late remediation is nevertheless possible, it would be more efficient to avoid the emergence of these deficiencies early in life (Cunha and Heckman, 2007).

These findings about the development process of a child's abilities are important as Cunha et al. (2006) have found that children diverge very quickly in terms of their development of cognitive as well as non-cognitive skills according to the input received during the sensitive phases of early childhood. This has substantial and far-reaching implications for a child's later life given the large evidence on ability as a predictor for school success, wages, crime involvement and other spheres of life (Heckman, 1995; Heckman et al., 2006; Borghans et al., 2008). We also know that returns to schooling and job training are lower for individuals with lower skill levels (Carneiro and Heckman, 2003), which justifies early intervention on efficiency grounds as high returns may be expected from remediation for disadvantaged children (Blau and Currie, 2006).

So far, the bulk of this research has been undertaken in industrialised countries.[2] Little is known about the potentially enormous implications of these findings in the developing country context (Grantham-McGregor et al., 2007). In most developing

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[1] 'A major reason for the greater resemblance [...] is that families have greater effects on their younger than older children' (Scarr, p. 11: 1992).

[2] In fact, most studies even use the same data set, the US National Longitudinal Survey of Youth (NLSY).

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countries school quality is despicably low, and while demand for schooling from households may be reflected as quite high in terms of school enrolments, it has been well documented that the achievement levels of children especially in rural schools still continue to lag (Gonzalez et al., 2004). In order to improve school performance and a child's chances of succeeding in later life, the literature discussed gives strong reason to shift focus from schooling towards other factors influencing a child's development of cognitive and non-cognitive traits during early childhood. Whether a child is ready for and achieves progress in school depends to a large extent on the child's cognitive attainment level, but also hinges to a non-negligible extent on her social and emotional development, a component mostly forgotten in the developing country context. In a recent study, Grantham-McGregor et al. (2007) find that both poverty and bad home environment conditions result in child stuntedness hampering early child development. The authors go on to show how these early childhood disadvantages affect later period skill development: children who are stunted at early stages tend to perform poorly later on at school. Taking this analysis further, Walker et al. (2007) chart out channels that are most likely to affect early childhood development, leading to child stuntedness. Important factors, include what the authors term 'Psycho-social Risk Factors' (PRF) and childhood poverty. The authors describe PRF as a combination of parenting factors (child-learning opportunities, caregiver sensitivity), and contextual factors (maternal depression and exposure to violence). Hence, high PRF and childhood poverty can lead to childhood stuntedness which subsequently leads to adverse cognitive and non-cognitive skill acquisition outcomes. A previous analysis using the first round of data of the 'Young Lives' survey in India's state of Andhra Pradesh for eight-year-old children by Galab et. al. (2006) found that girls lagged in achievement compared to boys, children of uneducated parents are at a disadvantage, and more importantly, that there is a clear interplay between school and home. The authors assert that while it may be that child learning is determined at school, home environment remains crucial in fostering child achievement. They argue that children tend to perform better on literacy and numeracy tasks if parents place high value on schooling (therefore investing more in their child's education) and actively support/help their children at home.

Despite these recent advances in the literature, little is known as to how a child's cognitive and non-cognitive skills interact and how a child's environment, including family, affects cognitive as well as non-cognitive development in a developing country context. Some of the assumptions made in the analysis of children's skill acquisition in the industrialised world may not be realistic in a developing country. For example Cunha and Heckman (2007) assume that parents care for children and invest in their development exclusively for altruistic motives. This assumption certainly needs to be

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relaxed in an economically deprived environment. Moreover, there may be environmental factors in shaping a child's skill development that should receive more attention in developing countries. The literature on developing countries has for example shown the importance of social networks for poor households in coping with common adversities (Fafchamps and Gubert, 2006). Therefore, it may be important to explicitly take account of the role played by social networks in skill acquisition.

The objective of our analysis is therefore to investigate determinants of a child's development of cognitive and non-cognitive skills over various phases of childhood, paying particular attention to self- and cross-productivity effects within a developing country context. Self-productivity refers to any effect of past periods' cognitive/non-cognitive skills on the current period's cognitive/non-cognitive skills respectively, while cross-productivity refers to any effect of past periods' cognitive/non-cognitive skills on current period non-cognitive/cognitive skills. For this purpose, we estimate a Linear Structural Relations (LISREL) model which allows us to estimate latent cognitive and non-cognitive skill levels as well as parental investment and to link these variables to observed child, parental and household characteristics. Building on Cunha and Heckman (2007, 2008), we specifically examine the dynamics of both cognitive and non-cognitive skills as well as their interplay over time. In Section 2, we discuss our methodology for the skill acquisition model. Section 3 describes the data used for our empirical investigation, while Section 4 lays out its estimation procedure. Section 5 presents our results and findings. Section 6 concludes.

2 Methodology

Our main interest lies in investigating the various determinants of skill formation with a particular focus on the effects of a child's past cognitive and non-cognitive skill levels in determining current levels of the same. This includes self-productivity as well as cross-productivity effects. In order to achieve this, we follow Cunha and Heckman (2008) in writing a child's skill level at age t as a function of the child's past level of skills, current parental investment, and other contemporaneous variables including child, caregiver, and household characteristics.

$$\theta_t^k = f(\theta_{t-1}^k, \theta_t^I, X_t) \tag{1}$$

where θ_t^k denotes a child's skill level of skill k for age t, with $k \in \{C, N\}$ and $t \in \{0, ..., T\}$. θ_t^I denotes parental investment at age t, and X_t denotes a vector of child, caregiver and household characteristics. Importantly, function (1) allows for self-

productivity, i.e., θ_{t-1}^N and θ_{t-1}^C having an effect on θ_t^N and θ_t^C respectively, and cross-productivity, i.e., θ_{t-1}^N and θ_{t-1}^C having an effect on θ_t^C and θ_t^N respectively. In order to take account of the genetic endowment with which a child is born, we assume that each child is born with an individual initial set $\theta_o = (\theta_o^C, \theta_o^N)$. It is this initial set of skills which introduces - in principle unobserved - heterogeneity across children.[3] Todd and Wolpin (2007) propose to capture genetic endowment through a functional relationship such as

$$\theta_{it}^k = f(\theta_{it-1}^k, \theta_{it}^I, X_{it}, \mu_i) \tag{2}$$

where i denotes individuals. Todd and Wolpin (2007) propose to take first differences of a linear specification of (2) to eliminate μ_i. Purging a linear specification of (2) through first-differences relies on the fact that the *expression* of unobserved genetic endowment is constant over time - which appears a rather strong assumption. The problem with such value-added specifications, as pointed out by Andrabi et. al. (2008), is that it fails to account for the dynamic nature of achievement gains, wherein individual level heterogeneity entering in each period interacts with the achievement level in the past period. Using data from Pakistan, the authors find that the value-added specification perform worse than cross-sectional comparisons. Instead of first-differences, we use several control variables that enter the set of conditioning variables of the regression function as proxies for unobserved child heterogeneity. For the 'younger' cohort, our data on child characteristics covers the period from before birth through age one. Controlling appropriately for unobserved initial conditions for the 'older' cohort is more challenging as we do not have data on their characteristics at the time of birth. Instead, we rely on child height, the child's caste and information on whether the child was born in the village where she currently resides. Keeping in mind the difficulty of using proxy variables to capture unobservables in the skill production function (Todd and Wolpin, 2003), we discuss the relationship of these variables to both measured and unobserved inputs in the production function in more detail in Section 3.2.

However, apart from children having unobserved genetic characteristics, there also exist problems with unobservability of important features of observed inputs. Probably most importantly, quality of parental investment is unobserved. As noted by Waldfogel, 'maternal sensitivity is the most important predictor of child social and emotional

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[3]Note that there is an important distinction between heterogeneity and uncertainty caused by unobserved genetic endowment. Heterogeneity refers to individuals making choices based on their knowledge about their specific type whereas uncertainty refers to a situation where the type is unknown (Browning and Carro, 2006). It appears, therefore, more appropriate to regard a child's genetic endowment for the one-year-old children in our data as causing uncertainty rather than heterogeneity.

development' (Waldfogel, p. 62: 2006), which is unobserved.[4] To the extent that our observed measures for the latent variables capture such unobservables, the measurement model mitigates this problem. Endogeneity may also arise from a simultaneous relationship between a child's ability and parental investment as parents may invest more/less in children with higher skill levels which leads to a simultaneity bias in the coefficient associated with parental investment (Becker and Tomes, 1976). In order to account for potential endogeneity, we also estimate the model instrumenting for parental investment. We use household specific shocks affecting household wealth and a child's birth order as instruments. Validity of these instruments rests on the assumption that their effect on child outcomes works exclusively through parental investment conditional on a set of control variables. This appears to be a credible assumption as children will be affected by unexpected shocks to household wealth only through adjustments made by parents in their investment in their children. Tominey (2009) demonstrates the importance of parental income shocks for child cognitive skill formation using Norwegian data where the effect of the shocks works through their impact on parental investment.[5] Ginja (2010) has more detailed data for the US that allows her to investigate the specific ways in which parents adjust investment in their children in response to unemployment shocks. She finds that parents react in terms of their allocation of time spent with children. These empirical findings, albeit derived from developed country data, suggest that income and local labour market shocks indeed affect children through changes induced in parental investment. Similarly, in developing countries, birth order may have an important effect on the investment made by parents in children. Although birth-order has been used as a direct determinant of child outcome measures such as (post) birth weight (Rosenzweig and Wolpin, 1988), we believe that its impact on cognitive and non-cognitive skills works through parental investment rather than directly conditional on a set of control variables including household size. For example, as suggested by Behrman and Taubman (1986), in a developing country setting where children serve old-age insurance purposes, parents may choose to invest more in lower birth order children because the financial returns to their investment are more likely to available when they need it. Price (2008) provides evidence for the US that the effect of birth order on child outcomes works indeed through parental investment in the form of time spent with a child. Over the course of childhood, first-born children receive more

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[4]To some extent, as described in the data section later, our PRF variable captures such sensitivity as the indicators used include variables proxying parental care exerted on the child, such as breast-feeding or intensity of antenatal care. Unfortunately, we do not possess similar measures for five-, eight-, and twelve-year-old children.

[5]Tominey (2009) distinguishes between permanent and transitory income shocks, finding that permanent shocks have a larger impact on younger children whereas the opposite holds for transitory shocks.

parental input in form of 'quality' time spent with their parents than higher birth-order children.[6] We find these instruments to be highly correlated with parental investment, which is confirmed by the first-stage results reported in Tables 6b, 7, and 8 in Section 5.

Given that we only have data for two moments in time for each cohort, our analysis simplifies compared to that of Cunha and Heckman (2008). We are only able to estimate a single transition, for initially one-year- and eight-year-old children to age five and twelve respectively. We therefore estimate a simple recursive system of equations:

$$\begin{pmatrix} \theta_{t-1}^C \\ \theta_{t-1}^N \end{pmatrix} = \Gamma_{t-1}\theta_{t-1}^I + \Upsilon_{t-1}X_{t-1} + \begin{pmatrix} \zeta_{t-1}^C \\ \zeta_{t-1}^N \end{pmatrix} \tag{3a}$$

$$\begin{pmatrix} \theta_t^C \\ \theta_t^N \end{pmatrix} = B_t \begin{pmatrix} \theta_{t-1}^C \\ \theta_{t-1}^N \end{pmatrix} + \Gamma_t\theta_t^I + \Upsilon_t X_t + \begin{pmatrix} \zeta_t^C \\ \zeta_t^N \end{pmatrix} \tag{3b}$$

We make the assumptions that $E(B) = 0$, $E(\Gamma) = 0$, $E(\Upsilon) = 0$, $Cov(B,\Gamma) = 0$, $Cov(B,\Upsilon) = 0$ and $Cov(\Upsilon,\Gamma) = 0$. While system (3) is relatively straightforward to estimate under these assumptions due to its recursive structure, the main problem arises from the fact that skills and parental investment are latent variables and have to be estimated given available indicators through confirmatory factor analysis. More specifically, given our objective to estimate (3), we are only interested in a single measure for the respective latent variable and therefore employ a one-factor model. The one-factor models for the latent skill variables are written as follows

$$X_{i,t-1}^k = \Lambda_{oi,t-1} + \Lambda_{1i,t-1}^k\theta_{t-1}^k + \epsilon_{1i,t-1}^k \tag{4a}$$

$$X_{i,t}^k = \Lambda_{oi,t} + \Lambda_{2i,t}^k\theta_t^k + \epsilon_{2i,t}^k \tag{4b}$$

with $k \in \{C, N, I\}$. X represents observed measures of the latent variable with $i = 1, ..., m_t^k$ denoting the different available indicators for the specific latent variable. θ is the factor for the latent variable k with $k \in \{C, N, I\}$ and ϵ is an error term where θ and ϵ are unobserved. $\Lambda_{i,t}$ represents factor loadings and $\Lambda_{io,t}^k$ is a measure-specific intercept. In order to estimate the model, we have to make several distributional assumptions. First, the factor and the error term are uncorrelated and have an expected

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[6]'Quality' time is defined as activities carried out jointly with a parent where 'either the child was the primary focus of the activity or in which there would be a reasonable amount of interaction, such as eating together' (Price, 2008: 244).

value of zero. Second, the errors are independent over time and across children. Thirdly, we assume that the relationship between the factor and the observed variables is linear.[7] Finally, the scale of the common factor is fixed by setting the first factor loading equal to one.[8] The estimated factor score is then predicted as the conditional mean of the latent variable given the observed variables.

We allow latent cognitive and non-cognitive skill variables for the same age of a child to covary, and for parental investment indicators also across age. In contrast, we set all off-diagonal elements of the variance-covariance matrix for the errors of the factor models to zero, i.e., $Cov(\epsilon_t^q, \epsilon_t^p) = 0$, $Cov(\epsilon_t^q, \epsilon_{t-1}^p) = 0$ and $Cov(\epsilon_t^q, \epsilon_{t-1}^q) = 0$ for $q, p \in \{C, N, I\}$, which leaves us with two diagonal matrices. While the assumption of diagonal error matrices for the factor models helps achieving identification of the model, it may appear restrictive - in particular with regard to parental investment. We allow for the possibility that the variance-covariance matrix for the system (3) has off-diagonal elements not equal to zero for cognitive and non-cognitive skill levels at age eight (Equation 3a) and twelve (Equation 3b).

Before proceeding to the estimation of the model, we have to ensure that it is identified. As suggested by Jöreskog and Sörbom (1978), an estimation-based check for identification of the model is to look at the information matrix obtained from the maximum likelihood estimation. If the matrix is positive definite, Jöreskog and Sörbom suggest that the model is highly likely to be identified. It is preferable, however, to ensure identification before we proceed with the estimation step of the analysis. To prove identification, we have to identify the joint distributions of $\{\theta_{i,t-1}^C, \theta_{i,t-1}^N\}_{t-1}$, $\{\theta_{i,t}^C, \theta_{i,t}^N\}_t$, $\{\theta_{i,t-1}^I\}_{t-1}$, $\{\theta_{i,t}^I\}_t$, $\{\epsilon_{i,t-1}^k\}_{t-1}^i$, $\{\epsilon_{i,t}^k\}_t^i$ and the factor loadings $\{\lambda_{i,t-1}^k\}_{t-1}^i$ and $\{\lambda_{i,t}^k\}_t^i$ for $k \in \{C, N, I\}$. In order to achieve this, we have to identify the variances and covariances of the latent variables by showing that all latent variables can be solved for in terms of the variances and covariances of the observed indicators. Once we have demonstrated that the parameters of the measurement model are identified in this way, the parameters of the recursive model can be identified by solving them in terms of the covariances among the factors (Long, 1983).

We have assumed above that covariances for the latent variables are set to zero for all off-diagonal elements of the covariance matrix for θ except for latent variables for

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[7]Cunha, Heckman, and Schennach (2006) analyse the more general case of non-linear systems.

[8]Alternatively, we could set the factor variance equal to one, which would result in an equivalent model as restricting the first factor loading to one. However, the latter restriction appears to be preferable from the point of view of factorial invariance (Rabe-Hesketh and Skrondal, 2004).

the same age, and parental investment latent variables also across age. Together with the assumption that the variance-covariance matrix for the errors of the factor models is a diagonal matrix, this implies that most covariances are set to zero. We only have to ensure identification of the non-zero off-diagonal elements. In order to see that they are identified, we first show that the factor loadings are identified by dividing (5b) by (5a) which express covariances of latent variables in terms of covariances of observed variables where $k, l \in \{C, N\}$. We assume without loss of generality two observed indicators $m_t^q = m_{t-1}^q = 2$ with $q \in \{C, N, I\}$ for each latent variable (subscripts for factor loadings omit m^q for ease of presentation).

$$Cov(X_{1,t}^k, X_{1,t}^l) = Cov(\theta_t^k, \theta_t^l) \tag{5a}$$

$$Cov(X_{1,t}^k, X_{2,t}^l) = \lambda_t^k Cov(\theta_t^k, \theta_t^l) \tag{5b}$$

$$\frac{Cov(X_{1,t}^k, X_{2,t}^l)}{Cov(X_{1,t}^k, X_{1,t}^l)} = \lambda_t^k \tag{5c}$$

Given the factor loadings in (5c), the covariances across latent skills for the same age are identified, as they can be written as the ratio of the observed covariance of observed indicators and the identified factor loading.

$$Cov(\theta_t^k, \theta_t^l) = \frac{Cov(X_{1,t}^k, X_{2,t}^l)}{\lambda_t^k} \tag{6}$$

where $k \neq l$. In case $k = l$, we proceed in a slightly modified way. First we note that

$$Var(X_{1,t}^k, X_{1,t}^k) = Var(\theta_t^k) + \epsilon_t^k \tag{7a}$$

$$Cov(X_{1,t}^k, X_{2,t}^k) = \lambda_t^k Var(\theta_t^k) \tag{7b}$$

$Var(\theta_t^k)$ is identified as it is given by

$$Var(\theta_t^k) = \frac{\lambda_t^k Var(\theta_t^k)}{\lambda_t^k} \tag{8}$$

which implies that also ϵ_t^k is identified. Finally, for the case of parental investment, where we allow latent variables to be correlated across age, identification is shown by

$$Cov(X_{1,t-1}^I, X_{1,t}^I) = Cov(\theta_{t-1}^I, \theta_t^I) \tag{9a}$$

$$Cov(X_{2,t-1}^I, X_{1,t}^I) = \lambda_{t-1}^I Cov(\theta_{t-1}^I, \theta_t^I) \tag{9b}$$

$$\frac{Cov(X_{2,t-1}^I, X_{1,t}^I)}{Cov(X_{1,t-1}^I, X_{1,t}^I)} = \lambda_{t-1}^I \tag{9c}$$

and following the same logic as above,

$$Cov(\theta_{t-1}^I, \theta_t^I) = \frac{Cov(X_{2,t-1}^I, X_{1,t}^I)}{\lambda_{t-1}^I} \tag{10}$$

and then to identify the variances and error terms

$$Var(X_{1,t-1}^I, X_{1,t-1}^I) = Var(\theta_{t-1}^I) + \epsilon_{t-1}^I \tag{11a}$$

$$Cov(X_{1,t-1}^I, X_{2,t-1}^I) = \lambda_{t-1}^I Var(\theta_{t-1}^I) \tag{11b}$$

$$Var(\theta_{t-1}^I) = \frac{\lambda_{t-1}^I Var(\theta_{t-1}^I)}{\lambda_{t-1}^I} \tag{11c}$$

where again errors are identified given that we have identified variances and covariances in (11c).

3 Data

We use data from the India part of the Young Lives (YL) project. YL is a long-term study of childhood poverty being carried out in Ethiopia, India (in the state of Andhra Pradesh), Peru and Vietnam. The broad objective of the YL project is to improve understanding of the causes and consequences of childhood poverty and to examine how policies affect childrens' well-being. Extensive child, household and community level questionnaires are administered to capture information on various aspects of the child's life including household demographics, care-giver background, child health (both physical and mental), economic shocks, household consumption, as well as social, economic and environmental context of each community. The YL survey involves tracking 12,000 children (two cohorts) growing up in the four developing countries over 15 years. Currently we are able to use information from two rounds of data collection for Andhra Pradesh, India. In Round 1, 2000 children aged around one (the 'younger' cohort) and 1000 children aged around eight (the 'older' cohort) were surveyed in 2002. Following up, Round 2 involved tracking the same children and

surveying them in 2006 at age five and twelve respectively.

The sample of children is representative of the three regions of Andhra Pradesh: Rayalseema, Coastal Andhra and Telangana. The sampling process was fourfold. First, six districts were selected based on the classification of poor/non-poor given by their relative levels of development. In the second stage, twenty sentinel sites within these districts were identified based on the same classification. Subsequently, one village was randomly selected from approximately four to five villages that comprised a sentinel site. The questionnaires were then administered to around 100 one-year-old and 50 eight-year-old children in these villages. Data was collected through household questionnaires, child questionnaires and a community questionnaire. Our estimation incorporates this survey design, wherein we use regions as our stratification variable and the sentinel sites as our clustering variable.

We use data obtained from both cohorts of children available in the YL survey. The two cohorts allow us to investigate two distinct periods of childhood. During the early childhood years, the transition between age one and five, a child still depends fully on her parents and family. The first few years of a child's life are decisive for the child's later physical and psychological well-being. The child learns during these years above all how to self-regulate, i.e., how to control her attention, emotions and behaviours. At the same time, the child acquires crucial cognitive skills, above all in terms of language acquisition. Therefore, the data on these early childhood years allow us to analyse factors influencing the foundations of skill formation, paying particular attention to a child's physical condition and her home environment. The data on the eight- to twelve-year-old cohort provides information on school-age children. Children at that age are concerned with the development of reflection - both on their own and others' thinking - and begin to think ahead in time and make plans for their future assuming responsibility for their actions. This goes along with increased social and emotional awareness. It is an age at which children begin to realise that they live in a society which sets challenges for them and they start figuring out how to find their own position within it. Apart from increasing cognitive skills, it is important for children to build confidence during this time, as it will be crucial later when they become more independent. An important change in a child's life during that period is a shift in importance of interaction with parents to peer interaction. Yet, while peer interaction becomes an essential part of a school-age child's existence, parents remain at the center of the child's life. Their role now shifts towards regulating a child's behaviour through monitoring and discipline (Waldfogel, 2006). In particular, the data on older children allows us to specifically analyse the dynamics of cognitive and non-cognitive skill formation and influences exerted by the child's immediate environment.

3.1 Latent variable indicators

Given that cognitive and non-cognitive skills and parental input are in principle unobserved, we have to treat them as latent variables for which we need to find observed indicators. Our data set provides us with multiple measures of child cognitive and non-cognitive skills as well as measures for parental investment, for both cohorts. We note here that the survey questionnaires differed slightly between Round 1 and Round 2. Although there is significant overlap between questions asked, we find that some indicators differ between the two rounds. However, as our interest lies in estimating latent variables, i.e., cognitive/non-cognitive achievement and parental investment, we are able to identify indicators for each of these in both rounds. As a result, these indicators can be different for the same cohort between the two rounds, but essentially lend to measurement in similar ways.

We rely on a range of observed indicators, for each cohort, to estimate our latent variables of interest: cognitive ability, non-cognitive ability, parental investment, child health, and PRF. Table A provides a comprehensive list and description of variables that we use as indicators in the measurement model to measure the above-mentioned items. Among the variables used to estimate the psycho-social risk factors are measures capturing antenatal conditions as there is evidence in the literature suggesting that fetal experiences exert a powerful effect on child outcomes (Almond, 2006). As indicators of child health we use anthropometry z-scores, i.e., weight for age and height for age and whether the child has suffered from serious illness. For children aged one, we do not observe any measures of cognitive and non-cognitive skills and therefore rely on child stuntedness as our outcome of interest.

The measures used to capture cognitive skills aim to capture a child's general intelligence and his ability to solve abstract problems. As such, measures for cognitive skills differ from those for non-cognitive skills which represent aspects of a child's personality, including timidity, extraversion, motivation, self-confidence etc. (Borghans et al., 2008). While we have test scores for a child's writing ability for both eight- and twelve-year old children, we use reading as well as Raven Progressive Matrices test scores for eight-year old children whereas numeracy and Peabody Picture Vocabulary test scores are used for twelve-year old children. The resulting estimated factor scores for cognitive ability at age eight and twelve are nevertheless comparable as these tests capture for both age groups both *fluid* and *crystallized* intelligence, i.e., a child's ability to solve novel problems as well as her ability to apply acquired knowledge and skills (Borghans et al., 2008). For the 'younger' cohort, we only have measures of a child's

cognitive achievement at age five. We use the Peabody Picture Vocabulary test score as well as scores from the Cognitive Development Assessment Quantitative Test. The measurement of non-cognitive skills is in general less straight-forward due the weaker theoretical guidance with regard to the definition of the concept of non-cognitive skills and their measurement (see Borghans et al., 2008) and the limited information available from the survey questions. We use different measures for children across age where all measures aim to capture different traits of a child's personality.

In construction of aggregate scores for cognitive outcomes, we make use of scores calibrated using Item Response Theory (IRT) instead of raw aggregates of all sub-items. Aggregation does not account for differences between the individual questions on the test: the probability of giving a correct response to some questions depends on a child's ability, the level of difficulty of that particular item and its discriminating power between high and low ability individuals. Using IRT, we specify a three parameter logistic model for the probability of a correct response by an individual to the different test questions. The three parameters are: item discrimination, item difficulty and the lower asymptote for the probability function denoting random guessing on an item. Using maximum likelihood we obtain the expected score on each section of the test as our outcome variable. We significantly reduce measurement error in estimating latent cognitive ability by this procedure.

3.2 Initial Conditions

As discussed in Section 2, the production function for a child's cognitive and non-cognitive skills includes unobserved initial conditions, which influence the skill formation process. Due to the availability of only two periods and doubts regarding the required assumption of initial conditions exerting a constant impact on skill formation, we do not rely on fixed-effects or first-differencing of the data to address this problem. Instead, for the 'younger' cohort, we have a large set of information on child and mother characteristics, including child height and weight, how long the child was breast-fed, how many documents were issued at birth, whether the mother received ante-natal care, and whether she was depressed during pregnancy. These measures reflect well child-specific initial conditions and enter the analysis for the 'younger' cohort through the PRF variable for the equation for children aged one. For the 'older' cohort, we do not have data on child characteristics at age one or before. Instead, we use child anthropometries, specifically child height as a control. In a recent study, Weedon et al. (2007) establish that height is a typical 'polygenic trait'. The study finds that common variants in the HMGA2 oncogene were associated with height. As far as associations,

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the research highlights that 'up to 90% of the variation in height among most human populations can be attributed to DNA' (Weedon et. al., p. 2: 2007). In addition, as mentioned in the Introduction, there is an expanding literature arguing that genome expression depends on environmental factors (Rutter, 2006). The idea is that genes determine a child's predisposition to develop a certain trait, but that environmental factors trigger the expression of the gene (Currie, 2009). This justifies the use of a child's caste as an additional control for unobserved initial conditions. In addition, we use information about whether the child was born in the same village in which she currently lives. This is the only information on the child at the moment of birth available for the 'older' cohort and captures variation in the impact of a child's environment on the expression of her genetic endowment. Hence, conditioning on variation in children's location of birth captures variation in children's unobserved genetic endowment. Importantly, these proxy variables are assumed to measure omitted initial conditions up to random error and we assume that the proxies are uncorrelated with potential random measurement error in other input variables. This avoids introducing bias when including these proxies (Todd and Wolpin, 2003).

3.3 Home environment and other input measures

Further, we have information on a range of home inputs, child characteristics and caregiver characteristics for both cohorts for both survey rounds. We use, as measures for home environment, various household level attributes: household size, location (whether urban or rural), social networks (given by indicators such as number of groups a household is affiliated to, community based participation of household, kinship ties within the community of household), and information on how long the household resides already in the village. We also classify households as poor/non-poor using monthly per-capita expenditure information based on a poverty line of Rs. 292.95 and Rs 542.89 for rural and urban areas respectively in the state of Andhra Pradesh (GOI, 2007).[9] For child characteristics, we use information on the number of siblings measuring the number of children in a household, gender as there may exist differences both in the development process and in the treatment by parents, and number of years of schooling attained. Additionally, we account for the type of school (public or private) that the child is enrolled in. Finally, the YL questionnaires explicitly identify and administer questionnaires to the caregiver of the child, which allows us to include education of the caregiver as a variable of interest as suggested in Todd and Wolpin (2007). In addition,

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[9]Household consumption expenditure comprises the expenditure on food, non-food items and consumer durables. Expenditure per capita calculations take into account the age/sex specific equivalence factors.

we construct from the information in the caregiver questionnaire a variable reflecting the degree of parental altruism towards the child. A common assumption in the existing literature is that the only motivation for parents to raise a child is altruism (Cunha and Heckman, 2007). Yet, it is a well-known fact that this assumption is unlikely to hold in an economically deprived environment such as Andhra Pradesh where children serve both as a source of current income and means of providing income when parents are too old to work. Nevertheless, we believe that also parents in deprived environments ideally want to see their children grow to become healthy and happy individuals. In order to reflect this tension between parental interests and control for effects from varying degrees of altruism across the sample, we constructed a variable reflecting parents' motivation to have the YL child. This information is only available for Round 2 data and consists of answers given by parents regarding their primary motivations to have the child.

4 Estimation

Beginning with the younger cohort, we note that, better child health or lack of child stuntedness is known to be associated with later period skill accumulation (Grantham-McGregor et al., 2007; Walker et al., 2007; Currie, 2009). Here, our objective is to establish links between childhood poverty, PRF and early child health, where PRF is treated as a latent variable which is predicted by the indicators described in Table A. Subsequently we test whether early childhood health impacts cognitive/non-cognitive outcomes at age five. Hence, for the 'younger' cohort, our structural model (3) simplifies as (3a) contains only observed child health as the dependent variable, which is the only period $t-1$ variable feeding into (3b). Instead of parental investment for one-year-old children in (3a), latent PRF is used to reflect parental input. For the 'older' cohort, Table A shows that we possess sufficient indicators to estimate the full measurement model. The estimated factors are used in the estimation of the complete structural model (3). It is therefore the 'older' cohort that allows us to investigate the presence and importance of self- and cross-productivity of skill levels.

As discussed in the previous section, in estimating the factor models, we set $\lambda_{o,t}^k = 1$ with $k \in \{C, N, I\}$ to fix the scales of the measurement in the latent variables. When including the exogenous covariates, there is one disadvantage in using LISREL, which we employ for our estimation. The explanatory variables have to be introduced into the model as artificial latent variables by setting their factor loadings equal to one and zero for all other observed covariates. Moreover, the unique factor variance is set to zero. This implies that the explanatory variables are treated as response variables for

which multivariate normality is assumed. We estimate (4) without intercepts as we use mean centered observed indicators $X_{i,t}^k$ with $k \in \{C, N, I\}$.

In principle, the recursive model could be estimated using OLS if we assume that the latent variables are independent of the error term ζ_t^k for $k \in \{C, N\}$. More specifically, (3a) could be consistently estimated applying OLS under the assumption that $Cov(\theta_{t-1}^I, \zeta_{t-1}) = 0$. Then also (3b) could be consistently estimated using OLS under the additional assumption that not only $Cov(\theta_t^I, \zeta_t) = 0$, but also $Cov(\theta_{t-1}^k, \zeta_t) = 0$ for $k \in \{C, N\}$. This is the case since we have assumed that $Cov(\zeta_t, \zeta_{t-1}) = 0$. This means that we can regard θ_{t-1}^k as statistically predetermined with regard to θ_t^k. Obviously, this requires us to assume that errors are serially uncorrelated, i.e., $Cov(\theta_{t-1}^k, \zeta_t) = 0$.[10] In order to relax the assumption that $Cov(\theta_t^I, \zeta_t) = 0$, as discussed in Section 2, we instrument θ_t^I using economic shocks to household wealth and a child's birth order. Validity of these instruments was discussed in Section 2. Instead of using OLS, we estimate the system (3) using Full Information Maximum Likelihood (FIML). FIML not only provides us with the most efficient estimators of system (3), it also tackles the problem of missing data, a common occurrence with perception based response questions. Using FIML, enabling listwise deletion, we are able to integrate out the missing data from the sample likelihood.

An important contribution of the analysis of Cunha and Heckman (2008) was to anchor scores of skills in a child's adult earnings. We lack such information on a child's eventual success in life which impedes anchoring of cognitive and non-cognitive scores in order to generate a cardinal measure of skills. Instead, we have to rely on the ordinal measures our data generates. This implies that we can compare a child's performance only relative to the other children in the sample. In a cross-section, this is unproblematic; however, ideally we would like to be able to verify whether a child has advanced in terms of her skill levels over time. This is not possible in absolute terms; we can only measure whether a child has moved up in the relative ranking vis-à-vis the other children in the sample.

5 Results

Because we are mainly interested in investigating the presence of self-productivity and cross-productivity, we focus in our graphical analysis on the 'older' cohort.

Figures 1-4 plot the conditional probability density of the skill level for a twelve-year-old child on her skill level at age eight $\hat{f}(\theta_t^k | \theta_{t-1}^k)$ with $k \in \{C, N\}$. The density is

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[10]This assumption is also made by Cunha and Heckman (2008).

estimated nonparametrically using a likelihood cross-validated bandwidth based on a Gaussian Kernel (Li and Racine, 2007).[11] Examining these plots for the 'older' cohort allows us to look for preliminary evidence of self- and cross-productivity.

With the probability density mass concentrated along the diagonal in Figure 1, there is strong evidence that a child has a higher cognitive skill level at age twelve conditional on her having achieved a high cognitive skill level at age eight. Moreover, the relationship appears to be linear, providing support to our linear specification of the system in (3). This represents pronounced evidence in favour of the presence of self-productivity for the formation of cognitive skills. In contrast, the conditional probability density plot 2 for non-cognitive skills is less clear-cut. The probability density mass appears to be larger for lower values of non-cognitive skills for children aged eight as well as twelve. This suggests that a child has lower non-cognitive skills at age twelve conditional on having had a lower non-cognitive achievement score at age eight. Yet, this kind of relationship is less evident for children with higher non-cognitive achievement. Hence, the evidence provided in plot 2 for self-productivity between the non-cognitive skill level at age eight and the cognitive skill level at age twelve appears to be less pronounced than for cognitive skills. The density plots examining cross-productivity 3 and 4 have a similar shape as the non-cognitive skill plot 2. Plotting the density of cognitive skill levels at age twelve conditional on non-cognitive skill levels at age eight, plot 3 shows that lower non-cognitive achievement at age eight is associated with a relatively large range of cognitive skill levels at age twelve. This points to a possibly weak relationship between non-cognitive skill levels at age eight and cognitive achievement at age twelve, a finding which we will confirm below. Plot 4 of non-cognitive skills at age twelve conditional on cognitive skills at age eight provides some evidence for the presence of cross-productivity with a probability mass slightly more closely aligned along the diagonal. Thus, children with lower cognitive skill levels at age eight tend to have lower non-cognitive skill levels at age twelve. In brief, the conditional probability density plots point to the presence of self-productivity and cross-productivity for both cognitive and non-cognitive skills although the relationship appears to be more pronounced for cognitive skill levels at age eight affecting cognitive and non-cognitive skill levels at age twelve.

Table 1 shows the pairwise Spearman rank correlation matrix of the predicted latent variables.[12] For the 'younger' cohort, the correlation matrix contains correlations for cognitive, non-cognitive skills, parental investment at age five, a child's health condition and a measure of psycho-social risk factors. This measure of psycho-social risk

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[11]We use the *np* package in R to estimate the conditional density (Hayfield and Racine, 2008).

[12]Rank correlation coefficients are more robust to the presence of outliers and therefore appear in our setting preferable over Pearson's product-moment correlation coefficient.

factors is negatively correlated with a child's health condition. It is also negatively correlated with cognitive and non-cognitive skill levels as well as parental investment at age five. Child health at age one itself is strongly positively correlated with cognitive and non-cognitive abilities, suggesting early-age health has important implications for later skill formation. The table also shows that higher levels of parental investment are associated with higher levels of both cognitive and non-cognitive skills. For the 'older' cohort, the matrix shows correlations of the skill variables and parental investment for both age eight and twelve. The matrix confirms our graphical findings that there exists a positive association between a child's skill level at age eight and her eventual skill level at age twelve, both within the same skill and across skills. The extremely high correlation coefficient for cognitive skills at age eight and twelve is particularly interesting as it suggests a very close relation between a child's cognitive ability level at age eight and age twelve. Similar to the younger cohort, we find the parental investment variable for eight- as well as twelve-year-old children to be positively correlated with skill levels contemporaneously and over time. Therefore, the correlation matrix provides further evidence in favour of the presence of both self-and cross-productivity.

Before we proceed with a discussion of the results of estimating the structural model (3), Tables 2 and 3 contain summary statistics for all the variables used in the structural model. While many variables, such as gender or the number of siblings, have a straightforward and intuitive meaning, interpreting variables that we have constructed is much less straightforward. For example our variable proxying social networks, HH Social Connectedness, has no direct intuitive interpretation, apart from a purely directional interpretation that 'more is better'. Tables 4 and 5 provide summary statistics of the indicator variables used in the measurement models. The Appendix contains the estimates of the measurement models in Tables 13 to 16; although we do not discuss the results here.

We first report results for the younger cohort. Column (1) of Table 6a and Columns (1) and (2) of Table 6b present results assuming that $Cov(\theta_t^I, \zeta_t) = 0$. Whereas Column (2) of Table 6a and Columns (3) and (4) of Table 6b present results from an IV specification of the production function, directed at addressing the issue of endogenous parental investment.[13] We note that the results for child health as an outcome do not differ much between the two specifications. We see that household poverty and psycho-social risk factors exert a statistically significant negative influence on child health at age one. Both household poverty and high psycho-social risk factors adversely affect child health, causing child stuntedness. A negative association between lower socioe-

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[13] A test of overidentifying restrictions is found to be consistent with exogeneity of the instruments.

conomic status, high psycho-social risk factors and child health is consistent with the existing literature (for a survey of the relevant literature see Currie, 2009). Given this, we go on to establish the effect of child health on learning outcomes for the child aged five. For both the non-IV and IV specifications we find that child health positively affects child cognitive skills and this effect is statistically significant. Its effect on child non-cognitive skills is not significant. These results are consistent with the literature discussed in the Introduction that link early child stuntedness with later period skill development and attribute the lack of development in the child's early stages to certain home environment factors, i.e., PRF and poverty (see also Currie, 2009). Parental investment has a positive and significant effect on child cognitive outcomes. This result holds even after instrumenting for parental investment. However the coefficient on parental investment vis-à-vis non-cognitive outcomes is different for the two specifications (IV and non-IV). Comparing Column (2) and (4) of Table 6b we find that the effect of parental investment on child non-cognitive outcomes goes from being not significant to positive and significant in the IV specification. A possible explanation for this downward bias in endogenous parental investment is that parents adjust their inputs according to a child's skill levels. The bottomline is that parental investment matters; both for cognitive and non-cognitive outcomes of children at age five. Since we regard the IV specification as our preferred model, we focus our remaining discussion of the results for five-year old children on the IV specification (Columns (3) and (4)). Caregiver education exerts a positive and significant effect on child cognitive as well as non-cognitive achievement. Well-educated parents produce well-educated offspring, a fact well established in many previous studies: 'one of the important roles that parents play in their child's development has to do with the stimulation of cognitive and language growth in the first few years of life' (Waldfogel, p. 49: 2006). Also, our measure of a household's social network shows a positive statistically significant effect on cognitive skills levels, while the effect is negative for non-cognitive skills.[14]

Next, we discuss the results for the 'older' cohort. As, before we present results from both specifications, non-IV (Columns (1) and (2)) and IV (Columns (3) and (4)). For eight year old children, we see from Column (1) of Table 7, that parental investment has a significant positive effect on cognitive skill formation suggesting that increasing parental investment by one standard deviation increases cognitive skill levels by little

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[14]The latter effect is quite counterintuitive. This is perhaps because, we use as one of ours indicator for non-cognitive skills, how well the child fares at pre-school (if we believe that children usually learn important social skills at pre-school rather than academic lessons). A child who does not enroll in pre-school, misses out on social interaction amongst peers and thus is given a value 0. As a result, it may be that parents who have a strong kinship network, choose to not send their children to preschool and instead rely on their social capital networks to raise their child.

more than half a standard deviation. At the same time, Column (2) shows that parental investment has no significant effect on non-cognitive skill accumulation, while the sign is still positive. These results change remarkably when we instrument for parental investment (see Columns (3) and (4)).[15] The coefficient on parental investment becomes insignificant with respect to cognitive achievement whereas for non-cognitive achievement it is positive and significant. In particular, with reference to non-cognitive achievement we find that the magnitude of the coefficient on parental investment in the instrumented regression increases substantially. As for five-year old children, this suggests a downward bias in the coefficient associated with parental investment which may be the result from the simultaneous relationship between parental input and a child's non-cognitive skill levels.

As before, we focus our remaining discussion of results for children aged eight to only the IV specification. Apart from parental investment, we find that child height and caregiver education affect child cognitive outcomes positively. Inline with the existing literature, we find boys to lag behind girls in their development of cognitive skills (Parcel and Menaghan, 1994), although the opposite is true for non-cognitive skills. We find that children attending private *elementary* schools perform much better on achievement tests compared to their public school counterparts, a result well-established for India in previous research studies (Kingdon, 1996; Muralidharan and Kremer, 2006). For non-cognitive skills, we find significant positive effects from a child being located in an urban area and negative effects from larger households, possibly reflecting a lack of parental attention to the child. Additionally, we find the length of time a household resides in the village to be positively associated with a child's non-cognitive achievement, which points to the importance of a stable environment for children to develop their personality. We also report results for a specification omitting the variables proxying initial conditions in Table 11 in the Appendix. While the magnitude of the coefficients associated with parental investment slightly increase, the results are qualitatively very similar.

We now examine self- and cross-productivity effects. Table 8 reports results of the 'older' cohort at age twelve with Columns (3) and (4) displaying those from an IV specification.[16] The results show that cognitive skills acquired at age eight, affect positively both cognitive and non-cognitive skills at age twelve. These results hold for both the

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[15]Again, we cannot reject the null hypothesis of exogeneity of the instruments using a Sargan test of overidentifying restrictions.

[16]Again, a test of overidentifying restrictions is found to be consistent with exogeneity of the instruments.

IV and non-IV specifications.[17] Thus we find evidence for the dynamic persistence of cognitive skills as also of its contribution towards developing non-cognitive skills at a later stage (as cross-productivity effects). For the IV specification, increasing cognitive skills at age eight is associated with a higher level of cognitive skills at age twelve of slightly less than half a standard deviation. For non-cognitive skills, the association is economically smaller, an increase of one standard deviation of cognitive skill levels at age eight is associated with an increase of non-cognitive skills levels at age twelve of a fifth of a standard deviation. In contrast, we find no such evidence for non-cognitive skills acquired at age eight. Its effect on both cognitive and non-cognitive skills at age twelve is insignificant. This result differs from Cunha and Heckman (2008) who found evidence in favour of cross-productivity of non-cognitive on cognitive skills and not vice versa. As Cunha and Heckman (2008), however, we find substantial evidence in favour of parental investment, which exerts a significant and positive effect on cognitive and non-cognitive skill acquisition at this age. Again, these results do not differ much between the IV and non-IV specifications. The effect of parental investment, however, is more than two times larger in magnitude for non-cognitive achievement as compared to cognitive achievement inline with the findings by Cunha and Heckman (2008).

Restricting now our attention to only the IV specification, we find, a positive association between the years a child has spent in school and her cognitive and non-cognitive achievement. This positive relation between schooling and skill formation has also been found in the existing literature (Cahan and Cohen, 1989). Interestingly at this age, our results suggest that attending a *public secondary* school has a positive effect on raising cognitive and non-cognitive achievement scores. This is in sharp contrast to the results for eight-year-old children, who perform better when attending a *private primary* school. One reason, perhaps, is that the growth and spread of private schools is confined to primary schooling, its presence remaining remarkably scarce within the secondary schooling sector. Moreover government subsidies are abundant in better quality public secondary schools (Kingdon, 1996). Much of the research on private schooling in India and other developing countries has focused on elementary schools. Further research into the nature and effects of private schooling for secondary schools is required to understand its implications. Caregiver education has a statistically significantly and positive effect for both cognitive and non-cognitive skills, inline with our findings for children aged five and eight. Again, the results for a specification without the proxies for initial conditions, which are reported in Table 12 in the Appendix, are qualitatively very similar to the specification accounting for initial conditions although

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[17]We note however that the magnitude of coefficients reduces slightly for the IV specifications vis-à-vis both cognitive and non-cognitive achievement.

there is a slight increase in the coefficients associated with cognitive skill levels at age eight.

Finally, we report the extent of measurement error by examining the the share of the total residual variance for each measurement indicator. As in Cunha and Heckman (2008) we measure this by decomposing the total unobserved variance of each measurement variable into two components: one that is due to the factor score and the other that can be attributed to the noise associated with the indicator. This implies that $(\sigma_{it}^k)^2 = (\Lambda_{it}^k)^2(\sigma_t^k)^2 + (\sigma_{\epsilon,it}^k)^2$; where Λ_{it}^k is the factor loading associated with each measurement, $(\sigma_t^k)^2$ denotes the variance of the latent variable k at period t and $(\sigma_{\epsilon,it}^k)^2$ is the variance of the uniqueness in measurement i at period t. The extent of measurement error or the share of the total residual that is due to the uniqueness is $s_{\epsilon,it}^k = \frac{(\sigma_{\epsilon,it}^k)^2}{(\sigma_{it}^k)^2}$. Table 9 and 10 report estimates of the error variance associated with each measurement equation for parental investment, cognitive skills and non-cognitive skills. We find a fair amount of noise associated with each indicator variable. Still, there are some variables for which the latent variables account for a large part of their variance. This is the case for caregiver education (where child PRF at age one explains 86% of total variance), CDA-Q test score (child cognitive skill at age five accounting for 63% of total variance), reading level at age eight (57% explained by cognitive skill at age eight), math test score at age twelve (59% explained by cognitive skill at age twelve) and child social trust score at age twelve (69% explained by non-cognitive skill at age twelve). The unobserved variance for these variables, therefore, prove useful in predicting the factor.

One of the contributions of Cunha and Heckman (2007) is to carve out sensitive and critical periods for skill formation during childhood. In our case, we have data only for a single transition for each cohort, from age one to five, and from age eight to twelve, which does not allow us to compare transitions over time for a single cohort. This is a disadvantage with regard to determining sensitive periods for skill formation. The concept of critical periods, however, does not seem to be uncontroversial, if we understand critical in the sense that a child must be exposed to a certain experience during a specific period of early childhood in order to fully acquire a certain skill. Waldvogel (2006) argues that this is generally not the case for skill formation in children. Only for very few competencies relating to some aspects of language acquisition require specific input during a well-determined period of early childhood. Hence, we regard our inability to determine critical periods as less important.

6 Conclusion

Recent research in economics has demonstrated the importance of early childhood for the development of the crucial skill set necessary for socio-economic success in later life. This research has shown that the acquisition of cognitive and non-cognitive skills begins from the very nascent stages of childhood and that these skills interact throughout a child's development process. These insights motivate the investigation of the determinants of these skills beyond formal schooling focusing in particular on self- and cross-productivity effects. So far, this research has been almost exclusively focused on children in industrialised countries.

Extending this research to the developing country context promises important insights with regard to finding answers to the question as to what constitutes an 'enabling' environment for a child's successful development. To this purpose, there are valuable lessons to be learnt from firstly exploring and ascertaining the link between cognitive and non-cognitive achievement and analysing this linkage in the context of a child's (immediate) environment in a developing country. Yet, conducting this kind of research in a developing country context is in many ways challenging as children face a drastically different environment to their peers in industrialised countries. Nevertheless, building on the recent contributions of Cunha and Heckman (2007, 2008) and exploiting a novel rich data set covering different periods of childhood, we estimate a structural model to investigate skill formation of children in Andhra Pradesh. Most importantly, for our 'older' cohort, we find evidence for the presence of self-productivity for cognitive skills and cross-productivity of cognitive on non-cognitive skills during the transition from eight to twelve years. We also find statistically significant evidence for parental investment, as measured by our latent variable, to contemporaneously exert an economically positive influence on skill formation for five-, eight- and twelve-year-old children. Our results also point to a large number of other important determinants of skill formation including child, caregiver and household characteristics and notably also school type. The data available for our 'younger' cohort allows us to investigate the importance of earliest parental care and child health as well as the importance of child health achieved at age one for skill levels at age five. We find that so called psycho-social risk factors have a statistically significant effect on child health at age one. These factors are reflected in parental care during pregnancy as well as during the first few months of a child's life. Considering that we also find child health as measured for children at age one to represent a statistically significant determinant for a child's cognitive ability at age five, this provides powerful evidence to shift attention to providing parents with support from the earliest days of pregnancy onward.

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Table A : Measurement Model Indicators

	Cognitive Ability	Non-cognitive Ability	Parental Investment
Age 8: Older Cohort, Round 1	• Scores from the Raven's Progressive Matrices Aptitude Test • Reading Level • Writing Level	Child Mental Ability Indicators from the Strengths and Difficulties Questionnaire (SDQ) devised by Dr. Robert Goodman { • Emotional Conduct • Hyperactivity • Pro-Social Behaviour • Conduct Problems	• Do parents spend money on child's education? • Does child work at home or outside? • How many years back was child made to start formal schooling? • How often does child see father (daily, weekly, once a month, once a year)

Age 12:
 	
Older Cohort, Round 2
	• IRT scores from the Peabody Picture Vocabulary Test
	• Numeracy: child can perform simple multiplication
	• Writing Level
		Child Personality Measures: indicated from questions rated on the Likehart Scale by child {
		• Friendliness
		• Pride
		• Determination
		• Social Trust
		• Group Membership
			• Proportion of total household expenditure on following received by child:
			  ○ Education
			  ○ Health
			  ○ Clothing
			• How often does child see father (daily, weekly, once a month, once a year)

Age 1: Younger Cohort, Round 1			Psychosocial Risk Factors: • Caregiver education • No doctor present at birth? • Months left without breastfeeding • Level of antenatal care • Unwanted pregnancy? • Caregiver depression

Age 5:
 	
Younger Cohort, Round 2
	• IRT scores from the Peabody Picture Vocabulary Test
	• Scores from the Cognitive Development Assessment - Quantitative Test
		• Level of fluency and communication in native language
		• Performance in pre-school (interactive and social nature)
		• Does child travel to school with friends, parents or alone?
			• Proportion of total household expenditure on following received by child:
			  ○ Education
			  ○ Health
			  ○ Clothing
			• How often does child see father (daily, weekly, once a month, once a year)

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Figure 1: Cognitive (Age 8) vs Cognitive (Age 12): Conditional Probability Density Function
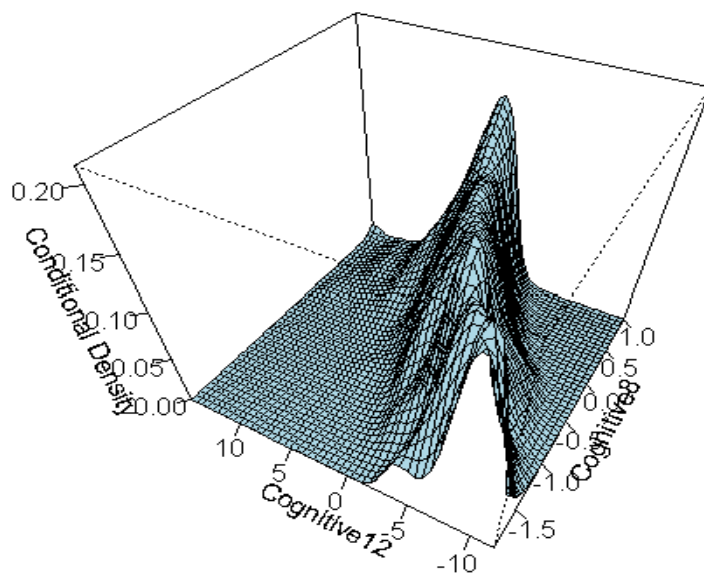
Figure 2: Non-cognitive (Age 8) vs Non-cognitive (Age 12) Skill Levels: Conditional Probability Density Function
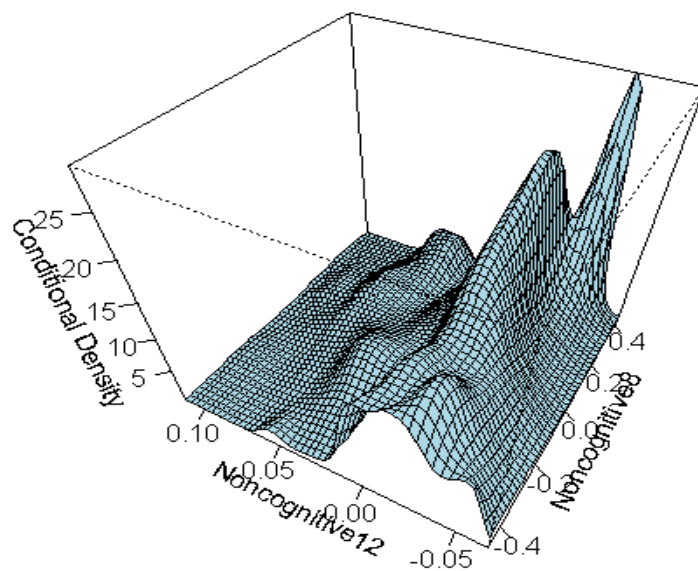
Figure 3: Non-cognitive (Age 8) vs Cognitive (Age 12) Skill Levels: Conditional Probability Density Function
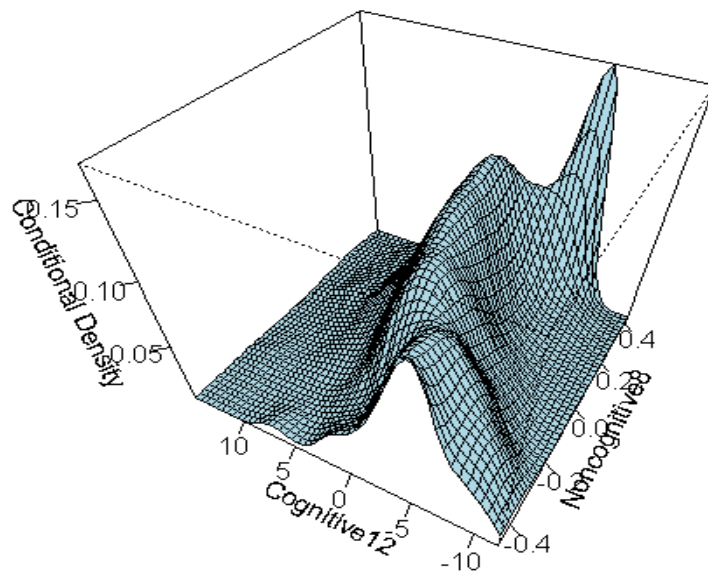
Figure 4: Cognitive (Age 8) vs Non-cognitive (Age 12) Skill Levels: Conditional Probability Density Function
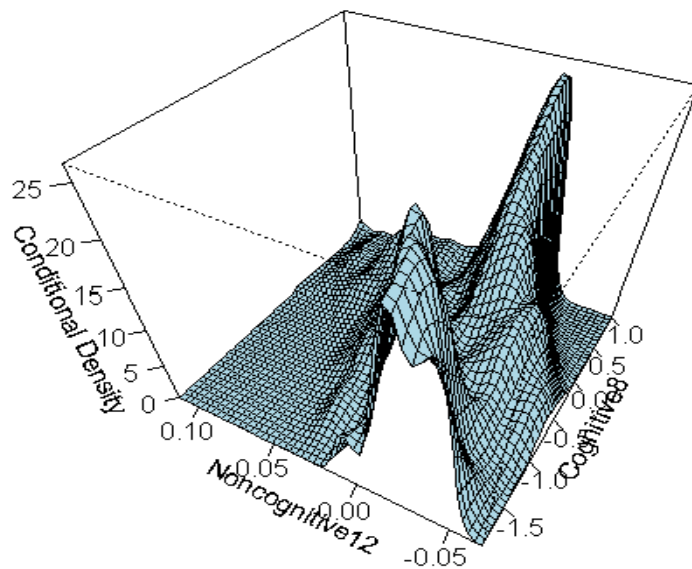
Table 1: Pairwise Spearman Rank Correlation Matrix
Table A: Age 1 and 5

	CS (Age 5)	NCS (Age 5)	Child Health (Age 1)	PI (Age 5)	PRF (Age 1)
Cognitive Skills (Age 5)	1.0000				
Non-cognitive Skills (Age 5)	0.8708**	1.0000			
Child Health (Age 1)	0.8688*	0.8617**	1.0000		
Parental Investment (Age 5)	0.7400**	0.7285**	0.7711**	1.0000	
PRF (Age 1)	-0.9341**	-0.8964**	-0.9308***	-0.7497**	1.0000

Table B: Age 8 and 12

	CS (Age 12)	NCS (Age 12)	CS (Age 8)	NCS (Age 8)	PI (Age 12)	PI (Age 8)
Cognitive Skills (Age 12)	1.0000					
Non-cognitive Skills (Age 12)	0.7641**	1.0000				
Cognitive Skills (Age 8)	0.9348***	0.6011**	1.0000			
Non-cognitive Skills (Age 8)	0.6231**	0.4276**	0.7346**	1.0000		
Parental Investment (Age 12)	0.7231**	0.7627**	0.7128**	0.7476**	1.0000	
Parental Investment (Age 8)	0.7914**	0.6373**	0.8586***	0.8328**	0.7607**	1.0000

Notes:
1. Standard Errors in parentheses.
2. + indicates significance at 10%; * at 5%; ** at 1%.

Table 2: Summary Statistics: Age 1 and 5

Table A: Age 1

Variable	No. Obs.	Median	Mean	St. Dev.
PRF[2]	1950	0.0164	0.245	3.04
CH Health[2]	1950	0.037	1.174	0.554
Poor	1914	0.692	0.698	0.092
CH Male	1950	0	0.463	0.499
CH Caste[3]	1950	0	0 .205	0.404
CH Siblings	1950	0	0.708	1.022
HH Size	1950	5	5.425	2.369
HH Urban	1950	0	0.244	0.429
HH Social Connectedness[5]	1950	-0.208	0.006	0.482

Table B: Age 5

Variable	No. Obs.	Median	Mean	St. Dev.
Cognitive Skills[2]	1950	-0.758	0.489	22.45
Non-cognitive Skills[2]	1950	-0.38	-0.018	1.29
Parental Investment[2]	1950	-0.009	-0.007	1.06
Parent Altruism[4]	1950	0	0.463	0.499
CH Siblings	1950	1	1.443	1.006
CH Height	1942	103.975	103.219	10.298
CG Education	1950	0	3.643	4.498
HH Size	1950	5	5.516	2.225
HH Social Connectedness[5]	1950	-.058	.0003	.654
CH Birth Order	1936	1	1.638	0.956
HH Shocks[6]	1942	0.044	-0.001	1.473

Notes:
1. CH: Child; CG: Caregiver; HH: Household.
2. Estimated latent variables.
3. Indicator of whether child belongs to a non-SC/ST and non-backward caste community.
4. Normalised on a scale of 0 to 1; is a combination of the responses to the questions on why parents feel it is important to have children.
5. An index (based on factor analysis) of the household's responses to questions of its kinship support base in community, how active it is (membership in societies etc.), level of trust within community.
6. Represents the change in household wealth over the two periods (i.e wealth$_{age=1}$-wealth$_{age=5}$).

Table 3: Summary Statistics: Age 8 and 12

Table A: Age 8

Variable	Obs.	Median	Mean	Std. Dev.
Cognitive Skills[2]	994	0.085	0.042	1.408
Non-cognitive Skills[2]	994	0.055	0.004	0.196
Parental Investment[2]	994	0.007	-0.000	0.066
CH Siblings	994	2	1.813	1.184
CH Height	994	118.1	118.016	6.312
CH Male	994	1	0.509	0.500
CH Caste[4]	994	0	0.216	0.412
CH Born in Village	994	1	0.599	0.490
Public School	994	1	0.767	0.423
CG Education	994	4.605	4.628	0.037
Parent Altruism[3]	993	0.704	0.702	0.092
HH Size	994	5	5.548	2.039
HH Social Connectedness[5]	994	-0.033	0.0004	0.488
HH Urban	994	0	0.242	0.429
HH in Village[6]	994	13	16.048	8.932
CH Birth Order	994	2	2.312	1.394
HH Shocks[7]	994	1	0.554	0.497

Table B: Age 12

Variable	Obs.	Median	Mean	Std. Dev.
Cognitive Skills[2]	994	-0.633	0.117	8.03
Non-cognitive Skills[2]	994	-0.003	-0.000	0.064
Parental Investment[2]	994	-0.006	0.001	0.06
CH Height	985	141.2	140.845	11.61
CH Siblings	994	2	1.836	1.116
CH Caste[4]	993	0	0.206	0.405
CH No. of Years of Schooling	980	6	5.601	1.263
Public School	994	1	0.628	0.484
CG Education	993	0	2.709	4.033
HH Size	994	5	5.197	1.832
HH Social Connectedness[5]	992	-0.024	0.002	0.669
HH Urban	994	0	0.251	0.434
CH Birth Order	994	2	2.312	1.394
HH Shocks[8]	994	-0.009	-0.027	1.337

Notes:
1. CH: Child; CG: Caregiver; HH: Household.
2. Estimated latent variables.
3. Normalised on a scale of 0 to 1; is a combination of the responses to the questions on why parents feel it is important to have children.
4. Indicator of whether child belongs to a non-SC/ST and non-backward caste community.
5. An index (based on factor analysis) of the household's responses to questions of its kinship support base in community, how active it is (membership in societies etc.), level of trust within community.
6. Indicates the number of years household has been located in the village.
7. Dummy variable indicating whether the household experienced any economic shock that that resulted in serious loss of wealth, over the last four years.
8. Represents the change in household wealth over the two periods (i.e wealth$_{age=8}$-wealth$_{age=12}$).

Table 4: Summary Statistics: Indicators for Latent Variables, Age 1 and 5

Variable	Obs.	Median	Mean	Std. Dev.
Age 1				
Ante-natal Care[2]	1896	1.00	1.06	1.07
No Doc. at Birth	1923	0.00	0.47	0.50
Breastfeeding Duration[3]	1923	0.00	1.30	3.86
Unwanted Pregnancy	1910	0.00	0.08	0.27
Freq. See Dad[4]	1930	0.00	0.04	0.20
CG Depressed	1840	0.00	0.30	0.46
CG Education[4]	1950	15.00	11.75	4.41
Weight Z-Score	1934	-1.84	-1.835	0.937
Height Z-Score	1934	-1.63	-1.611	1.00
Age 5				
Peabody PVT Score	1950	34.05	44.22	29.03
CDA-Q Test Score	1950	10.00	9.51	2.68
Pre-School Status[5]	1950	0.00	1.74	1.83
CH Fluent in Native Lang	1950	1.00	0.90	0.30
CH Travels[6]	1950	3.00	2.46	0.87
Prop. Clothing Exp.	1925	0.50	0.62	0.34
Prop. Edu. Exp.	1925	0.20	0.24	0.25
Prop. Health Exp.	1950	0.13	0.13	0.17
Freq. See Dad	1913	2.00	1.91	0.31

Notes:
1. CH: Child; CG: Caregiver.
2. On a scale of 0-3; 0 indicates high level of AN care, 3 indicates no AN care.
3. Indicates number of months child was left without breastfeeding, from a recommended period of 16 months.
4. These variables have been rescaled; higher values indicate high neglect (higher freq of not seeing dad, and low level of caregiver education).
5. 0 indicates child does not attend pre-school; how the child fares in preschool (conditional on attendence) is given on a scale of 1-5, where 5 is excellent and 1 is poor.
6. Indicates whether child travels alone (1), with parents (2), with friends (3), or does not travel at all (0).

Table 5: Summary Statistics: Indicators for Latent Variables, Age 8 and 12

Variable	Obs.	Median	Mean	Std. Dev.
Age 8				
Raven's Score	989	23.00	22.97	5.30
Reading Level[2]	985	4.00	3.08	1.05
Writing Level[3]	964	2.00	2.09	0.68
Hyperactivity Score	993	2.00	1.73	0.59
Emotional Symptoms Score	993	2.00	1.34	0.86
Pro-Social Behaviour Score	994	2.00	1.70	0.64
Conduct Problems Score	994	2.00	1.24	0.91
Freq. See Dad[4]	965	2.00	1.87	0.41
Spend on Education	994	0.00	0.09	0.29
Does Child Work	994	1.00	0.67	0.47
Child Started School[5]	987	2.00	1.96	0.57
Age 12				
Peabody PVT Score	994	100.41	96.16	33.01
Math Test Score	994	6.00	5.91	2.64
Writing Level[3]	969	3.00	2.65	0.58
CH Friendliness Score	994	0.48	0.47	0.14
CH Group Membership	994	0.00	0.02	0.10
CH Self-Pride Score	994	0.64	0.64	0.13
CH Determination Score	994	0.72	0.71	0.12
CH Social Trust Score	994	0.95	0.88	0.20
Prop. Clothing Exp.	983	0.50	0.62	0.32
Prop. Edu. Exp.	983	0.30	0.31	0.22
Prop. Health. Exp.	994	0.13	0.13	0.17
Freq. See Dad[4]	913	2.00	1.84	0.40

Notes:
1. CH: Child.
2. On a scale of 1-4; 1 indicates cannot read at all, 4 indicates reads fluently.
3. On a scale of 1-3; 1 indicates cannot write at all, 4 indicates can write fluently.
4. Indicates whether child sees biological father, daily (2), monthly (1), once a year or never (0).
5. Indicates number of years since parents started school for child.

Table 6: Results 'Younger' Cohort

(a): Child Health - Age 1

	(1) Child Health	(2) Child Health (IV)
PRF	-0.571**	-0.545**
	(0.131)	(0.131)
Poor	-0.186**	-0.190**
	(0.055)	(0.055)
CH Male	0.117**	0.115**
	(0.044)	(0.044)
CH Caste	0.222**	0.225**
	(0.060)	(0.060)
CH Sibling	-0.072**	-0.074**
	(0.024)	(0.024)
HH Size	0.019[+]	0.021[+]
	(0.011)	(0.011)
HH Social Connectedness	0.067	0.068
	(0.047)	(0.047)
HH Urban	0.156*	0.180**
	(0.065)	(0.065)
Observations	**1950**	**1950**

(b): Skill Accumulation - Age 5

	(1) Cognitive	(2) Non-Cognitive	(3) PI (First Stage)	(4) Cognitive (IV[a])	(5) Non-Cognitive (IV[a])
CH Health	2.163**	-0.001	0.021**	1.841**	0.059
	(0.702)	(0.008)	(0.060)	(0.716)	(0.043)
Parental Investment	31.696**	0.060	–	32.943**	2.140**
	(5.870)	(0.065)		(6.273)	(0.390)
CH Siblings	0.469	-0.035**	-0.030**	0.680	0.116**
	(0.669)	(0.008)	(0.06)	(0.689)	(0.042)
CH Height	0.217**	-0.001	0.002**	0.216**	-0.014**
	(0.057)	(0.001)	(0.000)	(0.057)	(0.004)
CG Education	1.572**	-0.003	0.014**	1.547**	0.073**
	(0.161)	(0.002)	(0.001)	(0.164)	(0.010)
Parent Altruism	25.622**	0.304**	0.039	25.421**	-0.828*
	(6.234)	(0.007)	(0.049)	(6.248)	(0.379)
HH Size	-0.318	-0.002	-0.013**	-0.253	0.026
	(0.283)	(0.003)	(0.002)	(0.288)	(0.017)
HH Social Connectedness	3.376**	-0.014	0.006	3.335**	-0.177**
	(0.888)	(0.010)	(0.007)	(0.890)	(0.054)
HH Shocks	–	–	-0.010**	–	–
			(0.003)		
CH BO	–	–	-0.032**	–	–
			(0.006)		
Observations	**1950**	**1950**	**1950**	**1950**	**1950**

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Notes:
2. Standard Errors in parentheses.
3. [+] indicates significance at 10%; * at 5%; ** at 1%.
4. CH: Child; CG: Caregiver; HH: Household.

Table 7: Results 'Older' Cohort

(a): Skill Accumulation - Age 8

	(1) Cognitive	(2) Non-Cognitive	(3) PI First Stage	(4) Cognitive (IV)	(5) Non-Cognitive (IV)
Parental Investment	12.424**	0.115	–	0.286	2.347**
	(4.241)	(0.546)		(1.238)	(0.813)
CH Height	0.049*	0.011*	-0.001	0.031*	0.012*
	(0.020)	(0.020)	(0.001)	(0.014)	(0.006)
CH Siblings	0.344**	-0.028	-0.024*	-0.052	0.031
	(0.124)	(0.030)	(0.010)	(0.104)	(0.027)
CH Male	0.461	0.058	-0.013	-0.249**	0.115**
	(0.380)	(0.044)	(0.011)	(0.106)	(0.048)
CH Caste	-0.326	0.131$^+$	0.036$^+$	0.260*	0.056
	(0.280)	(0.079)	(0.018)	(0.126)	(0.071)
CH Born in Village	-0.356	0.030	0.013	-0.281$^+$	0.009
	(0.017)	(0.063)	(0.013)	(0.148)	(0.068)
Public School	-1.275*	0.069	0.008	-0.644**	0.058
	(0.580)	(0.061)	(0.021)	(0.277)	(0.088)
CG Education	-0.036	0.009	0.004	0.083**	-0.002
	(0.051)	(0.009)	(0.003)	(0.029)	(0.007)
Parent Altruism	-0.693	0.485	0.034	0.425	0.391
	(1.487)	(0.325)	(0.072)	(0.500)	(0.289)
HH Size	-0.112	-0.022$^+$	0.007$^+$	-0.009	-0.034**
	(0.077)	(0.012)	(0.004)	(0.049)	(0.012)
HH Social Connectedness	0.745*	0.019	-0.024	0.029	0.091
	(0.371)	(0.083)	(0.017)	(0.166)	(0.073)
HH Urban	-0.150	0.237*	-0.029	-0.050	0.182$^+$
	(0.765)	(0.108)	(0.028)	(0.251)	(0.106)
HH in Village	0.019	0.006**	-0.001	0.001	0.008*
	(0.017)	(0.003)	(0.008)	(0.008)	(0.003)
HH Shocks	–	–	-0.088**	–	–
			(0.023)		
CH Birth Order	–	–	0.003	–	–
			(0.004)		
Observations	**994**	**994**	**994**	**994**	**994**

Notes:
2. Standard Errors in parentheses.
3. $^+$ indicates significance at 10%; * at 5%; ** at 1%.
4. CH: Child; CG: Caregiver; HH: Household.

Table 8: Results 'Older' Cohort

(a): Skill Accumulation - Age 12

	(1) Cognitive	(2) Non-Cognitive	(3) PI First Stage	(4) Cognitive (IV)	(5) Non-Cognitive (IV)
Cognitive Skills	3.770**	0.013**	0.006$^+$	2.799**	0.008**
	(1.430)	(0.004)	(0.003)	(0.977)	(0.003)
Non-Cognitive Skills	-1.307	-0.009	-0.030*	-0.416	-0.006
	(1.708)	(0.001)	(0.013)	(1.583)	(0.013)
Parental Investment	10.251**	0.214**	–	10.743**	0.221**
	(3.849)	(0.047)		(4.008)	(0.048)
CH Height	-0.024	0.000	0.000	-0.026	0.000
	(0.019)	(0.000)	(0.000)	(0.020)	(0.000)
CH Siblings	-0.023	0.000	-0.016**	-0.205	0.000
	(0.428)	(0.002)	(0.005)	(0.327)	(0.002)
CH Caste	-0.899	0.006	0.008	-0.181	0.009*
	(0.683)	(0.004)	(0.006)	(0.663)	(0.004)
CH No. of Years of Schooling	-0.150	0.002	0.012**	1.246**	0.007**
	(0.470)	(0.003)	(0.003)	(0.493)	(0.003)
Public School	2.904**	0.063**	0.000	2.700**	0.062**
	(1.127)	(0.014)	(0.012)	(1.045)	(0.014)
CG Education	0.070	0.002$^+$	0.001	0.172$^+$	0.002**
	(0.107)	(0.001)	(0.001)	(0.099)	(0.001)
HH Size	0.003	0.001	-0.002	0.051	0.001
	(0.127)	(0.001)	(0.002)	(0.087)	(0.001)
HH Social Connectedness	0.912*	0.003	0.008$^+$	0.706	0.002
	(0.475)	(0.003)	(0.004)	(0.425)	(0.003)
HH Urban	1.066	0.011	0.042**	1.178	0.011
	(1.388)	(0.008)	(0.013)	(1.351)	(0.008)
HH Shocks	–	–	-0.004*	–	–
			(0.002)		
CH BO	–	–	0.004	–	–
			(0.003)		
Observations	**994**	**994**	**994**	**994**	**994**

Notes:
2. Standard Errors in parentheses.
3. $^+$ indicates significance at 10%; * at 5%; ** at 1%.
4. CH: Child; CG: Caregiver; HH: Household.

Table 9: Latent Variable and Inputs: Measurement Error (Age 1 to 5)

	Share of Total Residual Variance	
	Factors	Measurement Error
PRF (Age 1)		
Ante-natal Care	0.051	0.949
No Doc. at Birth	0.128	0.872
Breastfeeding Duration	0.029	0.971
Unwanted Pregnancy	0.005	0.995
Freq. See Dad	0.000	
CG Depressed	0.035	0.965
CG Education	0.865	0.135
Child Health (Age 1)		
Weight Z-Score	0.809	0.191
Height Z-Score	0.597	0.403
Cognitive Skills (Age 5)		
Peabody PVTS score	0.341	0.659
CDA-Q Test Score	0.630	0.370
Non Cognitive Skills (Age 5)		
Pre-School Status	0.187	0.813
CH Fluent in Native Lang	0.002	0.998
CH Travels	0.084	0.916
Parental Investment (Age 5)		
Prop. Clothing Exp.	0.270	0.730
Prop. Edu. Exp.	0.517	0.483
Prop. Health Exp.	0.013	0.987
Freq. See Dad	0.004	0.996

Notes: The measurement errors are derived as follows: Let $(\sigma_t^k)^2$ denotes the variance of the latent variable k at period t. For each measurement i on the latent variable k, the total residual variance is $(\sigma_{it}^k)^2 = (\Lambda_{it}^k)^2(\sigma_t^k)^2 + (\sigma_{\epsilon,it}^k)^2$ where Λ_{it}^k is the factor loading associated with each measurement and $(\sigma_{\epsilon,it}^k)^2$ is the variance of the uniqueness in measurement i at period t. The share of the total residual variance that is due to the factor is $s_t^k = \frac{(\Lambda_{it}^k)^2(\sigma_t^k)^2}{(\sigma_{it}^k)^2}$ and the share of the total residual that is due to the uniqueness is $s_{\epsilon,it}^k = \frac{(\sigma_{\epsilon,it}^k)^2}{(\sigma_{it}^k)^2}$.

Table 10: Latent Variable and Inputs: Measurement Error (Age 8 to 12)

	Share of Total Residual Variance	
	Factors	Measurement Error
Cognitive Skills (Age 8)		
Raven's Score	0.074	0.926
Reading Level	0.577	0.423
Writing Level	0.049	0.951
Non Cognitive Skills (Age 8)		
Hyperactivity Score	0.019	0.981
Emotional Symptoms Score	0.220	0.780
Pro-Social Behaviour Score	0.034	0.966
Conduct Problems Score	0.227	0.773
Parental Investment (Age 8)		
Freq. See Dad	0.00029	0.9997
Spend on Education	0.025	0.975
Does Child Work	0.005	0.995
Child Started School	0.014	0.986
Cognitive Skills (Age 12)		
Peabody PVT Score	0.045	0.955
Math Test Score	0.594	0.406
Writing Level	0.469	0.531
Non Cognitive Skills (Age 12)		
CH Friendliness Score	0.200	0.800
CH Group Membership	0.008	0.992
CH Self-Pride Score	0.368	0.632
CH Determination Score	0.331	0.669
CH Social Trust Score	0.693	0.307
Parental Investment (Age 12)		
Prop. Clothing Exp.	0.106	0.894
Prop. Edu. Exp.	1.195	-0.195
Prop. Health. Exp.	0.004	0.996
Freq. See Dad	0.007	0.993

Notes: The measurement errors are derived as follows: Let $(\sigma_t^k)^2$ denotes the variance of the latent variable k at period t. For each measurement i on the latent variable k, the total residual variance is $(\sigma_{it}^k)^2 = (\Lambda_{it}^k)^2(\sigma_t^k)^2 + (\sigma_{\epsilon,it}^k)^2$ where Λ_{it}^k is the factor loading associated with each measurement and $(\sigma_{\epsilon,it}^k)^2$ is the variance of the uniqueness in measurement i at period t. The share of the total residual variance that is due to the factor is $s_t^k = \frac{(\Lambda_{it}^k)^2(\sigma_t^k)^2}{(\sigma_{it}^k)^2}$ and the share of the total residual that is due to the uniqueness is $s_{\epsilon,it}^k = \frac{(\sigma_{\epsilon,it}^k)^2}{(\sigma_{it}^k)^2}$.

APPENDIX

Table 11: Results 'Younger' Cohort: Without Initial Conditions

(a): Skill Accumulation - Age 8

	(1) Cognitive	(2) Non-Cognitive	(3) PI First Stage	(4) Cognitive (IV)	(5) Non-Cognitive (IV)
Parental Investment	13.613**	0.403	–	0.452	2.720**
	(4.607)	(0.631)		(1.367)	(0.970)
CH Siblings	0.328**	-0.021	-0.022*	-0.072	0.031
	(0.119)	(0.031)	(0.010)	(0.092)	(0.030)
CH Male	0.395	0.055	-0.009	-0.258**	0.099**
	(0.372)	(0.046)	(0.009)	(0.099)	(0.049)
Public School	-1.296*	0.029	0.004	-0.675**	0.037
	(0.585)	(0.074)	(0.019)	(0.275)	(0.095)
CG Education	-0.043	0.011	0.004	0.086**	-0.001
	(0.054)	(0.010)	(0.003)	(0.031)	(0.007)
Parent Altruism	-0.876	0.470	0.037	0.414	0.403
	(1.632)	(0.377)	(0.037)	(0.471)	(0.326)
HH Size	-0.108	-0.024$^+$	0.007$^+$	-0.001	-0.034**
	(0.074)	(0.013)	(0.004)	(0.044)	(0.013)
HH Social Connectedness	0.766*	0.014	-0.024	-0.018	0.082
	(0.396)	(0.093)	(0.017)	(0.158)	(0.077)
HH Urban	-0.164	0.278*	-0.024	-0.043	0.213$^+$
	(0.780)	(0.113)	(0.025)	(0.229)	(0.113)
HH in Village	0.020	0.008**	-0.001$^+$	-0.001	0.009*
	(0.018)	(0.003)	(0.001)	(0.007)	(0.004)
HH Shock	–	–	-0.081**	–	–
			(0.021)		
CH BO	–	–	0.003	–	–
			(0.003)		
Observations	**994**	**994**	**994**	**994**	**994**

Notes:
1. Standard Errors in parentheses.
2. $^+$ indicates significance at 10%; * at 5%; ** at 1%.
3. CH: Child; CG: Caregiver; HH: Household.

Table 12: Results 'Older' Cohort: Without Initial Conditions

(a): Skill Accumulation - Age 12

	(1) Cognitive	(2) Non-Cognitive	(3) PI First Stage	(4) Cognitive (IV)	(5) Non-Cognitive (IV)
Cognitive Skills	3.963**	0.015**	0.006$^+$	2.861**	0.009**
	(1.569)	(0.005)	(0.003)	(1.023)	(0.003)
Non-Cognitive Skills	-1.191	-0.007	-0.024*	-0.268	-0.005
	(1.571)	(0.010)	(0.011)	(1.451)	(0.012)
Parental Investment	10.407**	0.214**	–	11.011**	0.221**
	(3.969)	(0.047)		(4.184)	(0.048)
CH Siblings	-0.138	0.000	-0.015**	-0.196	0.000
	(0.423)	(0.002)	(0.005)	(0.312)	(0.002)
CH No. of Years of Schooling	-0.236	0.002	0.012**	1.259**	0.008**
	(0.518)	(0.003)	(0.003)	(0.491)	(0.003)
Public School	3.051**	0.062**	0.001	2.681**	0.061**
	(1.151)	(0.013)	(0.012)	(1.051)	(0.014)
CG Education	0.038	0.002$^+$	0.001	0.183$^+$	0.002**
	(0.116)	(0.001)	(0.001)	(0.108)	(0.001)
HH Size	-0.013	0.001	-0.002	0.054	0.002
	(0.134)	(0.001)	(0.002)	(0.088)	(0.001)
HH Social Connectedness	0.938*	0.003	0.008$^+$	0.696	0.002
	(0.477)	(0.003)	(0.004)	(0.422)	(0.003)
HH Urban	0.889	0.010	0.041**	1.113	0.012
	(1.402)	(0.008)	(0.013)	(1.346)	(0.008)
HH Shock	–	–	-0.003*	–	–
			(0.002)		
CH BO	–	–	0.004	–	–
			(0.003)		
Observations	**994**	**994**	**994**	**994**	**994**

Notes:
1. Standard Errors in parentheses.
2. $^+$ indicates significance at 10%; * at 5%; ** at 1%.
3. CH: Child; CG: Caregiver; HH: Household.

Table 13: Factor Loading: Outcome Variables; 'Older' Cohort

Dependent variable:	Cognitive Skills (Age 12)	Non-cognitive Skills (Age 12)	Cognitive Skills (Age 8)	Cognitive Skills (Age 8)
Peabody PVT Score	1.00	- -	- -	- -
Math Test Score	0.291** (0.079)	- -	- -	- -
Writing Level	0.059** (0.015)	- -	- -	- -
CH Friendliness Score	- -	1.00	- -	- -
CH Group Membership	- -	0.133** (0.051)	- -	- -
CH Self-Pride Score	- -	1.286** (0.177)	- -	- -
CH Determination Score	- -	1.077** (0.171)	- -	- -
CH Social Trust Score	- -	2.599** (0.467)	- -	- -
Raven's Score	- -	- -	1.00	- -
Reading Level	- -	- -	0.552** (0.145)	- -
Writing Level	- -	- -	0.105** (0.043)	- -
Emotional Symptoms Score	- -	- -	- -	1.00
Conduct Problems Score	- -	- -	- -	1.075** (0.186)
Hyperactivity Score	- -	- -	- -	0.202^{+} (0.115)
Pro-Social Behaviour Score	- -	- -	- -	0.400** (0.108)

Table 14: Factor Loading: Explanatory Variables; 'Older' Cohort

Dependent variable:	Parental Investment (Age 12)	Parental Investment (Age 8)
Prop. Clothing Exp.	1.00	- -
Prop. Edu. Exp.	2.331** (0.386)	- -
Prop. Health. Exp.	0.105** (0.041)	- -
Freq. See Dad	0.328+ (0.186)	- -
Spend on Education	- -	-1.445** (0.708)
Freq. See Dad	- -	0.219 (0.229)
Child Started School	- -	2.137* (0.896)
Does Child Work	- -	1.00

Table 15: Factor Loading: Outcome Variables; 'Younger' Cohort

Dependent variable:	Cognitive Skills (Age 5)	Non-cognitive Skills (Age 5)	Child Health (Age 1)
CDA-Q Test Score	0.068** (0.005)	- -	- -
Peabody PVT Score	1.00	- -	- -
Pre-School Status	- -	1.00	- -
CH Travels	- -	-0.317** (0.040)	- -
CH Fluent in Native Lang.	- -	-0.018 (0.011)	- -
Weight Z-Score	- -	- -	1.00
Height Z-Score	- -	- -	1.198** (0.083)

Table 16: Factor Loading: Explanatory Variables; 'Younger' Cohort

Dependent variable:	Parental Investment (Age 5)	Psycho Risk Factors (Age 8)
Unwanted Pregnancy	- -	0.083** (0.027)
No. Doc. at Birth	- -	0.735** (0.087)
Breastfeeding Duration	- -	-2.724** (0.458)
Ante-natal Care	- -	1.00
CG Education	- -	16.895** (1.721)
CG Depression	- -	0.354** (0.057)
Freq. See Dad	- -	-0.005 (0.019)
Prop. Clothing Exp.	1.00	- -
Prop. Edu. Exp.	1.009** (0.064)	- -
Prop. Health Exp.	0.107** (0.026)	- -
Freq. See Dad	-0.116* (0.049)	- -