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Human Capital Development and Parental Investment in India. *

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Abstract

We estimate production functions for cognition and health for children aged 1-12 in India, where over 70 million children aged 0-5 are at risk of developmental deficits. The inputs into the production functions include parental background, prior child cognition and health, and child investments. We use income and local prices to control for the endogeneity of investments. We find that cognition is sensitive to investments throughout the age range we consider, while health is mainly affected by early investments. We also find that inputs are complementary, and crucially that health is very important in determining cognition. Our paper contributes in understanding how investments and early health outcomes are important in child development.

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1 Introduction

In emerging and rapidly developing countries such as India, a high level of human capital may offer a way to escape poverty and take advantage of the new opportunities that arise. However, soon after birth (if not before) children from poorer backgrounds fall behind in every aspect of human capital development, including health and cognition, potentially depriving them of such opportunities.[1] Indeed 52% of the 137 million children aged 0-5 in India are at risk of developmental deficits.[2] It is thus important to understand how human capital is formed, how health may cause deficits in cognitive development, what role can investment in children play, and what is the relative importance of family background and child initial conditions in driving child development.

There is strong evidence showing that children's early experiences have long lasting effects, with implications for adult outcomes and even inter-generational transmission of human capital. Yet we still do not fully understand the mechanisms through which the many components of human capital develop and how different inputs interact in a dynamic fashion to shape the overall development of a child. There is growing consensus on the presence of important dynamic complementarities and interactions among different inputs and factors, but only a few studies have quantified them (see Del Boca, Flinn, and Wiswall (2014), Currie and Almond (2011), Cunha, Heckman, and Schennach (2010), Cunha and Heckman (2007), and Heckman (2007)).

This paucity of evidence is partly explained by the small number of longitudinal data following children over time; by the intrinsic difficulty of obtaining high quality measures of development in different domains; by the difficulty in measuring inputs for children; and by the fact that these inputs are not assigned exogenously but determined by individual choices. As a result, our understanding of how the components of human capital are formed is relatively limited in developed countries, and even more limited in develop-

[1]For a few examples, see Fernald, Weber, Galasso *et al.* (2011), Grantham-McGregor, Cheung, Cueto *et al.* (2007), Hamadani, Tofail, Huda *et al.* (2014), Rubio-Codina, Attanasio, Meghir *et al.* (2014), and Currie (2011).

[2]See for example Lu, Black, and Richter (2016).

ing countries. And yet, if we are to design interventions that will increase human capital and thereby improve individual productivity this knowledge is critical, particularly in the context of rapidly growing economies like India.

In this paper, we study the dynamic production of cognition and health - two important constituents of human capital- throughout childhood, from birth to age 12. We focus on these dimensions of human capital because both are likely to be key determinants of future productivity and the ability to acquire future skills through more advanced education. In addition, there are likely to be important interactions between these two factors that we cannot understand by examining one or the other in isolation. In a developing country like India, where rates of child malnutrition and morbidity are high, such considerations are particularly important.

Studying the development of cognition and health is particularly important given the evidence regarding their sensitivity to environmental factors, positive or negative. For example, cognition and health are both vulnerable to environmental risks that range from the presence of pollutants and sources of infection, to insufficient nutritional resources, to the lack of affection and stimulation.[3] Poverty has been shown to be an important determinant of the exposure to such risk factors. There is evidence that poorer children are more vulnerable to early life shocks and that they experience more frequent and larger early life shocks (see Case, Lubotsky, and Paxson (2002), Currie and Hyson (1999) and Currie and Stabile (2003)).

A number of studies have shown that some of the deficits acquired through poverty can be reversed by well designed interventions. An important example is the Jamaica home visiting intervention whose long term effect on cognition is described in Walker, Chang, Powell, and Grantham-McGregor (2005) and has also been shown to have labour market impacts.[4] The Jamaica intervention has been replicated in various modified forms:

[3]Almond, Edlund, and Palme (2009), Chay and Greenstone (2003), Currie, Neidell, and Schmieder (2009), and Currie and Neidell (2005) provide evidence on children's vulnerability to environmental risks. Almond (2006) and Bleakley (2007) show that children experience long term effects from exposure to infection. Bharadwaj, Løken, and Neilson (2013), Behrman (1996), and Field, Robles, and Torero (2009) demonstrate vulnerability to nutritional resources and micronutrient deficiencies.

[4]See Gertler, Heckman, Pinto, Zanolini, Vermeersch, Walker, Chang-Lopez, and Grantham-McGregor

for example Attanasio, Fernández, Fitzsimons *et al.* (2014) report that their scaleable intervention produced 26% of a standard deviation improvement in cognition. Moreover, a number of health and nutrition interventions have shown benefits not only on health, but also on cognition, which emphasizes the importance of considering the interactions between health and cognition.[5] A number of authors have pointed to this link between health and child development. For example, Figlio, Guryan, Karbownik *et al.* (2014) find that in the U.S. early health effects on cognition are constant throughout children's school careers and invariant to school quality and family background. Moreover, Campbell, Conti, Heckman *et al.* (2014) show that the Abcederian program, an early stimulation intervention, had long run health effects.[6] . It is well established that interventions targeting health can have impacts on cognitive development. We build on these results in this paper by examining how cognition and health interact and evolve over a long period of childhood, the role of parental investments and the child's environment in this process, and the importance of dynamic complementarities in development among a relatively deprived population of children in an important developing country.

Delivering interventions and ensuring their impacts are sustained over time requires understanding how parents make investment decisions, how these decisions are affected by their own and their child's background, and how effective investments are in changing the course of development of these children. Underlying parental decisions are the perceived technology of human capital formation as well as the overall economic environment. In this sense, India is a particularly interesting country. The growing economic opportunities, particularly in cities, may offer the right incentives for parents to invest. At

(2013) and Engle, Black, Behrman *et al.* (2007).

[5]There is an important literature on health intervention and their impact on child development, including cognition. See, Glewwe and Miguel (2008), Hoddinott, Maluccio, Behrman *et al.* (2008) (the Guatemala intervention); Bharadwaj, Løken, and Neilson (2013);Banerjee, Cole, Duflo *et al.* (2007);Miguel and Kremer (2004); Grantham-McGregor, Powell, Walker *et al.* (1991); Lucas, Morley, and Cole (1998); Sazawal, Bentley, Black *et al.* (1996); Heckman, Moon, Pinto *et al.* (2010).

[6]Other important studies in this area include Glewwe, Jacoby, and King (2001), Glewwe and King (2001), Glewwe and Jacoby (1995), Sakti, Nokes, Hertanto *et al.* (1999), Black (2003), Bleakley (2010), Clark, Jukes, Njagi *et al.* (2008), Chong, Cohen, Field *et al.* (2016) and Kippler, Tofail, Hamadani *et al.* (2012). For an examination of the effect of cognition on later health see Ludwig and Miller (2007).

the same time, poor children in India suffer huge amounts of deprivation as we document later in the paper.

The cohort data collected by the Young Lives Project starting in 2002 offers a unique opportunity to examine these issues in some detail. We use data collected on the same children from age 1 to age 12. The data focuses on child development, and provides numerous measures of child health, nutritional status, and cognitive ability.[7] In addition it has a rich set of household characteristics, including measures of material investments in children, household resources, and household structure.

Using this data we estimate a joint model for the production of cognition and health, and parental investment decisions from age 1 to age 12, following the nonlinear latent factor approach of Cunha, Heckman, and Schennach (2010). Investments depend on the parental and child levels of human capital as well as on exogenous cost shifters, such as prices of relevant goods and parental resources. The model allows us to directly characterize the process of development for health and cognition, as well as how parents invest in their children.

To estimate the model we first estimate the distribution of observed measurements, which we approximate by a mixture of normals. We then use this information along with the moments from the measurement equations that relate observed data to latent factors to extract the joint distribution of the latent factors. This joint distribution of latent factors completely describes the underlying production functions of human capital and the investment behavior of parents. In practice, the parameters of the production functions and investment equations are recovered by drawing data sets from the distribution of latent factors and applying nonlinear least squares.

An important feature of our paper is that we treat parental investments as endogenous. We allow for the possibility that parents react to unobserved human capital shocks by changing how much they invest in their children. We find that parents compensate

[7]The Young Lives survey collected data on two cohorts: one from age 1 to 12, which we use and one from age 8 to 18. In our study we only use the younger cohort, observed up until the age of 12. This is because the sample size for the older cohort is much smaller, leading to imprecise results.

for adverse shocks to their children. To address the endogeneity of investments we use a control function approach; our instruments include prices of goods relevant to children as well as parental resources. In the paper, we discuss the validity of these instruments and provide a robustness analysis.

We find that investments depend strongly on household resources and prices. We also find that investments have a strong influence on cognitive and (to a lesser degree) health development throughout childhood (although the effect declines by age 12). These two facts together are consistent with and can explain the existence of wealth gaps in child development. They also provide further confirmation that interventions aimed at increasing parental investments can improve child development.[8] The other central result is that ill-health at young ages, associated with malnutrition, can have a long-term impact on cognitive development. This confirms the important role that endemic diseases can have in determining cognitive deficits among the poor, and the potential role of interventions improving the health environment in which children grow up.[9]

Our paper builds on a number of earlier papers that estimate production technologies for child development in the United States using NLSY data, such as Heckman, Schennach, and Williams (2010), Cunha and Heckman (2007, 2008), Bernal (2008), and Todd and Wolpin (2007). More recently Agostinelli and Wiswall (2016a) discuss a number of estimation issues relating to the latent factor approach, which are relevant to this context. The two papers closest to this paper are Cunha, Heckman, and Schennach (2010) and Del Boca, Flinn, and Wiswall (2014).

Cunha, Heckman, and Schennach (2010) develop the dynamic latent factor approach we follow in this paper. They use this approach to estimate the process of cognitive and noncognitive skill accumulation over two stages of childhood for children in the U.S. aged 0-14, using NLSY data. We do not model noncognitive skills (which we do not observe) as they do, but emphasize the interaction between health and cognition and

[8] Attanasio, Fernández, Fitzsimons, Grantham-McGregor, Meghir, and Rubio-Codina (2014); Walker, Chang, Powell, and Grantham-McGregor (2005).

[9] In a follow up paper to this one we also examine evidence from Peru and Ethiopia. See Attanasio, Meghir, Nix, and Salvati (2017).

allow investments to react to time varying unobserved shocks.

Our study is also related to that of Del Boca, Flinn, and Wiswall (2014), which uses the PSID to estimate a structural model of parental investments in resources and time on children within a lifecycle model of the household. In their model child quality (human capital) is measured by cognition and parents define their investments in time and resources taking into account the dynamic production function. In our context human capital has two dimensions (health and cognition). But more importantly, we do not estimate a model of household decision making. A reason for not doing this is that we did not wish to assume that parents know the production function of human capital, given recent evidence (Cunha, Elo, and Culhane, 2013). Thus parental decisions are reflected in a reduced form investment equation, of interest in its own right, and the production functions are estimated without imposing the restriction that parents know them.

In the next section, we describe our data and descriptive features of child development in India. In Section 3, we present our model for the production of cognitive skills and health over the child's life-cycle and describe how we deal with the endogeneity of parental investments and measurement error. In Section 4 we introduce a simple approach to estimate the model and discuss how to interpret the estimates. The main results and robustness exercises are in Section 5 and counterfactual exercises are in Section 6. Section 7 concludes.

2 Data and descriptive results

We use longitudinal data from the Young Lives Survey. The survey started in 2002 with two cohorts. We use data from the younger cohort which has a much larger sample size of 2,011 children. Data was collected in four rounds at ages 1, 5, 8, and 12.

Children were selected from the Hyderabad district and a 'poor' and 'nonpoor' district in each of the 3 major regions in Andhra Pradesh: Coastal Andhra, Rayalaseema, and

Telangana, for a total of 7 districts. Within these 7 districts, there are 98 separate communities. Since Young Lives aims to document child poverty, it deliberately over sampled poor communities. As a result, while households from different socio-economic backgrounds are included, the sample is not representative. The data collected is extremely detailed, and we use information from household questionnaires, child questionnaires, and community questionnaires.

We restrict our sample to children observed in all rounds. This leaves us with 1,910 children. As these numbers indicate, attrition was very low. Total attrition from round 1 to round 4 was 4.8%. These figures include attrition due to mortality, with 2.2% of children dying from ages 1 to 12.[10]

In Table 1, we present descriptive statistics on child household characteristics at baseline. Around 76% live in rural communities, 54% of children are male, and household size is 5-6. Mothers are relatively young. The average age for the mothers at the start of the survey is just under 24.

In Table 2, we report additional statistics that vary across rounds. The sample is very poor with 40-60% below $2 per day.[11] A significant fraction of the children suffer from stunting, wasting and being underweight. Together, these indicators are suggestive of significant morbidity in this population. While poverty rates seem to decline as the cohorts age (in part reflecting economic growth in the area), health indicators do not improve. While stunting is effectively irreversible, one would hope that underweight and wasting would respond to the poverty reduction.

In addition to information on income, the survey contains information on a number of indicators that Young Lives uses to compute a wealth index, which is an average of

[10]For more information on the attrition in this data, see Galab, Kumar, Reddy *et al.* (2011). In contexts where child mortality is frequent, survival might be the only goal of households. In that case, a paper estimating the production of child survival might be more appropriate. While the mortality rate in our sample is much higher than in the U.S., mortality is still sufficiently rare to make our focus on human capital accumulation relevant.

[11]Income is computed by summing over income from all possible sources, including but not limited to income from wages, agricultural work, trade, self-employment, and transfers.

Table 1: Descriptive Statistics: Baseline

Household Characteristics	
Subject child is Male	0.54
Urban	0.24
Scheduled caste	0.18
Scheduled tribe	0.15
Hindu	0.88
Muslim	0.07
Number of children	1.89
	1.00
Number older siblings	0.69
	1.03
Household size	5.44
	2.36
Mother Characteristics	
Mother weight	46.39
	9.39
Mother years of school	3.62
	4.42
Mother's age	23.66
	4.35
Observations	1,910

Note: Standard deviations in italics.

measures of housing quality, consumer durables, and access to services.[12] While its mean is not easy to interpret, the evidence on the standard deviation indicates that within our sample there is a considerable degree of heterogeneity in socio-economic background.

In Table 2 we also report expenditures on books for children over time. In the analysis that follows, our parental investment factor will be based on a number of expenditures parents make on the focus child at each age, including purchases of books and stationery, clothing, shoes and uniforms. We do not include food expenditures (which is not measured separately for children) and public goods like housing. To put the combination of

[12]For more information on the computation of the wealth index, see Kumra (2008).

Table 2: Descriptive Statistics: Across Rounds

	Age 1	Age 5	Age 8	Age 12
Child Characteristics				
Fraction stunted	0.31	0.36	0.30	0.29
Fraction underweight	0.32	0.45	0.46	
Fraction wasted		0.19	0.28	0.33
Height for age Z-score	-1.30	-1.66	-1.45	-1.45
	1.48	*0.99*	*1.04*	*1.03*
Raw score PPVT test		27.47	58.51	43.08
		21.10	*30.43*	*7.82*
Amount spent on books		3.48	8.98	13.00
		5.40	*13.02*	*16.97*
Household Economic Wellbeing				
Annual income		873.57	1407.98	1749.95
		1219.24	*2033.67*	*1841.78*
Wealth index	0.40	0.46	0.51	0.59
	0.20	*0.20*	*0.18*	*0.17*
Percent below $2/day		0.63	0.45	0.27
Child Work				
Daily hours chores		0.06	0.34	0.82
Daily hours family business		0.00	0.01	0.12
Daily hours paid work			0.01	0.05

Income and amount spent on books are annual amounts in the past 12 months in USD. At age 5, 1USD≅45INR, at age 8, 1USD≅49INR, and at age 12, 1USD≅62INR. Income consists of earnings from all sources, including but not limited to wage work, agricultural work, self-employment and other transfers. The drop in the raw PPVT score at age 12 is due to the fact that in this round a smaller selection of questions were asked, although the questions were spaced throughout the test (including both easy and more difficult words). Standard deviations are reported below the estimates in italics, as applicable.

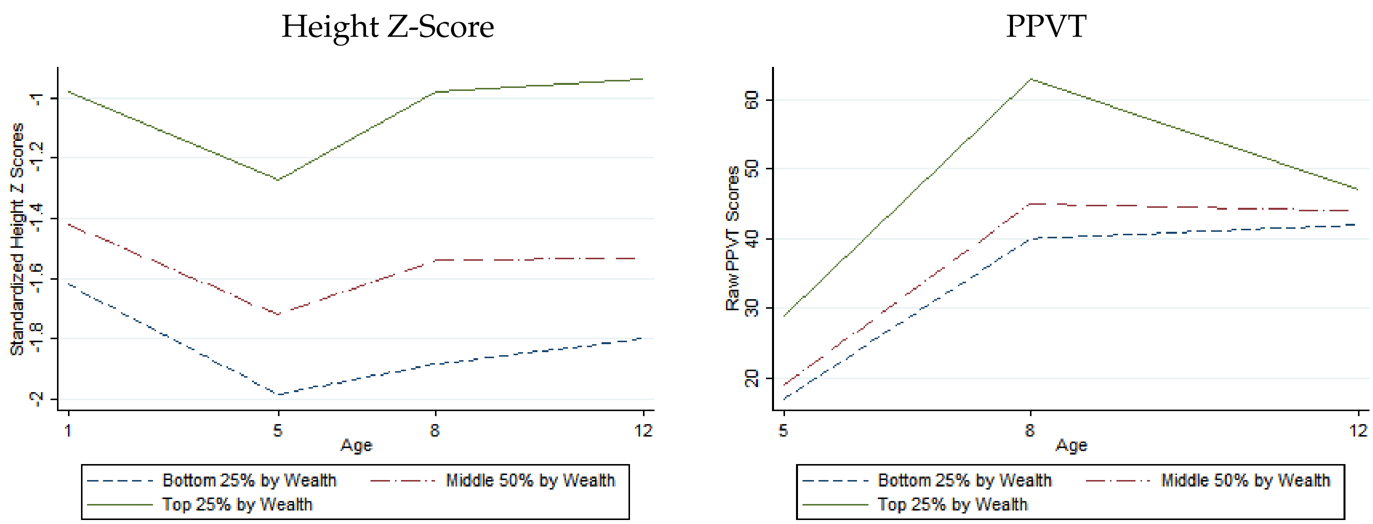
the investment goods we do use in context, the various expenditures we use as measures of investments are on average 4% to 5.5% of the household budget across ages. While from a percentage point of view the amounts look substantial, one has to remember that many of these households are extremely poor and hence the investments are quite low in absolute value. Parents have very high aspirations for their children: among the 5 year olds, 55% of children's parents would like to see their children become doctors, engineers, and teachers (the remaining 45% report a variety of careers, most of which are similarly ambitious). Among the 12 year olds, 99% of parents hope their children complete more than 10 years of schooling.

Children spend minimal time working at family businesses and doing chores at home. By age 12, children spend approximately an hour a day helping out at home, on the farm, or at the family business. Almost no children do paid work outside of the home.

Child outcomes vary substantially with wealth. To illustrate this, in Figure 1 we plot average z-scores for height per age and raw PPVT scores against age for three groups of children: those living in families in the bottom quartile of the wealth index, those in the middle 50%, and those in the top quartile of the wealth index. The differences between the bottom 25% and the top 25% of the wealth distribution in height per age is about 0.8 of a standard deviation of the z-score at age 1. The middle 50% are slightly closer to the bottom 25% than to the top 75%. These scores get worse at age 5, but to a lesser degree for the top 25%. At age 8, the difference between the top 25% and the other two groups increases again, but remains relatively constant at age 12.

Moving to differences in language development, we find that at age 5 there is little difference between the bottom 25% and middle 50% of the wealth index, but there is a gap between these two groups and the top 25%. The differences decline slightly for the middle 50% by age 8, who also open up a gap relative to the bottom 25%. The gaps between all groups narrow significantly at age 12.

Figure 1: Wealth Gradient in Height and in the Peabody Picture Vocabulary Test(PPVT)



3 Human Capital Accumulation and Parental Investment

To understand the process of human development and the role of parental investment, it is useful to specify a formal structure that makes the various channels clear. One issue, of course, is that parental choices might react to the level of current development and/or to shocks to the process, making the identification of their causal impact difficult to identify.

We start by assuming that human capital at the start of adult life has two relevant dimensions, which in our context are cognition and health:

$$H_a = H(\theta_a^c, \theta_a^h) \tag{1}$$

Our empirical analysis emphasizes health because it is a major concern in developing countries. Children in developing countries begin life with lower levels of health. Moreover, throughout childhood they are more frequently exposed to unhealthy environments and diseases such as diarrhea and malaria. In turn such morbidity, documented in our sample of children in the preceding section, may affect adult human capital and productivity through two channels: by directly shaping adult health and also by impacting cognitive development during childhood. In order to understand how adult human capital is formed we must understand how its constituents are determined throughout childhood. We follow Cunha, Heckman, and Schennach (2010) and express the evolution of cognition and health by a series of production functions over stages of childhood. At each stage the evolution of the two dimensions of human capital depends on the initial conditions, parental choices and other environmental variables.

$$\theta^c_{t+1} = G\left(\theta^c_t, \theta^h_t, \theta^I_t, X_t\right) \tag{2}$$
$$\theta^h_{t+1} = F\left(\theta^c_t, \theta^h_t, \theta^I_t, X_t\right) \tag{3}$$

where θ^I_t is an investment good that parents can buy in the market.[13]. The vector X_t includes parental background and temporal shocks, which we leave implicit for the moment.

The production functions define the dynamics of child development and the role that parental investment can play in defining its path. These investments are the result of household choices, as parents trade off current household utility with the future development of the child. They depend on the marginal product of investments at different stages, the available resources, the prices of investment goods and, importantly, on parents beliefs about the child development process. If parents are liquidity constrained, then the timing of income will also affect child development (Carneiro, Lopez-Garcia, Salvanes, and Tominey, 2015).

The main goal of this paper is the study of the production functions, the role played by investment, and how health and cognition interact. We do not estimate a structural economic model of parental investment decisions (as done in Del Boca, Flinn, and Wiswall

[13] In a more complete model we would allow for both material and time investments as in Del Boca, Flinn, and Wiswall (2014). However we do not include time here because in our empirical model we do not observe time inputs.

(2014)). As a result, while we cannot explicitly simulate the impact of potential interventions, our estimates are robust to assumptions on parental beliefs about the effectiveness of investments, their knowledge of the production functions, and the extent to which parents face constraints.

3.1 The production functions

The production functions for cognition and health at the various childhood stages define how initial conditions and investments get embodied in child human capital and how these relationships evolve over time. Given the available data we model the production of human capital in three stages: ages 1-5, 5-8 and 8-12. We denote child's age by t. Similarly to the model for cognitive and non-cognitive skills in Cunha, Heckman, and Schennach (2010), we assume a CES production function. Child's cognitive skills and health stock $\{\theta_{ct+1}, \theta_{ht+1}\}$ at any period $t+1$ are a CES function of the previous period stock of health and cognitive skills $\{\theta_{ct}, \theta_{ht}\}$, the amount parents choose to invest in their child θ_{It}, the parental stock of health θ_{hp}, the parental stock of cognitive skills θ_{cp}[14], a TFP term A_t, and a random shock μ_t. We assume that parental health and cognitive skills are fixed at their initial levels.[15] Thus we have that

$$\theta_{ct+1} = \left[\delta_{ct}(\theta_{ct})^{\rho_t} + \delta_{ht}(\theta_{ht})^{\rho_t} + \delta_{cpt}(\theta_{cp})^{\rho_t} + \delta_{hpt}(\theta_{hp})^{\rho_t} + \delta_{It}(\theta_{It})^{\rho_t}\right]^{\frac{1}{\rho_t}} A_{ct} \tag{4}$$

$$\theta_{ht+1} = \left[\alpha_{ct}(\theta_{ct})^{\zeta_t} + \alpha_{ht}(\theta_{ht})^{\zeta_t} + \alpha_{cpt}(\theta_{cp})^{\zeta_t} + \alpha_{hpt}(\theta_{hp})^{\zeta_t} + \alpha_{It}(\theta_{It})^{\zeta_t}\right]^{\frac{1}{\zeta_t}} A_{ht} \tag{5}$$

[14]Parental health and cognitive skills may affect child health and cognitive outcomes through a variety of channels, including genetics as well as broader factors in the pre-birth and early life environment.

[15]As an anonymous referee suggested, this would be a poor assumption if parents are still accumulating cognitive skills, or their health status is rapidly changing. In particular, young mothers in India may be experiencing more growth in human capital relative to older mothers in more developed countries. In our data, we find that parental human capital is not changing (at least not in the measures we observe). We also control for mother's age, which may capture unobservable maternal human capital accumulation.

where

$$
\begin{aligned}
A_{ct} &= exp\left(\delta_{0t} + \delta_{Xt}X_t + u_{ct}\right) \\
A_{ht} &= exp\left(\alpha_{0t} + \alpha_{Xt}X_t + u_{ht}\right)
\end{aligned}
$$

and where the δs and the αs sum to one respectively within each period.

The parameters of the production function all vary with age t. u_{ct} and u_{ht} are unobserved shocks to child cognition and health respectively. Total factor productivity depends on X_t, which includes family composition, birth order, gender, mother's age, ethnicity, and caste. These variables capture heterogeneity in child rearing practices. Allowing for family composition is meant to capture the possibility that there are spillover effects from one child to another.

The parameters ρ_t and ζ_t determine the elasticity of substitution between the various inputs in the cognition and health production function, respectively. If they are equal to one, the production functions are linear and the inputs are perfectly substitutable. If these parameters are zero, then the prodution functions are of the Cobb-Douglas type and the elastcity of substitution is equal to unity; when these parameters are greater than one then the inputs are complementary. In other words, these parameters can capture the extent to which the productivity of child investments vary with the child's background and with parental characteristics. These are all potential sources of lifecycle inequality.

As determinants of the production function we also include mother's age, caste, and ethnicity in X_t. Given the much lower age at marriage in India relative to more developed countries, mother's age may be an important determinant of child human capital development. Regarding caste and ethnicity, there is substantial evidence that these characteristics play important roles in child development in India (for example, see Jayachandran and Kuziemko (2011)).

3.2 Investment

Investments reflect parental choices. These choices depend on parental preferences for child quality, the budget constraint they face (including whether they can borrow) and their beliefs about the effectiveness of these investments. Without separate information on such beliefs, estimating a structural model would require assuming that parents know the true production functions, which goes against existing evidence for the poor in both developed and developing countries (Cunha, Elo, and Culhane, 2013; Attanasio, Cunha, and Jervis, 2015; Boneva and Rauh, 2015). Thus, in this paper we estimate a reduced form investment equation that depends on parental background, the current state of cognition and health of the child, and household characteristics. We assume that investment also depends on prices and parental resources. These equations are consistent with the structural model described in the Appendix, as well as potentially more general models.

Since there is no obvious price index for child investments and we cannot construct one because we do not observe the shares going to children out of total expenditure, we include a vector of prices for relevant goods (food, medications, educational goods and clothing) in an unrestricted fashion.[16] The prices capture the effect of both current prices and household expectations of future prices. Finally, we also include current resources.

The empirical specification for investment θ_{It} is

$$ln\theta_{It} = \gamma_0 + \gamma_{ct} ln\theta_{ct} + \gamma_{ht} ln\theta_{ht} + \gamma_{cpt} ln\theta_{cp} + \gamma_{hpt} ln\theta_{hp} + \gamma'_{Xt} X_t + \gamma'_{pt} lnp_{It} + \gamma_Y ln\theta_{Yt} + v_t \tag{6}$$

where v_t reflects random shocks, and θ_{Yt} represents parental resources, lnp_{It} represents log prices for child investment goods. All other variables are as defined in the production functions.

[16] Constructing a price index would require measuring the budget shares for the various goods devoted to children. However in many cases we do not know the amounts consumed by children.

3.3 Controlling for the endogeneity of Investments

If parents choose investment taking into account the evolution of human capital, then production function shocks may affect investments in children. In our reduced form framework this implies that the shocks v_t in the investment function (6) may be correlated with those of the production function, u_{ct} and u_{ht}, making investments endogenous. To allow for this endogeneity we use a control function approach. Specifically we assume that

$$\begin{aligned} E\left(u_{ct}|Q_t, Z_t\right) &= \kappa_c v_t \\ E\left(u_{ht}|Q_t, Z_t\right) &= \kappa_h v_t \end{aligned} \tag{7}$$

where Q_t is the set of variables in the production functions (including investment) and Z_t are the instruments, which are included in the investment equation and excluded from the production function. To control for endogeneity we thus include the estimated residual from the investment equation, $\hat{v}_t$, as an additional regressor among those affecting TFP in the production functions.[17] Assuming that investments are exogenous amounts to imposing $\kappa_c = 0$ and $\kappa_h = 0$, with are testable hypotheses; our results indicate that investments are endogenous.

The choice of appropriate instruments is key for the validity of our approach. Our choice of instruments is driven by the structural model in the Appendix: they include prices as well as household resources, both of which reflect the budget constraint. The prices are measured at a local level and their validity as instruments rests on the assumption that their variability is due to supply side changes and do not relate to the shocks or unobserved inputs in the human capital production functions. Household resources is a valid instrument if it does not enter the production function or, in other words, is uncorrelated with the production function error term conditional on the included variables, such as parental cognition and health as well as other household characteristics.

[17]The residual v_t is a control function as in Gronau (1974), and Heckman (1979). For control functions in a nonparametric context see Newey, Powell, and Vella (1999) and Florens, Heckman, Meghir *et al.* (2008)).

The main risk for this assumption is that income is correlated with unobserved inputs or shocks to child development. However, given we include both the child initial conditions and the mother's human capital it is plausible that income is conditionally exogenous. Nevertheless, the prices have sufficient power for us to estimate the model without relying on income as an excluded instrument. We will find that our results are completely unaffected whether we use income as an excluded instrument or not.

3.4 The measurement system

We have rich data with multiple measurements for many variables that enter our production functions. This leads to two related challenges. First, how should we efficiently use all of the available data? Second, for many of the variables in our model, the measurements observed in the data are likely to be contaminated by measurement error. For example, weight, height, and self reported health status all provide imperfect proxies of child health. Using any one of these proxies without addressing measurement error is particularly troubling given that the production functions are nonlinear. As shown in Griliches and Ringstad (1970) this means that we cannot predict the sign of the bias.

In our model, the latent factor k which is observed with error is denoted as θ_{kt} and includes child health, child cognition, parental health, parental cognition, investments, and resources. All other variables in the model are assumed to be measured without error. We implement the factor analytic approach which was recently extended to nonlinear models in Cunha, Heckman, and Schennach (2010)[18]. The basic idea behind the approach is that one can relate observed measurements, like weight and height, to unobserved "latent" factors, like health. Let m_{jkt} denote the jth available measurement relating to latent factor k in time t. The assumption is that the measurements are error-ridden proxies for the latent factors. Identification will require at least two measures per factor and at least one factor with three measures. However, more measurements can improve precision.

[18]See also the results in Schennach (2004) and Hu and Schennach (2008)

We assume a semi-log relationship between measurements and factors θ_{kt}

$$m_{jkt} = a_{jkt} + \lambda_{jkt} ln\left(\theta_{kt}\right) + \epsilon_{jkt} \tag{8}$$

where λ_{jkt} is the factor loading and ϵ_{jkt} are measurement errors. The assumptions required for the non-parametric identification of the distribution of latent factors and also of the distribution of the measurement errors are derived in Cunha, Heckman, and Schennach (2010). They also discuss the more general case of identification when the mapping from the latent factors to the measures is unknown and nonseparable in the measurement error. However, we employ a simpler framework that is separable (as above) with normally distributed errors (ϵ_{jkt}) that are independent of the latent factors θ_{kt} and of each other.[19] Since neither location nor scale can be identified the mean of each log factor and the measurement errors are both normalized to zero and one factor loading is normalized to one for each case.[20]

The scale of the latent factor is set by the choice of which measurement's factor loading is set to 1, which is salient for the interpretation of the estimates. As pointed out by Agostinelli and Wiswall (2016b), given the longitudinal nature of our model, valid inference across time is only possible if each latent factor is scaled in the same way in every period. One way to meet this condition is to normalize each factor on the same measure every period. Our data is sufficiently rich that we are able to do this for our model. For child cognitive skills we always normalize the loading on PPVT to one. Similarly, child health is always normalized on height z scores, investments are normalized on amount spent on books, parental health is normalized on mother's weight, parental cognitive skills is normalized on mother's years of schooling, and resources are normalized on in-

[19]The assumptions listed above are more restrictive than necessary for identification. It is possible to allow for more than one factor to load onto a measure so long as there is at least one measure that relates exclusively to one factor. Moreover, it is also possible to allow for measurement errors to be correlated with each other, so long as one has 3 measurements for at least one factor.

[20]This implies that the coefficients $a_{j,k,t}$ will be equal to the mean of each measurement. As pointed out in Agostinelli and Wiswall (2016b), this assumption would be unappealing if it restricted the production of skills to be mean log-stationary, which would only be consistent with Cobb Douglas production functions. This is not the case if we include a TFP term in the production functions, as we do here.

come.

4 Estimation

We estimate the model in three steps. In the first step, we estimate a joint distribution (as a mixture of normals) for all observed measures and variables that enter the production functions and investment equation. In a second step we use minimum distance to estimate the joint distribution of the latent factors and all other variables that are used in the model. In the third step we simulate draws from the joint distribution to construct a synthetic dataset allowing us to estimate the parameters of the investment equation and the production functions. We explain each step in this section.

We assume that the joint distribution of the log latent factors is a mixture of normals. We view this as an approximation to the underlying distribution. The departure from normality is important. The production function can be interpreted as the conditional mean of an output in period $t+1$ given the inputs in period t. Under joint normality, this conditional mean is linear. Thus, assuming normality would restrict our production functions to be Cobb-Douglas (linear in logs) with the estimated substitution elasticity equal to 1.

Formally, let θ represent variables observed with measurement error. Let F_θ denote the joint distribution of all log latent factors in our model across all periods t.[21] Then:

$$F_\theta = \tau \Phi\left(\mu_A, \Omega_A\right) + (1-\tau)\, \Phi\left(\mu_B, \Omega_B\right) \tag{9}$$

where $\tau \in [0,1]$ is the mixture weight and $\Phi\left(\mu, \Omega\right)$ is the CDF of a normal distribution with mean vector μ and variance-covariance matrix Ω.

We cannot estimate this equation directly, since we do not observe θ. Instead, we use the measurement system expressed here in matrix form

[21] Demographic variables that can be 0 enter in levels as opposed to logs.

$$M = \mathbf{\Lambda} ln\theta + \mathbf{\Sigma}\varepsilon$$

Where $\mathbf{\Lambda}$ is the matrix of factor loadings incorporating the normalizations and the zero restrictions (i.e. the restrictions that define what factors relate to what measures);[22] $\mathbf{\Sigma}$ is the diagonal matrix of standard deviations for the measurement errors and ε is a vector of mutually independent standard normal errors.

The structure of the measurement equations, with normal measurement errors and the fact that the factors are distributed as a mixture of normals, implies that the measurements are also distributed as a mixture of normals. Thus the distribution of M is given by:

$$F_M = \tau\mathit{\Phi}\left(\Pi_A, \mathit{\Psi}_A\right) + (1-\tau)\,\mathit{\Phi}\left(\Pi_B, \Psi_B\right) \tag{10}$$

where

$$\begin{aligned} \mathit{\Psi}_A &= \mathbf{\Lambda}^T \mathit{\Omega}_A \mathbf{\Lambda} + \mathbf{\Sigma} \\ \mathit{\Psi}_B &= \mathbf{\Lambda}^T \mathit{\Omega}_B \mathbf{\Lambda} + \mathbf{\Sigma} \\ \Pi_A &= \mathbf{\Lambda}\mu_A \\ \Pi_B &= \mathbf{\Lambda}\mu_B \end{aligned} \tag{11}$$

and where we impose the mean zero restriction

[22] For example, with 2 factors, cognition and health, with 3 and 4 measures respectively,

$$\mathbf{\Lambda} = \begin{bmatrix} 1 & 0 \\ \lambda_{2,C} & 0 \\ \lambda_{3,C} & 0 \\ 0 & 1 \\ 0 & \lambda_{2,H} \\ 0 & \lambda_{3,H} \\ 0 & \lambda_{4,H} \end{bmatrix}$$

$$\tau \mu_A + (1 - \tau)\, \mu_B = 0 \tag{12}$$

Based on these equations, estimation of the parameters of interest follows three steps[23]:

1. Use MLE to estimate τ, Π_A, Π_B, Ψ_A and Ψ_B from the data.
2. Use minimum distance to impose the restrictions in equations (11) and (12) as well as the normalizations and zero restrictions in $\boldsymbol{\Lambda}$ to recover $\boldsymbol{\Lambda}$, $\boldsymbol{\Sigma}$, μ_A, μ_B, Ω_A, Ω_B from Π_A, Π_B, Ψ_A and Ψ_B.
3. Draw a synthetic data set from this joint distribution to estimate the model using regression methods. The joint distribution includes the full amount of information in the data relevant to the model. The larger the data we draw the lower the simulation error.

Regarding the first step we use the Expectation Maximization (EM) algorithm of Dempster, Laird, and Rubin (1977) and further developed in Arcidiacono and Jones (2003). To summarize the procedure, we begin by guessing starting parameters for vectors of means, covariance matrices, and mixture weights.[24] In the E step we estimate the probability that a given observation is drawn from each of the two possible normal distributions, conditional on the observables. In the M step we maximize the conditional likelihood function and update the parameter estimates for each of the two normal distributions. In the case of a mixture of normals, the M step has analytical solutions, which helps with computational speed. We then iterate until convergence is reached.

Beyond the latent factors in our model we use extra variables as controls (such as number of children and gender) and instruments (such as prices). Hence the joint distribution

[23] Before performing these three steps, we suggest converting all measurements into z scores. This is not necessary for the method to work, but it does place all measurements on the same scale which speeds up convergence. The demeaning is without loss of generality, given the assumption that latent factors are mean zero. Dividing by the standard deviation can impact the estimates, but can easily be undone before estimating the production functions by simply multiplying the simulated factors by the standard deviation of the normalized measurement for each factor.

[24] In practice, we use k-means clustering when possible to obtain initial guesses for the means.

we estimate has to include these extra variables so as to reflect all the relevant dependencies in the data. To achieve this we treat these extra variables as error free measures and we expand the distribution of latent factors to include these extra variables. Thus, in step 1 we expand the measurement system to include these additional variables with no measurement error, i.e. we set the corresponding standard deviation in Σ to zero. The corresponding factor loading is also set to one. In this way we model the complete structure of dependence between all factors, including the controls and the instruments, with a joint mixture of normals.[25]

This augmented distribution is

$$F_{\theta,X} = \tau\Phi\left(\mu_A^{\theta,X}, \Omega_A^{\theta,X}\right) + (1-\tau)\,\Phi\left(\mu_B^{\theta,X}, \Omega_B^{\theta,X}\right) \tag{13}$$

where X represents the instruments and the demographic controls we use. The superscripts (θ, X) emphasize that the parameters of the augmented distribution include both the latent factors and these other variables. It is easy to extend this process to allow for a larger number of mixtures approximating more closely the actual distribution of latent factors.

To estimate confidence intervals and obtain critical values for test statistics we use the nonparametric bootstrap over *all* three steps. This takes into account both estimation error at each stage and simulation error.

4.1 Monte Carlo Simulation

To demonstrate that our approach is able to recover the values of a CES production function, we report results from 200 Monte Carlo Simulations, for two periods of childhood, with a data generating process designed to mimic our actual data. Specifically, first we generate the two baseline inputs (θ_1, X) from a mixture of two normals with parameter values based on our results in this paper and given in the first panel of Appendix Table

[25]While prices may be measured with error, what matter as far as their validity as instruments is concerned is that their measurement error be independent of the latent factors. Since they are collected separately at the village level this is a plausible assumption.

Table 3: Monte Carlo Simulations

Coefficient	A_1	δ_1	ρ_1	A_2	δ_2	ρ_2
True	0	0.69	-1	0	0.82	-1
Mean Estimate	0.09	0.68	-0.82	0.03	0.84	-0.66
Standard Dev.	0.01	0.01	0.11	0.01	0.01	0.15
True	0	0.69	-0.5	0	0.82	-0.5
Mean Estimate	0.04	0.69	-0.39	0.01	0.82	-0.34
Standard Dev.	0.01	0.01	0.08	0	0.01	0.12
True	0	0.69	0	0	0.82	0
Mean Estimate	0	0.69	0	0	0.82	0.01
Standard Dev.	0.01	0.01	0.05	0.01	0.02	0.11
True	0	0.69	0.5	0	0.82	0.5
Mean Estimate	-0.04	0.68	0.37	-0.01	0.82	0.34
Standard Dev.	0.01	0.01	0.10	0.01	0.01	0.14
True	0	0.69	1	0	0.82	1
Mean Estimate	-0.09	0.68	0.82	-0.02	0.84	0.68
Standard Dev.	0.01	0.02	0.13	0.01	0.01	0.18

Monte Carlo simulations with 200 replications. Each sample used is 2000 individual observations. Details in Appendix Table 9.

9. Next, we generate the output for the first and second periods using the following CES production functions, with the parameters given in the middle panels of Appendix Table 9.

$$ln\theta_2 = A_1 + \frac{1}{\rho_1} ln\left(\delta_1\theta_1^{\rho_1} + (1-\delta_1)X^{\rho_1}\right) + u_1$$
$$ln\theta_3 = A_2 + \frac{1}{\rho_2} ln\left(\delta_2\theta_2^{\rho_2} + (1-\delta_2)X^{\rho_2}\right) + u_2$$

Finally, we generate three measurements (m_j^{Θ}) for each of the four latent factors (θ_1, θ_2, θ_3 and X) using the parameters in the last panel in Appendix Table 9 and a measurement equation of the form:

$$m_j^{\Theta} = \lambda_j ln(\Theta) + \epsilon_j \tag{14}$$

where Θ is one of $\theta_t,\ t = 1,...,3$ and X All details of the simulated model are given in Appendix Table 9. The results are shown in Table 3.

The δ coefficient and the TFP show no bias whatsoever. The complementarity coefficient ρ has a small bias towards zero, although the true coefficient is always within the 95% confidence interval. Overall the standard deviations of the estimates are low, implying a high level of precision. At $\rho = 0$ there is no bias. Thus our estimator performs very well and at the same time provides estimates very fast.

5 Results

We start with a discussion of the properties of the measurement system. We then discuss the investment equations and production functions. We conclude the section with some robustness exercises.

5.1 The information content of measures

As part of the specification of the empirical model, we assign measurements (proxies) to factors. This approach has the advantage of using the rich data set in an efficient and parsimonious fashion. As mentioned above, we use a dedicated measurement system, so that each measure is assumed to depend only on one factor.

Table 4 shows the assignment of measures to latent factors. It also reports the signal to noise ratio, which captures the information content of each measure given the specification of the measurement system. The expression for the signal to noise ratio is:

$$s_j^{\ln \theta_{kt}} = \frac{(\lambda_{jkt})^2 \; Var(\ln \theta_{kt})}{(\lambda_{jkt})^2 \; Var(\ln \theta_{kt}) + Var(\epsilon_{jkt})} \tag{15}$$

We use a variety of tests related to child cognition, which change from age to age. However, we observe the Peabody Picture Vocabulary Test (PPVT) at every age, so we use this as the normalizing measure. This makes the comparisons over time plausible, as discussed in Agostinelli and Wiswall (2016b). The signal to noise ratios are all above 36%, which shows that most cognitive measures include a substantial amount of information. At the same time they also demonstrate the importance of allowing for measurement

Table 4: Signal to Noise Ratios

	Age 1	Age 5	Age 8	Age 12
		Child Cognition		
PPVT		51%	33%	39%
Math			74%	68%
English				64%
Language				50%
EGRA (rasch)			52%	
CDA (rasch)		36%		
		Child Health		
Height Z-Score	55%	72%	60%	60%
Weight Z-Score	81%	73%	77%	
Weight in kg				64%
Health Status	8%	1%	5%	
		Investments		
Books		22%	21%	30%
Clothing		38%	31%	44%
Shoes		43%	38%	30%
Uniform		11%	15%	19%
Meals/day		2%	5%	2%
Food groups/day		7%	6%	1%
		Resources		
Income		69%	84%	82%
Wealth		38%	49%	49%
		Parental Cognition (fixed over age)		
Mother's education		79%		
Father's education		55%		
Literacy		40%		
		Parental Health (fixed over age)		
Mother's weight		73%		
Mother's height		11%		

PPVT: Peabody Picture Vocabulary Test, EGRA: Reading comprehension test, CDA: Cognitive Development Assessment. Books, clothing, shoes and uniform measured in monetary units.

error. All these proxies are highly imperfect and could introduce serious bias of unknown sign if any measure were used on its own.

For health we use the z-score for height and weight per age, computed according to WHO algorithms.[26] Height may capture longer term health and nutrition issues while weight likely reflects shorter term health status. We also use the parental rating of health status when available, although at age 8 we use the child's rating of health status. We use the height Z-score to scale the health measure.

To capture investments, we use the same measurements at every age and we normalize on the amount spent on books. Generally the investment measures are quite noisy, again illustrating the importance of dealing with measurement error. As these measures make clear, our investment factor consists of material investments in children (and not time). There is no information on time spent with children, so we focus on one general investment measure that is defined by material resources.

We keep parental cognition constant over time and use mother's and father's education along with caregiver literacy as proxies. We find no evidence of systematic changes in the measures: of the small fraction who report differences in parental cognition measures over time, an equal number report increases and decreases which suggests measurement error. Moreover, we do not observe measures for parental cognition in the third round. For parental health we use mother's weight and height. Parental health is normalized on mother's weight and parental cognitive skills is normalized on mother's years of schooling. To measure resources we use both wealth and income. In doing this we obtain a less noisy measure of household spending power. Resources are always normalized on income. Additional summary statistics on all of the measurements are reported in the appendix.

Given the specification of the measurement system and the normalizations we employ, log cognition is measured in units of the PPVT test score which is the number of correct answers. Although we can take this measure as cardinal, it would be better to be

[26]We simply use the child's weight at age 12, as the WHO does not provide the relevant z-score algorithms for weight at this age.

able to express child cognition in terms of earnings or years of schooling: i.e. how does an extra PPVT score translate into earnings? This is the issue of anchoring discussed in detail by Cunha, Heckman, and Schennach (2010).[27] In practice one can anchor cognition and health to wages once the children have reached adulthood. However we only observe the children in our sample up to age 12 and thus no such conversion is possible. We are thus constrained to using PPVT units to measure cognition (a test that is widely used internationally and across ages) and the height Z-score for health, both of which we take to be cardinal. Finally, our investment measure is measured in monetary units, reflecting cost. The units we use for skills does not prevent us from estimating the importance of child investments and how cognition and health interact. However, the complementarity structure that we identify is conditional on the specific scale on which these constructs are measured. Using different scales via a general anchoring function, which may capture an underlying nonlinear monotonic transformation, could change the estimates of complementarity between inputs. Without extra assumptions this is unavoidable.

The distribution of the measures The mixing parameter τ is 0.61 (confidence interval [0.59,0.63]). This, together with the differences in the means and covariances across the mixtures, points to a substantial departure from the normal distribution overall. The extent to which the overall distribution departs from normality depends on the extent to which the means and variances of the corresponding normal distributions being "mixed" are different.[28]

5.2 Wealth, Cognition and Health: using the latent factors

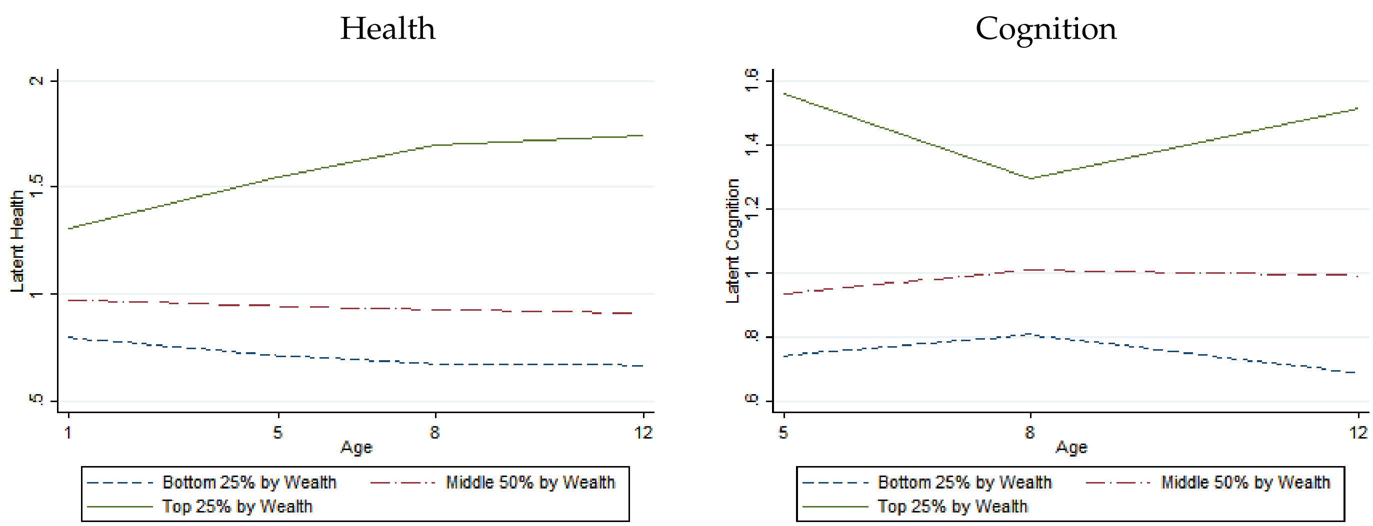
In Figure 2, we plot the mean of the health and cognitive factors against age for various wealth percentiles. This is a counterpart to the descriptive exercise in Figure 1, except that now we combine the various measures and strip out the measurement error component.

[27] See also Bond and Lang (2013), Currie (2009), Nielsen (2015a), and Nielsen (2015b))

[28] The estimates of the mean and variance-covariance matrices for the two mixtures are available upon request.

This leads to a much clearer picture revealing substantial differences in child development across the wealth distribution. The striking result here is that the largest differences seem to be between those in the top quartile of the distribution and those below the median. The health gap increases substantially with age. The gap in cognition seems to decline at the start and then rises again throughout the distribution.[29]

Figure 2: Wealth Gradient in latent Health and Cognition



5.3 The determinants of parental investments in children

While the production functions discussed below offer an insight into the process of child development, investments reflect parental behavior. Investment choices are a function of parental perception of child development, of their preferences, of their resources and of prices. Hence, understanding this investment process is at the heart of understanding some of the key origins of inequality and designing policies that will improve intergenerational mobility. Of course, this is predicated on the hypothesis that investments can alter the course of child development. We will show this is the case below, when we examine

[29]Because the log latent factors are normalized to mean 0 we cannot make statements about growth, but can make statements regarding relative growth across quintiles. In our model, the TFP term adjusts appropriately for growth.

the production functions.

In Table 5, we report the coefficient estimates for the investment equation (see equation 6) and the 90% bootstrap confidence intervals for the three age groups. In the investment equation for five year olds we do not include lagged cognition at age 1 because no measures are available. All variables except the 0/1 dummies are in logs so the coefficients are elasticities.

The coefficients on child health and cognition are positive for all ages, and significantly so at ages 5 and 12 for health and 8 for cognition. Effectively the results suggest that parents invest more in healthier and higher ability children when they are young. However, this effect weakens for older children.

Parental cognition and health are never significant determinants of investments for this population. Conditional on the number of children birth order does not seem to matter much. However, the number of children reduces investment and significantly so at the youngest age. Investments are lower for girls, which is consistent with what Barcellos, Carvalho, and Lleras-Muney (2014) find. However, the effects here are not significant.

Turning now to resources, we find a large and significantly positive effect at all ages with an elasticity between 0.45-0.65.[30] At age 8, for example, a 10% increase in resources leads to a 6.4% increase in child investments. To the extent that investments translate to better child outcomes (as we confirm below) these results point to one of the potentially important roots of inequality and are consistent with the wealth gaps in both cognition and health that we documented earlier. However, it is interesting to note that investments have an elasticity below one, making them a necessity. It is also important to see that the resource effect is *conditional* on parental health and cognition. The fact that parental background does not matter directly suggests that it works through available resources,

[30]Note that when we ran the model without using wealth indices as a second measurement on resources, and the effect was much lower. This suggests that attenuation due to measurement error is an important problem to be dealt with in these settings whenever possible.

Table 5: The Coefficients of the Investment Equations

	Age 5	Age 8	Age 12
		Child human capital	
Cognition		0.113 [0.03,0.17]	0.09 [−0.01,0.13]
Health	0.095 [0.05,0.13]	0.012 [−0.01,0.07]	0.051 [0,0.13]
Gender	−0.013 [−0.1,0.04]	−0.026 [−0.12,0.05]	0.056 [−0.04,0.16]
		Parental human capital	
Parental Cognition	0.01 [−0.06,0.07]	0.004 [−0.02,0.1]	−0.02 [−0.05,0.04]
Parental Health	−0.013 [−0.05,0.04]	−0.01 [−0.06,0.03]	−0.032 [−0.11,0.01]
		Prices	
Price Clothes	−0.063 [−0.15,0.02]	0.031 [−0.12,0.11]	0.099 [−0.02,0.23]
Price Notebook	−0.383 [−0.53,−0.23]	−0.196 [−0.37,−0.05]	−0.231 [−0.34,−0.13]
Price Mebendazol	0.047 [0.01,0.1]	−0.156 [−0.26,−0.11]	0.011 [−0.04,0.05]
Price Food	−0.082 [−0.28,0.2]	−0.328 [−0.66,0.04]	−0.256 [−0.47,−0.09]
		Household Characteristics	
Resources	0.457 [0.3,0.59]	0.644 [0.42,0.75]	0.587 [0.41,0.68]
Older Siblings	0.039 [−0.02,0.1]	0.058 [−0.01,0.11]	−0.032 [−0.09,0.03]
Number of Children	−0.096 [−0.14,−0.04]	−0.041 [−0.09,0.01]	−0.049 [−0.11,0.01]
Urban	0.349 [0.2,0.54]	0.103 [0,0.28]	0.066 [−0.09,0.23]
Hindu	−0.005 [−0.02,0.01]	−0.01 [−0.02,0.01]	0 [−0.01,0.01]
Muslim	−0.105 [−0.33,0.07]	−0.247 [−0.4,−0.05]	−0.02 [−0.27,0.15]
Mother's Age	0.014 [−0.12,0.14]	−0.141 [−0.26,0.08]	0.016 [−0.1,0.2]
Scheduled Caste	−0.074 [−0.17,0.05]	−0.066 [−0.21,0.1]	−0.269 [−0.42,−0.11]
Scheduled Tribe	0.073 [−0.05,0.2]	−0.106 [−0.23,0.05]	−0.254 [−0.4,−0.1]
BC Caste	−0.034 [−0.15,0.08]	0.061 [−0.06,0.22]	−0.169 [−0.3,−0.05]
Prices and Income (P-values)	0	0	0
Prices (P-values)	0	.005	.001

Note: 90% confidence intervals based on 100 replications in square brackets which do matter and are correlated with parental human capital.

Prices of child goods may well affect investments. Since we do not have a unique price index of investments we include individual prices of relevant goods; the estimated coefficients can be interpreted as a product of the investment price elasticity and the weight of each good in the price index. In this sense, all price effects should be negative. However, if the underlying model is more complex, with some alternative investment goods being complements and some being substitutes to the ones used to proxy investment in the measurement system, we could get positive price effects.

We estimate price effects by exploiting the spatial variation in prices at the community level. In most cases, the effect of prices is indeed negative, and in a number of cases quite strong. The food elasticity is small at age 5, but becomes much larger for ages 8 and 12, always below one though. The price of the deworming drug Mebendazol has a negative elasticity at age 8. Finally, the price of a notebook, relevant for schooling, has a strong negative impact at every age. Thus, overall prices matter, as we would expect. Indeed their joint significance is shown for each age at the bottom of the table: the p-values are lower than 0.5%. This is of substantive economic importance and also supports the value of our instruments to account for the endogeneity of investments.

The excluded instruments for estimating the effect of investment in the production function are the prices and resources and they are highly significant. The key justification for using resources as an excluded instrument lies in the fact that the production function includes sufficient background variables (parental and child cognition and health, and family composition), which control for the household characteristics that determine permanent wealth, allowing us to view resources as representing a random liquidity shock. However, this assumption is testable, since prices are highly significant and our model is identified just by these exclusion restrictions. We report these tests in the robustness section.

5.4 Production function estimates

We now turn to the estimation of the production functions (see equations 4 and 5), which define the way that health and cognition evolve over time. Our estimates characterize the process of child development and how it varies during childhood. They also allow for complementarities of different inputs and take into account explicitly the endogeneity of investment.[31]

Cognition As we would expect cognition is self-producing, which was also found by Cunha, Heckman, and Schennach (2010) in the US context. The effect becomes stronger with age, which perhaps points to the diminishing influence of environmental factors. One of the most important results, which in large part motivates this paper, is the impact of health on cognition. The result implies that ill health at an earlier age prevents cognitive development. Thus the high levels of morbidity among the poor in developing countries, which is documented in the first section, leads to developmental deficits in children with long term consequences. The influence of health on cognition is particularly high for younger children; for the 12 year olds it no longer has an impact.

We find that parental cognition matters for ages 5 and 12. In interpreting this result remember that we do not observe child cognition at age 1. Hence, parental cognition may enter strongly at age 5 because it is also capturing genetic endowment, earlier child skills, and earlier investments, all of which are unobserved. Controlling for child skills at later stages mitigates the influence of parental background.

The next crucial parameter is that on investment. We find that investments have a very large influence, which declines for age 12 children. This is again consistent with the decline in importance of environmental factors for cognitive development at older ages. This result is of critical importance because it demonstrates that interventions increasing parental investments can alter the path of child development in very poor contexts. It

[31]Results obtained considering investments as exogenous for the production functions are given in the appendix.

Table 6: Production of Cognitive Skills and Health with Endogenous Investments

	Cognition			Health		
Age	5	8	12	5	8	12
			Lagged Skills			
Cognition		0.29 [0.22,0.43]	0.6 [0.53,0.67]		−0.02 [−0.07,0.01]	−0.03 [−0.06,0.03]
Health	0.18 [0.11,0.25]	0.15 [0.1,0.19]	0.02 [−0.01,0.07]	0.69 [0.64,0.75]	0.82 [0.76,0.87]	0.92 [0.85,0.98]
			Investment and Parental Skills			
Investment	0.47 [0.31,0.56]	0.65 [0.47,0.75]	0.19 [0.07,0.29]	0.1 [0.01,0.2]	0.12 [0.06,0.21]	0.04 [−0.06,0.1]
Parent Cog	0.32 [0.25,0.39]	−0.01 [−0.1,0.06]	0.17 [0.13,0.21]	0.01 [−0.05,0.06]	0.03 [0,0.07]	0.04 [−0.01,0.06]
Parent Health	0.03 [−0.02,0.1]	−0.09 [−0.14,−0.02]	0.03 [0,0.07]	0.2 [0.15,0.28]	0.05 [0.02,0.08]	0.04 [0.02,0.09]
			Demographic Characteristics			
Num Child	0 [−0.02,0.01]	−0.01 [−0.03,0.02]	−0.03 [−0.05,−0.01]	0.01 [−0.01,0.02]	0 [−0.02,0]	0 [−0.01,0.01]
Older Sibs	0.01 [−0.01,0.03]	−0.01 [−0.03,0]	0 [−0.01,0.02]	−0.03 [−0.05,−0.01]	0 [−0.01,0.01]	0.01 [0,0.02]
Gender	0.01 [−0.01,0.02]	0.04 [0.02,0.05]	−0.01 [−0.02,0]	0 [−0.01,0.01]	0.01 [−0.01,0.01]	0.02 [0.01,0.02]
Urban	−0.01 [−0.01,0]	−0.03 [−0.03,−0.01]	−0.01 [−0.02,0]	0 [−0.01,0]	0.01 [0,0.01]	0 [−0.01,0]
Hindu	−0.01 [−0.03,0]	−0.01 [−0.03,0.01]	0.03 [0.02,0.05]	0.01 [−0.01,0.02]	0 [−0.01,0]	0 [−0.01,0.01]
Muslim	0 [0,0]	0 [0,0]	−0.01 [−0.01,0]	0 [0,0]	0 [0,0]	0 [0,0]
Mother Age	0.01 [0,0.03]	0.01 [0,0.03]	−0.01 [−0.02,0.01]	0 [−0.01,0.02]	0 [−0.01,0.01]	−0.02 [−0.02,0]
Sched Caste	0 [−0.02,0]	0.02 [0.01,0.03]	0.01 [0,0.02]	0 [−0.01,0.01]	0 [−0.01,0]	0 [−0.01,0.01]
Sched Tribe	0.06 [0.04,0.08]	−0.01 [−0.02,−0.01]	−0.01 [−0.01,0]	0.01 [0.01,0.02]	−0.01 [−0.02,−0.01]	0 [0,0.01]
BC Caste	−0.02 [−0.04,−0.01]	0 [−0.01,0.02]	0 [−0.01,0.01]	−0.02 [−0.03,−0.01]	0.01 [0,0.02]	0 [−0.01,0]
			Production function structure and test of exogeneity for investment			
(ρ, ζ)	−0.11 [−0.37,−0.01]	−0.06 [−0.19,0.07]	0.28 [0,0.35]	−0.03 [−0.22,0.03]	0.23 [0.05,0.36]	−0.2 [−0.2,0.18]
Subst. Elast	0.9 [0.73,0.99]	0.95 [0.84,1.07]	1.39 [1,1.54]	0.97 [0.82,1.04]	1.31 [1.05,1.56]	0.83 [0.83,1.23]
Log TFP	−0.03 [−0.09,0.04]	0.03 [−0.06,0.05]	0.03 [−0.03,0.07]	0.03 [0,0.08]	−0.02 [−0.04,0.03]	0 [−0.03,0.02]
Inv. Res	−0.39 [−0.54,−0.12]	−0.77 [−0.9,−0.53]	−0.21 [−0.31,−0.05]	−0.08 [−0.24,0.08]	−0.06 [−0.17,0.06]	0.01 [−0.1,0.1]

Notes: 90% confidence intervals based on 100 bootstrap replications in square brackets. "Subst. Elast": Elasticity of Substitution, "Inv. Res": Investment Residual, "Num child": number of children in the household.

also shows the importance of parental resources: we already showed that these exercise a major influence on the amount of investment; the picture is completed by now showing that lack of investment seriously inhibits child development.

In the last line of the table we show the coefficient on the investment residual. This is negative and significant. The negative coefficient indicates that parents compensate for negative shocks with more investments. Ignoring this leads to a serious underestimate of the impact of investment on child development, as shown in the OLS results reported in the Appendix, where the coefficient on investment is much lower.

Of the characteristics that affect TFP, the most notable are the positive effect for mother's age and a large and positive effect of belonging to a scheduled tribe. Being a boy has a positive impact on cognitive development (age 8) but a negative one later on (age 12).

Finally, we find evidence of complementarity among the inputs, implying larger returns to investment for higher ability and healthier children. The elasticity of substitution is about one for ages 5 and 8, but increases for age 12, in which case it is significantly larger than one, pointing to more substitutability amongst inputs than Cobb-Douglas. This complementarity is important because it is a potential source of inequality: wealthier parents invest more and their investments have cumulatively higher return, even if the children start from the same position. The fact that the initial position of the children of higher ability parents is in fact better, as shown in Section 2 in our context, only reinforces this fact.

Health The estimates for the health production function are reported in the right hand side of Table 6. Health is highly self-productive, but cognition has no impact on health. While parental cognition does not have much of an impact, parental health, which reflects mother's nutritional status, seems to matter for child health. Investments matter significantly for very young children: in other words, the resources invested by parents can alter the health status of young children, but do little at later ages. Finally, fewer older siblings and belonging to a scheduled tribe are associated with better health. Gender only seems to matter (favoring boys) at age 12

As before we find evidence of complementarity of inputs with the production function being Cobb-Douglas or (at age 8) allowing for a bit more substitutability. Investments are not endogenous for the health production function.

In interpreting these results, it is useful to remember that health is a combination of weight and height z-scores. These measures capture both longer term malnutrition as well as the cumulative effects of morbidity that prevents child growth. In many ways, this is a useful health measure because it focuses on longer term status that may be most pertinent for adult human capital.

5.5 Robustness to the use of resources as an instrument

We relax the exclusion restriction on income by including it in the production function. In Table 5, we showed that the effect of prices in the investment equation is strong enough to estimate the model, even without using income as an exclusion restriction. This means we can test whether income directly impacts the production of skills at these ages and more importantly, whether using it as an exclusion restriction affects our results in any substantive way.

Estimates of the production functions where income is included (and thus not used as an exclusion restriction) are presented in the Appendix Table 12. In Table 7 we present specification tests and we compare the coefficients of investment in the production function when we include and when we exclude income. Whether we use income as an instrument or not the coefficient of investment remains unchanged and the differences are never significant. However, excluding income from the production function of cognition is rejected at ages 5 and 8. In all other cases (age 12 and health at all ages) excluding income is not rejected. Whether income is included as an instrument or not leaves the results unaffected.

Table 7: Robustness to using resources as an excluded instrument

	Age 5		Age 8		Age 12	
			Child Cognition			
Coefficient on investment	0.47 [0.31,0.56]	0.43 [0.3,0.54]	0.65 [0.47,0.75]	0.63 [0.48,0.72]	0.19 [0.07,0.29]	0.19 [0.07,0.3]
P-value equality	0.056		0.352		0.694	
P-value excluding income		0.001		0.0002		0.452
			Child Health			
Coefficient on investment	0.10 [0.01,0.2]	0.12 [0.02,0.21]	0.12 [0.06,0.21]	0.12 [0.07,0.21]	0.04 [−0.06,0.1]	0.04 [−0.06,0.1]
P-value equality	0.210		0.571		0.878	
P-value excluding income		0.067		0.484		0.679

Notes: P-values for the tests computed using the bootstrap. "P-value equality": p-value for the equality of the income coefficients across the two specifications (with and without income as an excluded instrument). 90% confidence intervals in square brackets.

6 Using the Model

6.1 Implications for human capital accumulation in India

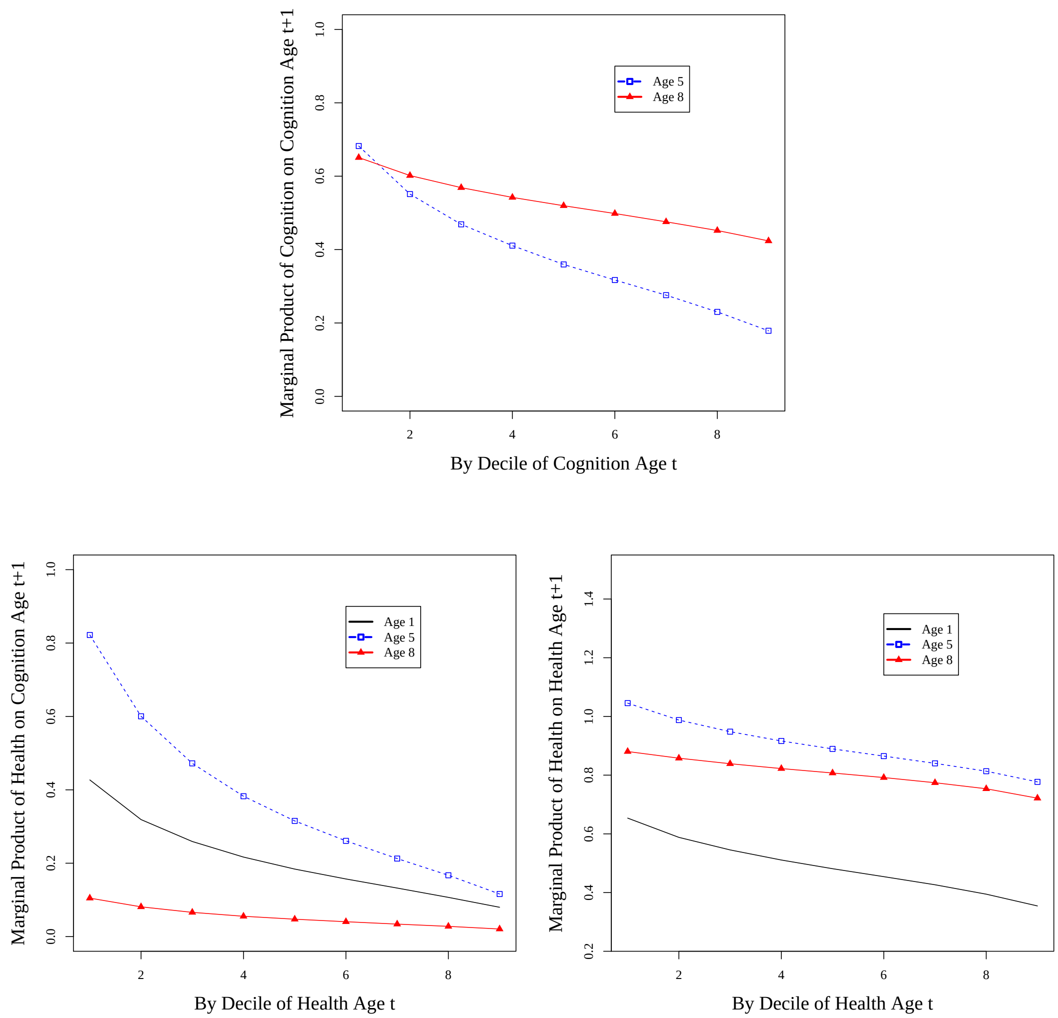
We now consider the implications of the estimated production functions for human capital accumulation through a series of graphs. In Figure 3, we show how changes in the current levels of cognition and health affect next period's levels, for different levels of initial cognition and health. These graphs also incorporate the endogenous response of current period investments. The the x-axis is the decile of cognition (top panel) and health (bottom).

An important result here is that the persistence of cognition (top graph) is substantially higher for lower cognition levels, and is lower at younger ages. This points both to the fact that other external factors are more at play early on and that such external factors (positive or negative) are more important for children with higher levels of initial cognition.[32]

The bottom left graph shows that health at lower ages affects the development of cognition; the impact is largest for the most unhealthy children. This demonstrates the role that endemic diseases (such as diarrhea, malaria, parasitic worms and others), which lead to low nutritional status, can have in inhibiting children from reaching their full

[32] Remember we do not observe cognition at age 1 so it is not possible to consider all ages.

Figure 3: Marginal Product of Health and Cognition



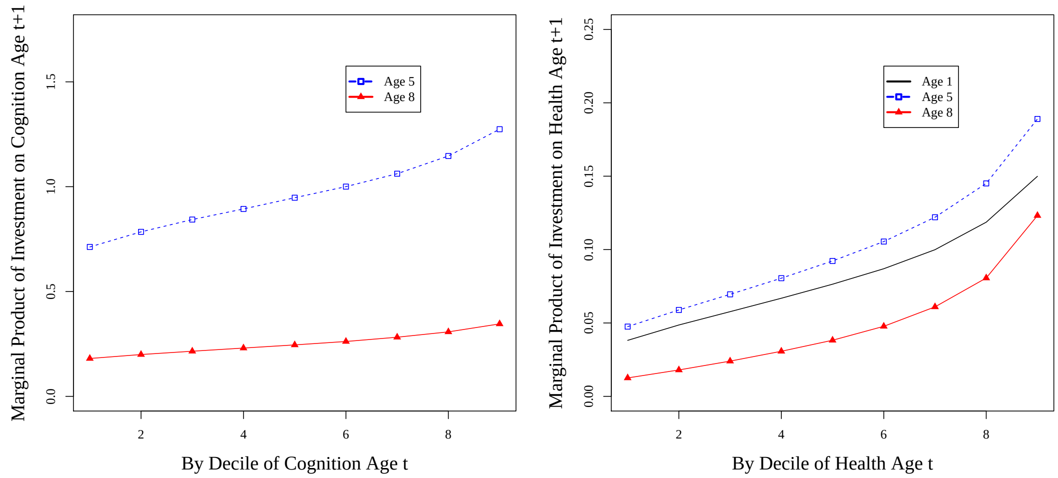
Note: The y-axis represents the impact on the outcome in question, in standard deviation units, of increasing cognition or health by one standard deviation.

potential in developing countries. From the bottom right graph it is also evident that health is highly persistent, and even more so for lower health children. Thus, ensuring good health early on is crucial for future outcomes.

An issue of central importance is the extent to which investments in children can actually change the course of their development. We illustrate the implications of the parameter estimates on this question in Figure 4.

When considering the production of cognitive skills (left hand graph) we see that the productivity of investments is much higher at younger ages: investments are more able

Figure 4: Marginal Product of Investment on Health and Cognition



Note: The y-axis represents the impact on the outcome in question, in standard deviation units, of increasing cognition or health by one standard deviation.

to affect cognition earlier on. The effect of investments on health is not significant at the oldest age, but has a small and positive impact at younger ages. There appears to be positive complementarity of these investments with the level of health or cognition. Thus, early investments are most productive for immediate improvements in cognition and, to a lesser degree, health. However, the degree of persistence of cognitive development is central to propagating the effects of successful early investments, which we explore in more detail next.

6.2 Dynamic impact of two possible interventions on skills and inequality

We now implement two counterfactual scenarios. These are meant to illustrate the implications of the model and so we do not focus on how they would be implemented in practice. First, we analyze the impact of a one time transfer of income equal to 25% of the mean income in the entire sample. We report the results separately for the bottom 25%, the middle 50%, and the top 25% of households. The first row of figures depicts the impact of such a transfer at age 5, the second row at age 8, and the third row at age 12.

The figure depicts the resulting change in standard deviation units of cognition (left) and health (right) at each age relative to the baseline.

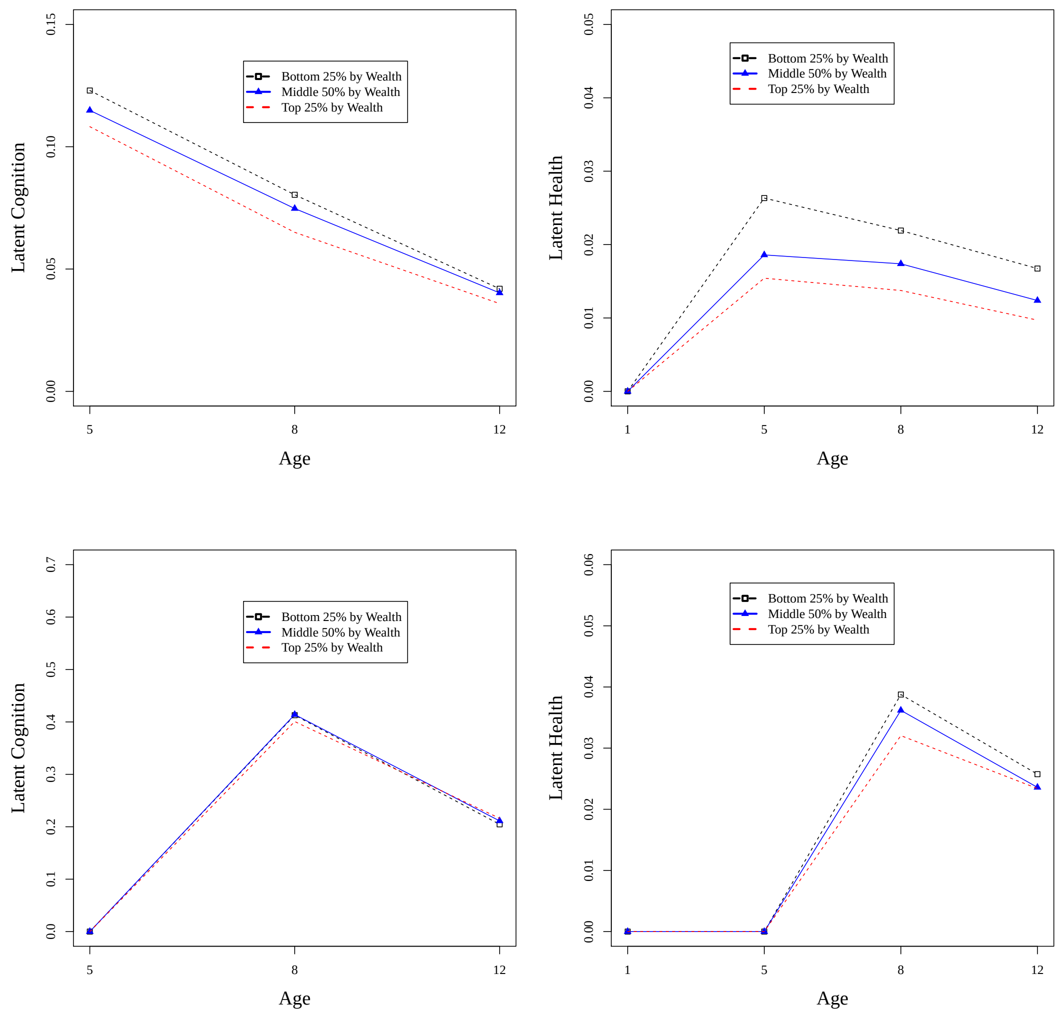
The results from the income transfer are shown in Figure 5. We assume that the income is spent entirel y in the age at which is is given (and is not saved). The impact of income on investments is determined by the investment equations we estimated. As we would expect, cognition and health increase as a result of this intervention. The impact is always larger for poorer children, and substantially so for the early transfer. In terms of timing, the largest impact is obtained if the transfer takes place when the children are 8. Transfers at this age improve final health and cognition the most. The implication is that while early transfers are effective, better results can be expected with sustained interventions across all ages.

One central question in the literature and in this paper specifically is the extent to which ill-health and long term malnutrition, which are reflected in our health measures, can affect cognitive development. Our estimates imply that it can. To consider the extent to which this might be important for child development we implement an artificial intervention where we increase the health of children by 1 standard deviation of health in the population. We again analyze the effect separately for the poorest 25%, the middle 50%, and the richest 25%. We consider such an intervention at ages 5 and 8. The effects on health are always large and persistent as we could already predict based on the production function coefficients. The most interesting result here is the impact on cognition. In this case it is clear that improving health early has the best final outcome for cognitive development. Thus, interventions that address early health in childhood are likely to be very important in boosting both long term health and cognitive development.

6.3 When is it best to invest

In the final experiment we consider how an increase in overall investment should be distributed across ages to maximize child human capital as defined by equation 1. We assume that the latter is a Cobb-Douglas production function of cognition and health, each

Figure 5: Dynamic Impact of Income Transfer

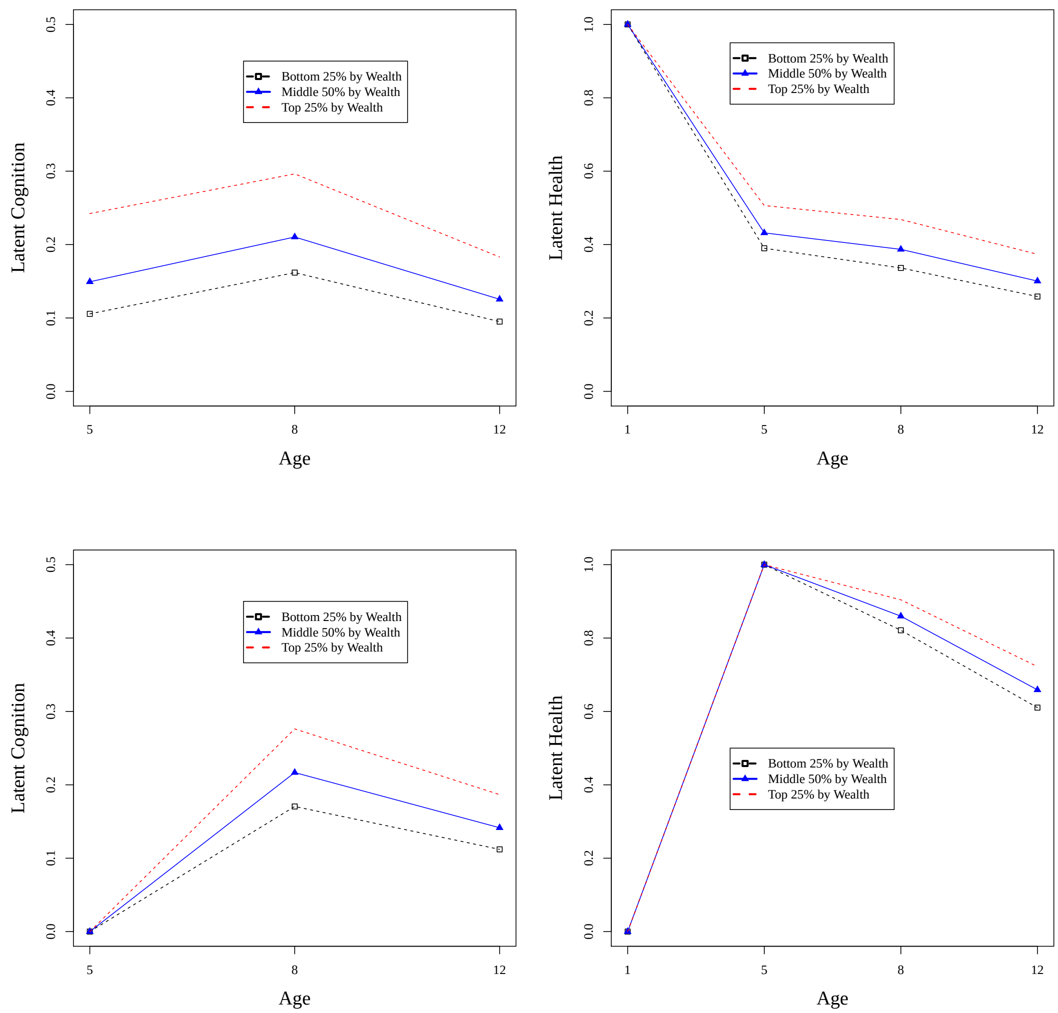


Note: The y-axis represents the impact on cognition (left) and health (right) of an income transfer equal to 25% of mean income in the entire sample. In the top two graphs the transfer is made at age 5. In the lower two graphs it is made at age 8.

with a 50% share. We take each household in our synthetic data set of 10,000 households and we consider the optimal allocation of extra investment, equal to a fixed amount of one standard deviation of total investment in the sample, for every child. We then group the results by resources: the lowest 25%, the middle 50% and the top 25%.

The results are presented in Table 8. We notice that the bulk of the increase should be allocated at age 8 (which means in the period between age 5 and age 8). However we

Figure 6: Dynamic Impact of Health Intervention



Note: The y-axis represents the impact on cognition (left) and health (right) of artificially improving health by 1 standard deviation. In the top two graphs the transfer is made at age 5. In the lower two graphs it is made at age 8.

also notice that the poorer households (first row) should receive much more at an earlier age relative to the richer ones (last row). Note that this is conditional on the investments already made by these families, and so does not necessarily correspond to the optimal allocation of all investments across childhood.

This discussion does not address the issue of implementation of such an intervention. In practice this could involve a combination of parenting interventions and income trans-

Table 8: The optimal path of increments to investment

Household resources	Age		
	5	8	12
Lowest 25%	0.083	0.78	0.14
Middle 50%	0.062	0.82	0.12
Highest 25%	0.045	0.87	0.083

Notes: The numbers show how one standard deviation of increase in investment is distributed across childhood stages. Each number is the proportion of the transfer allocated to the respective childhood stage. The amount of transfer is the same irrespective of the initial household income.

fers targeted to women.[33] However, to quantify how this should best be done we would need a structural intertemporal model, including intrahousehold considerations.

7 Conclusion

In this paper, we examine the human capital development of children from age 1 to 12 and focus in particular on the role of parental investments and on how health and cognition interact. Our data is drawn from the younger cohort of the Young Lives Survey. We use the nonlinear latent factor model developed by Cunha, Heckman, and Schennach (2010) and we estimate a model of child investment jointly with the production functions for cognition and health. In our estimation approach investments are taken as endogenous and can respond to unobserved shocks affecting child human capital. Importantly, our estimation strategy relies on prices for child investment goods as instruments, which prove both to be important determinants of investments and are plausibly exogenous to human capital shocks. We also use household resources as an excluded instrument, but the results remain unchanged whether this is excluded from the production function or not.

We obtain a number of important results. First, ill health at a young age causes per-

[33]For examples of effective ECD interventions that involve parenting see Attanasio, Fernández, Fitzsimons, Grantham-McGregor, Meghir, and Rubio-Codina (2014); Walker, Chang, Powell, and Grantham-McGregor (2005).

manent cognitive deficits. This result is consistent with what has been learned from a number of interventions. Here we are able to trace the effects throughout childhood. The key implication is that we need interventions that address morbidity at an early age for children in poor environments. Second, investments in children are central in producing improved cognitive and health outcomes. Indeed, investments are important at all ages for cognition (albeit with a diminished impact by age 12) and up to age 8 for health. In interpreting this it is important to remember that our health measure relates to longer-term malnutrition. Finally, we find that there are important complementarities in the production function, such that the marginal product of investments increase with cognition and health. This fact accentuates lifetime inequalities and calls for special focus on interventions for children with lower initial conditions, all the while recognizing that such interventions are likely to be harder.

Understanding the development of human capital and how various components, such as health and cognition, interact is at the center of solving the problems of poverty and the intergenerational transmission of poverty. Our paper, together with others referred to here, demonstrate the complexity of the problem and point to the need for sustained intervention. The answer is unlikely to be a simple early versus late investment tradeoff, but rather designing optimal interventions over the entire span of childhood and addressing key issues at each stage. As our paper shows, early health interventions can provide crucial boosts in cognition. However, interventions and investments throughout childhood can improve cognition as well. Creative field experiemetns addressing these issues are likely to be important tools going forward.

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A Online Appendix

A.1 A simple model of parental investments

Consider a household that derives utility $u_t = u(c_t)$ from its own consumption c_t in each period. We denote the utility of the child by $v(H)$ where H is adult human capital. The lifecycle utility of the parent household from the moment they have a child is denoted by

$$U = \Sigma_{t=1}^{T} \beta^t u_t(c_t) + \beta^a \mu v(H_a) \tag{16}$$

where the child becomes an adult in time period $a < T$, β is the discount factor and μ is the altruism parameter that defines how much parents care about the utility of their adult child. Since the process of human capital accumulation is dynamic (Cunha, Heckman, and Schennach, 2010) the timing is important: after period a parents will act as if no child is present and the fact they had children before just acts as an effect on their wealth. However, before they may have to invest in each period to take advantage of the developmental capabilities of the child.

Specifically, human capital itself depends on cognition θ_a^c and health θ_a^h, so that

$$H_a = H(\theta_a^c, \theta_a^h) \tag{17}$$

In turn cognition and health are produced throughout childhood. This process is governed by production functions that define how these skills are determined in period $t+1$ as a function of inputs in period t.

$$\begin{aligned} \theta_{t+1}^c &= G\left(\theta_t^c, \theta_t^h, \theta_t^I, Z_t\right) && (18) \\ \theta_{t+1}^h &= F\left(\theta_t^c, \theta_t^h, \theta_t^I, Z_t\right) && (19) \end{aligned}$$

where θ_t^I is an investment good that parents can buy in the market.[34]. The vector Z_t includes parental background and temporal shocks, which we leave implicit for the moment.

The household is subject to the intertemporal budget constraint

$$A_{t+1} = (1+r)(A_t - c_t - p_t^I \theta_t^I + y_t) \tag{20}$$

where p_t^I represents the price of investment goods and y_t an uncertain income stream. The household's problem then is to maximize lifecycle utility subject to the human capital constraints (17, 18, 19) and the budget constraint (20). We can now characterize the problem through a Bellman equation. Denote the current value of the household as $V(A_t, \theta_t^c, \theta_t^h)$. Then we get that

$$\begin{aligned} V_t(A_t, \theta_t^c, \theta_t^h) &= max_{c_t, A_{t+1}, I_t} u(c_t) + \beta E_t V_{t+1}(A_{t+1}, \theta_{t+1}^c, \theta_{t+1}^h) \text{ for } t < a && (21) \\ V_t(A_t, \theta_t^c, \theta_t^h) &= max_{c_t, A_{t+1}} u(c_t) + \mu v(H_a) + \beta E_t V_{t+1}(A_{t+1}) \text{ for } t = a && (22) \\ V_t(A_t) &= max_{c_t, A_{t+1}} u(c_t) + \beta E_t V_{t+1}(A_{t+1}) \text{ for } t > a && (23) \end{aligned}$$

where the maximization takes place subject to the cognitive and health production functions and the budget constraints. From period a onwards this is a standard lifecycle maximization problem.The utility from the investments in children materializes in period a and defines the way that the value function in earlier periods depends on cognitive and health capital.

The first order conditions for investment in each period are given by

[34]In a more complete model we would allow for both material and time investments as in Del Boca, Flinn, and Wiswall (2014). However we do not include time here because in our empirical model we do not observe time inputs.

$$p_t^I = \frac{E_t V'_{\theta^c_{t+1}} G'_{\theta^c_{t+1}} + E_t V'_{\theta^h_{t+1}} F'_{\theta^h_{t+1}}}{V'_{A_{t+1}} + \lambda_t} \tag{24}$$

where a prime denotes a first derivative and where λ_t is the Lagrange multiplier on assets, which is positive for liquidity constrained individuals ($A_{t+1} > 0$) and zero otherwise. According to this result investments in children are driven by the relative value of child investments (the numerator) to the marginal utility of consumption (the denominator). The altruism parameter as well as the way health and cognition translate to human capital are embedded in the derivatives of the value function. The way current increases in health and cognition affect future outcomes defines the dynamics of investment and are reflected in the derivatives of the value function with respect to health and cognition. The presence of liquidity constraints raises the marginal utility of consumption for households and reduces investments in children.

An important question is whether the parents know the production function that governs child development. In the first order conditions above the relevant production function is the one perceived by the parents. If perception and reality diverge the sequence of investments will not be optimal, even from the parents perspective.

A.2 Simulations

In Table 9 we report the parameter values used for the simulations presented in the main text. The values are based on our estimates. In the table, X corresponds to parental cognition, and θ_1, θ_2, and θ_3 correspond to latent health at ages 1, 5, and 8 respectively. For the measurement error of the production functions we took the values estimated from the residual in producing health at ages 5 and 8.

A.3 Assignment of measures to latent factors

In Table 10 we present the descriptive statistics from the sample for the measurements that are assigned to each factor, excluding those measurements whose loadings are nor-

Table 9: Parameters for the Monte Carlo Exercises

Parameters		True value
Distribution of baseline log factors ($ln\theta_1, lnX$)		
μ_A	Mean vector of mixture A	(-0.1,0.15)
μ_B	Mean vector of mixture B	(-0.4,0.6)
Σ_A	Var-cov of mixture A	$\begin{pmatrix} .56 & .07 \\ .07 & .48 \end{pmatrix}$
Σ_B	Var-cov of mixture B	$\begin{pmatrix} .5 & .16 \\ .16 & .83 \end{pmatrix}$
τ	Mixture weight	0.6
1st stage production function		
A_1	TFP	$\{0,1\}^*$
δ_1	Share parameter	0.69
ρ_1	Complementarity parameter	$\{-1,-0.5,0,0.5,1\}^*$
2nd stage production function		
A_2	TFP	$\{0,1\}^*$
δ_2	Share parameter	0.82
ρ_2	Complementarity parameter	$\{-1,-0.5,0,0.5,1\}^*$
Random shocks to production functions		
Σ_{u_1}	SD of u_1	0.54
Σ_{u_2}	SD of u_2	0.23
Measurement Equations		
λ_X	Measurement loadings for X	(1,0.85,0.72)
λ_{θ_1}	Measurement loadings for θ_1	(1,1.2,0.37)
λ_{θ_2}	Measurement loadings for θ_2	(1,1.01,0.14)
λ_{θ_3}	Measurement loadings for θ_3	(1,1.13,0.29)
σ_X	Measurement error SD for X	(.16,.37,.49)
σ_{θ_1}	Measurement error SD for θ_1	(.43,.18,.91)
σ_{θ_2}	Measurement error SD for θ_2	(.26, .26,.97)
σ_{θ_3}	Measurement error SD for θ_3	(.37,.21,.93)

*These are the values we will assume in the various simulations. When ρ is 0, we simulate and estimate a Cobb Douglas. We report estimates for TFP of 0, the other results are available on request.

malized to 1 (presented in Table 2 in the main text). Note that amount spent on child investment goods is in Rhupees, not USD.

A.4 Additional results

Table 11 gives parameter estimates for the production functions for cognition and health when we do not control for the endogeneity of investments. Table 12 reports estimates where income is included in the production functions, using only prices as instruments. In addition, estimates where investments are normalized on the measurement of the amount spent on clothing as opposed to the amount spent on books are available on request. The results change very little.

Table 10: Summary Statistics: Child Measurements Younger Cohort

	Age 1	Age 5	Age 8	Age 12
Child Health				
Weight for age Z-score	-1.51	-1.87	-1.88	.
	1.09	0.94	1.06	.
Weight in kg	7.89	15.02	19.67	31.08
	1.16	1.93	3.06	6.87
Child Cognition				
Math test	.	.	.	12.76
	.	.	.	6.61
English test	.	.	.	13.61
	.	.	.	4.39
Language test	.	.	.	13.39
	.	.	.	4.47
Rasch score CDA test	.	300.18	.	.
	.	49.75	.	.
Rasch score Egra test	.	.	300.01	.
	.	.	15.02	.
Investments				
Amount spent clothing	.	410.43	754.05	1572.37
		384.69	689.04	1567.96
Amount spent shoes	.	74.24	134.83	314.62
		87.38	144.57	365.81
Amount spent uniform	.	226.97	377.50	390.09
	.	223.11	294.77	655.70
Times child ate last 24 hrs	.	4.99	4.85	4.68
	.	1.07	1.10	0.99
Food groups in last 24 hrs	.	5.78	6.44	6.38
	.	1.55	1.63	1.63
Parental Cognition (fixed aross age)				
Father years of education	5.54			
	4.93			
Caregiver is literate? (0-2)	0.78			
	0.94			
Parental Health (fixed across age)				
Mother's height (cm)	151.43			
	6.53			

Higher values are always better. Z-scores are computed using WHO international standards. Rasch scores are internally standardized. Standard deviations are reported below the means.

Table 11: Production of Cognitive Skills and Health - Exogenous Investment

	Cognition			Health		
Age	5	8	12	5	8	12
				Lagged Skills		
Cognition		0.41 [0.29,0.53]	0.66 [0.6,0.7]		−0.01 [−0.06,0.02]	−0.04 [−0.05,0.03]
Health	0.23 [0.17,0.3]	0.2 [0.15,0.24]	0.04 [0.01,0.09]	0.7 [0.66,0.76]	0.82 [0.77,0.87]	0.92 [0.86,0.96]
				Investment and Parental Skills		
Investment	0.3 [0.2,0.4]	0.3 [0.17,0.44]	0.05 [0.02,0.1]	0.07 [−0.01,0.14]	0.09 [0.05,0.15]	0.04 [−0.03,0.07]
Parent Cog	0.39 [0.33,0.45]	0.09 [0.03,0.14]	0.2 [0.16,0.24]	0.02 [−0.03,0.06]	0.03 [0.02,0.07]	0.04 [0,0.06]
Parent Health	0.07 [0.01,0.14]	−0.01 [−0.06,0.07]	0.05 [0.02,0.09]	0.2 [0.16,0.29]	0.06 [0.03,0.08]	0.04 [0.02,0.09]
				Demographic Characteristics		
Num Child	0 [−0.02,0.01]	0 [−0.02,0.02]	−0.02 [−0.05,−0.01]	0.01 [−0.01,0.02]	0 [−0.02,0]	0 [−0.01,0.01]
Older Sibs	0.01 [−0.01,0.02]	0 [−0.03,0.01]	0 [−0.02,0.02]	−0.03 [−0.05,−0.01]	0 [−0.01,0.01]	0.01 [0,0.02]
Gender	0.01 [−0.01,0.02]	0.04 [0.02,0.05]	−0.01 [−0.02,0]	0 [−0.01,0.01]	0.01 [0,0.01]	0.02 [0.01,0.02]
Urban	−0.01 [−0.01,0]	−0.03 [−0.04,−0.02]	−0.01 [−0.02,0]	0 [−0.01,0]	0.01 [0,0.01]	0 [−0.01,0]
Hindu	−0.01 [−0.03,0]	0 [−0.02,0.01]	0.04 [0.02,0.05]	0.01 [−0.01,0.02]	0 [−0.01,0.01]	0 [−0.01,0.01]
Muslim	0 [−0.01,0]	0 [−0.01,0]	−0.01 [−0.01,0]	0 [0,0]	0 [0,0]	0 [0,0]
Mother Age	0.01 [0,0.02]	0.01 [0,0.03]	−0.01 [−0.03,0]	0 [−0.01,0.02]	0 [−0.01,0.01]	−0.02 [−0.02,0]
Sched Caste	0 [−0.02,0]	0.03 [0.02,0.04]	0.01 [0,0.02]	0 [−0.01,0.01]	0 [−0.01,0]	0 [−0.01,0.01]
Sched Tribe	0.07 [0.05,0.08]	−0.02 [−0.03,−0.01]	−0.01 [−0.01,0.01]	0.01 [0.01,0.02]	−0.01 [−0.02,−0.01]	0 [0,0.01]
BC Caste	−0.02 [−0.03,−0.01]	0.01 [0,0.03]	0 [−0.01,0.01]	−0.02 [−0.03,−0.01]	0.01 [0,0.02]	0 [−0.01,0]
				Production function structure and test of exogeneity for investment		
(ρ, ζ)	−0.13 [−0.31,−0.02]	−0.19 [−0.38,−0.06]	0.26 [0.01,0.34]	−0.04 [−0.23,0.03]	0.25 [0.05,0.41]	−0.2 [−0.24,0.22]
Subst. Elast	0.88 [0.76,0.98]	0.84 [0.73,0.95]	1.34 [1.01,1.52]	0.96 [0.81,1.03]	1.33 [1.05,1.69]	0.84 [0.8,1.28]
Log TFP	−0.05 [−0.1,0.02]	0 [−0.08,0.04]	0.02 [−0.03,0.07]	0.03 [0,0.08]	−0.02 [−0.05,0.02]	0 [−0.03,0.02]

Notes: 90% confidence intervals based on 100 bootstrap replications in square brackets. "Subst. Elast": Elasticity of Substitution, "Inv. Res": Investment Residual, "Num child": number of children in the household.

Table 12: Production of Cognitive Skills and Health with Income - Endogenous Investment

	Cognition			Health		
Age	5	8	12	5	8	12
			Lagged Skills			
Cognition		0.26 [0.21,0.4]	0.61 [0.53,0.69]		−0.01 [−0.07,0.02]	−0.03 [−0.05,0.04]
Health	0.15 [0.09,0.22]	0.13 [0.08,0.18]	0.02 [−0.01,0.07]	0.7 [0.65,0.76]	0.82 [0.75,0.87]	0.92 [0.85,0.97]
			Investment and Parental Skills			
Investment	0.43 [0.3,0.54]	0.63 [0.48,0.72]	0.19 [0.07,0.3]	0.12 [0.02,0.21]	0.12 [0.07,0.21]	0.04 [−0.06,0.1]
Parent Cog	0.37 [0.3,0.44]	0.06 [−0.03,0.1]	0.16 [0.11,0.2]	−0.01 [−0.07,0.04]	0.02 [0,0.06]	0.03 [−0.02,0.05]
Parent Health	0.05 [0,0.11]	−0.07 [−0.12,−0.01]	0.03 [0,0.07]	0.19 [0.14,0.27]	0.05 [0.02,0.08]	0.04 [0.02,0.09]
			Demographic Characteristics			
Numb Child	0 [−0.02,0.01]	−0.01 [−0.03,0.01]	−0.03 [−0.06,−0.01]	0.01 [−0.01,0.02]	0 [−0.02,0]	0 [−0.01,0.01]
Older Sibs	0 [−0.01,0.02]	−0.02 [−0.04,0]	0 [−0.01,0.02]	−0.03 [−0.05,−0.01]	0 [−0.01,0.01]	0.01 [0,0.02]
Gender	0.01 [−0.01,0.02]	0.04 [0.02,0.05]	−0.01 [−0.02,0]	0 [−0.01,0.01]	0.01 [−0.01,0.01]	0.02 [0,0.02]
Income	−0.11 [−0.16,−0.04]	−0.18 [−0.22,−0.07]	0.03 [−0.04,0.11]	0.05 [0,0.07]	0.02 [−0.04,0.05]	0.01 [−0.02,0.07]
Urban	0 [−0.01,0.01]	−0.02 [−0.03,−0.01]	−0.02 [−0.02,−0.01]	0 [−0.01,0]	0.01 [0,0.01]	0 [−0.01,0]
Hindu	−0.01 [−0.03,0]	−0.01 [−0.02,0.01]	0.03 [0.02,0.05]	0.01 [−0.01,0.01]	0 [−0.01,0]	0 [−0.01,0.01]
Muslim	0 [0,0]	0 [0,0]	−0.01 [−0.01,0]	0 [0,0]	0 [0,0]	0 [0,0]
Mother Age	0.01 [0,0.03]	0.02 [0.01,0.04]	−0.01 [−0.02,0]	0 [−0.01,0.02]	0 [−0.01,0.01]	−0.02 [−0.02,−0.01]
Sched Caste	−0.01 [−0.02,0]	0.01 [0.01,0.03]	0.01 [0,0.02]	0 [−0.01,0.01]	0 [−0.01,0]	0 [−0.01,0.01]
Sched Tribe	0.06 [0.04,0.07]	−0.02 [−0.03,−0.01]	−0.01 [−0.01,0.01]	0.01 [0.01,0.02]	−0.01 [−0.02,−0.01]	0 [0,0.01]
BC Caste	−0.02 [−0.03,−0.01]	−0.01 [−0.02,0.01]	0 [−0.01,0.01]	−0.02 [−0.03,−0.01]	0.01 [0,0.02]	0 [−0.01,0]
			Production function structure and test of exogeneity for investment			
(ρ, ζ)	1.04 [0.83,1.11]	1.05 [0.91,1.16]	1.32 [0.94,1.39]	0.94 [0.77,1.05]	1.26 [1.05,1.55]	0.83 [0.84,1.28]
Log TFP	0.08 [−0.01,0.16]	0.22 [0.08,0.29]	0 [−0.09,0.08]	−0.02 [−0.06,0.06]	−0.04 [−0.08,0.05]	−0.01 [−0.08,0.01]
Inv. Res	−0.35 [−0.5,−0.09]	−0.72 [−0.85,−0.51]	−0.22 [−0.32,−0.05]	−0.1 [−0.26,0.07]	−0.07 [−0.17,0.06]	0.01 [−0.1,0.1]

Notes: 90% confidence intervals based on 100 bootstrap replications in square brackets. "Subst. Elast": Elasticity of Substitution, "Inv. Res": Investment Residual, "Num child": number of children in the household.