NBER WORKING PAPER SERIES

HUMAN CAPITAL DEVELOPMENT AND PARENTAL INVESTMENT IN INDIA

Orazio Attanasio
Costas Meghir
Emily Nix

Working Paper 21740
http://www.nber.org/papers/w21740

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2015, Revised March 2019

We thank the editor Michèle Tertilt, five anonymous referees, Joseph Altonji, Richard Blundell, Teodora Boneva, Sarah Cattan, Flavio Cunha, James Heckman, Corina Mommaerts, Susanne Schennach and Matthew Wiswall for their useful comments and discussions; we are greatly indebted to Young Lives for generously sharing their data with us. Orazio Attanasio was partially financed by the ESRC Professorial Fellowship ES/K010700/1 and by the European Research Council Advanced Grants 249612. Costas Meghir thanks NIH for funding under grant R01 HD072120 as well as the Cowles foundation and the ISPS at Yale for financial assistance. Emily Nix obtained funding from an NSF Graduate Research Fellowship. All mistakes are our own. Comments and suggestions are welcome. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Human Capital Development and Parental Investment in India
Orazio Attanasio, Costas Meghir, and Emily Nix
NBER Working Paper No. 21740
November 2015, Revised March 2019
JEL No. I14,I15,I25,I32,J13,J24,O15

ABSTRACT

We estimate production functions for cognition and health for children aged 1-12 in India, based on the Young Lives Survey. India has over 70 million children aged 0-5 who are at risk of developmental deficits. The inputs into the production functions include parental background, prior child cognition and health, and child investments, which are taken as endogenous. Estimation is based on a nonlinear factor model, based on multiple measurements for both inputs and child outcomes. Our results show an important effect of early health on child cognitive development, which then becomes persistent. Parental investments affect cognitive development at all ages, but more so for younger children. Investments also have an impact on health at early ages only.

Orazio Attanasio
Department of Economics
University College London
Gower Street
London WC1E 6BT
UNITED KINGDOM
and NBER
o.attanasio@ucl.ac.uk

Costas Meghir
Department of Economics
Yale University
37 Hillhouse Avenue
New Haven, CT 06511
and IZA
and also NBER
c.meghir@yale.edu

Emily Nix
University College London
Institute for Environmental Design
and Engineering
Gower Street
London, WC1E 6BT
United Kingdom
e.nix@ucl.ac.uk

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. Indeed 52% of the 137 million children aged 0-5 in India are at risk of developmental deficits.[1] Therefore, policies addressing such deficits in child development are important. And while there is evidence that some interventions can be effective in improving the conditions for children born in disadvantaged circumstances, their design, implementation and targeting requires a good understanding of 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.[2] There is also evidence that poorer children are more vulnerable to early life shocks and that they experience adverse events more frequently (see Case, Lubotsky, and Paxson (2002), Currie and Hyson (1999) and Currie and Stabile (2003)). Yet, we still do not fully understand the mechanisms through which the many dimensions of human capital develop and how different inputs interact in a dynamic fashion over time 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

[1]See, for instance, Lu, Black, and Richter (2016). On the link between poverty and child development delays 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.* (2015), and Currie (2011).

[2]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.

only a few studies have quantified them.[3]

In this paper, we study the dynamic process of human capital accumulation, where we consider two key dimensions of development: cognition and health. We model the process through which children develop from birth to age 12, allowing for dynamic interactions among the various dimensions of development and accounting for the influence of parental investment amongst other factors. Our study takes advantage of the availability of a unique and high quality data set tracking child development from age 1 in India. Based on the estimates of our model, we analyze the process of human capital development during childhood and its implications for policy and intervention design and timing. We focus on cognition and health because these dimensions of human capital are likely to be key determinants both of future productivity and of the ability to acquire skills through more advanced education. In addition, there are likely to be important interactions between these two factors, which 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.

In order to estimate the model, we develop an econometric methodology for estimating human capital production functions. Our method, builds on the nonlinear latent factor approach of Cunha, Heckman, and Schennach (2010) and uses the additional identification results from Agostinelli and Wiswall (2016b) but is simpler and faster. The details of our econometric method are provided in the paper.

Our results yield a set of important findings that are key to understanding the deficits in child development in poor contexts. First, we find that health affects cognitive development, particularly at younger ages. The well-documented morbidity amongst poor populations, reflected in stunting, feeds into cognitive development generating permanent deficits in both health and cognition. These results imply that early health interventions are likely to be an important component in any policy that aims to improve human

[3]See Del Boca, Flinn, and Wiswall (2014), Currie and Almond (2011), Cunha, Heckman, and Schennach (2010), Cunha and Heckman (2007), and Heckman (2007).

capital development.[4]

Second, we find that cognitive development at younger ages is not highly persistent, which means that even highly successful interventions will display some fadeout, as has been documented by a number of studies.[5] This feature of the development process implies that policies designed to improve child development need to be sustained and followed up: while highly intensive interventions at an early age and in ultra poor populations have been shown to have long term effects (Gertler, Heckman, Pinto *et al.*, 2013) sustaining the impacts of less intense, scalable interventions in a broader population is likely to be more successful if supported by follow up interventions.

Third, we find that investments by parents are effective in developing cognition at all ages we consider, but much more so up to age 8. Investments also affect health but only in the first stage of childhood that we consider (up to age 5). Health outcomes, which are measured here mainly by height for age and weight for age, become highly persistent by age 8 and difficult to shift thereafter. The complementarity we identify between prior outcomes and investments imply that both early and later interventions are important for the final determination of human capital.

Finally, key determinants of parental investments in children are household resources, prices of key goods relevant for children and the number of children, which measures the extent to which resources need to be shared. The effect of resources goes some way in explaining the differences in investments and hence the wealth gaps in child development

[4] Attanasio, Baker-Henningham, Bernal *et al.* (2018) illustrate that a cognition and nutritional intervention taking place soon after birth and up to about age 2 did successfully increase height and cognitive development. Further references on health interventions and their impact on child development, including cognition, and consistent with the implications of our production function estimates include Glewwe and Miguel (2007), 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). Other important studies in this area include Figlio, Guryan, Karbownik *et al.* (2014), Campbell, Conti, Heckman *et al.* (2014), 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).

[5] See the longer term followups of child stimulation interventions in Walker, Chang, Powell *et al.* (2005a), Andrew, Attanasio, Fitzsimons *et al.* (2018).

that we document. Our results also highlight the empirical importance of accounting for the endogeneity of investments, which seem to respond positively to adverse shocks to child development. Ignoring this feedback underestimates the impact of investments and provides a distorted picture implying a much lower influence of parental actions and indirectly of resources available to them.

To highlight the implications of our estimates we simulate how certain interventions affecting investments or health can change child outcomes. Knowledge of the dynamic structure of the process for human capital formation is key for these exercises.

This study was made possible by the unique data collected by the Young Lives Project, starting in 2002. 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.[6] In addition, it has a rich set of household characteristics, including measures of material investments in children, household resources, and household structure. The availability of numerous high quality measures at multiple stages of childhood for cognition, health and investment expenditures in children as well as measures relating to the parents provides the ideal setting for implementation of the nonlinear factor model.

Our paper is related to a number of earlier studies that estimate production technologies for child development in the United States using NLSY data, such as Cunha, Heckman, and Schennach (2010), 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 identification and estimation issues relating to the latent factor approach, which are relevant to this context. We build on these contributions and introduce some methodolical innovations, which we discuss below, in the estimation of these models.

Two papers are closest to ours: first, Cunha, Heckman, and Schennach (2010) develop

[6]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.

the dynamic latent factor approach we follow in this paper.[7] 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 allow investments to react to time varying unobserved shocks.

Second, 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 complete 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. Having said that, our estimates of the production function of human capital are consistent with a variety of models of parental behaviour, including (but not exclusively) that developed by Del Boca, Flinn, and Wiswall (2014).

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.

[7] See also Schennach (2004) and Hu and Schennach (2008).

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.[8]

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.[9] A significant fraction of the children suffer from stunting, wasting and being underweight. Together, these indicators are suggestive of

[8]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.

[9]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 (Kg)	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.

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 measures of housing quality, consumer durables, and access to services.[10] While its mean is not easy to interpret, the evidence on the standard deviation indicates that within our

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

sample there is a considerable degree of heterogeneity in socio-economic background.

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*
Standardized PPVT test		0.01	0.74	1.75
		1.00	*0.88*	*1.01*
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.

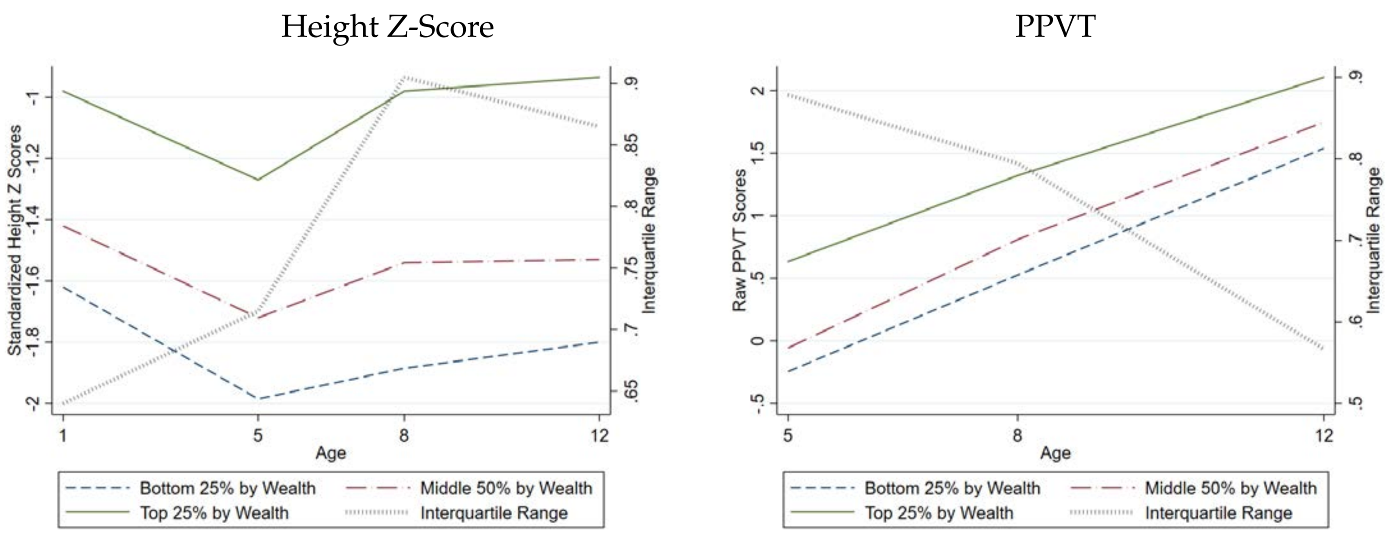
In Table 2, we also report expenditures on books for children over time. In the analysis that follows, our parental investment factor will be based on a number of expenditures parents make that focus on the child at each age, including purchases of books and stationery, clothing, shoes and uniforms. We do not include food expenditures (which is not measured separately for children) and public goods like housing. To put the combination of the investment goods we do use in context, they constitute on average of 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, as shown in Figure 1. There we plot average z-scores for height per age, and PPVT scores standardized (over all periods) 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. We also plot the difference between the top and the bottom 25% of wealth (measured on the right axis). The differences in height per age between the bottom and the top 25% of the wealth distribution is about 0.65 of a standard deviation of the z-score at age 1 and the gap grows to 0.85 of a standard score. The middle 50% are closer to those of the lower wealth quartile than the top one. These measurements thus show an increasing wealth gap in this long-term health measure.

Moving to language development, the PPVT grows with age as expected. We also find that at age 5 there is a small difference between the bottom 25% and middle 50% of the wealth index, but there is a much larger gap between these two groups and the top 25%. The differences decline slightly for the middle 50% by age 8, who also marginally increase their gap relative to the bottom 25%. The gaps between all groups narrow by age 12 and the wealth gap between top and bottom quartiles declines from 90% of a standard score to about 58% by age 12. Nevertheless, the gap in development across the wealth distribution remains persistent. As we shall see the use of a single measurement for health and cognition gives only a partial account of the wealth gap in development.

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



Note: Interquartile range refers to the difference in the Height Z-score and the PPVT respectively between the top and bottom quartile of wealth in our data. It is measured on the right axis, while the measures themselves are measured on the left axis.

Finally, in explaining investments we will be using the prices for food, clothing, notebooks and the medication for worms, Mebendazol, all of which are relevant for children. Descriptive statistics for these are presented in Appendix Table 11: they display substantial variation with standard deviations of the log ranging from 0.15 for food to 0.77 for Mebendazol.

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 it difficult to identify their causal impact.

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 current status of the human capital factors, parental choices and other environmental variables.

$$\theta_{t+1}^c = G\left(\theta_t^c, \theta_t^h, \theta_t^I, X_t\right) \tag{2}$$

$$\theta_{t+1}^h = F\left(\theta_t^c, \theta_t^h, \theta_t^I, X_t\right) \tag{3}$$

where θ_t^I is an investment good that parents can buy in the market.[11]. 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

[11] In a richer model, one would allow for both material and time investments as in Del Boca, Flinn, and Wiswall (2014) However, we do not consider time here because we do not observe time inputs in our data.

(as perceived by parents), the available resources and the prices of investment goods If parents are liquidity constrained, then the timing of income will also affect child development (Carneiro, Lopez-Garcia, Salvanes *et al.*, 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 (2014)). As a result, while we cannot explicitly simulate the impact of potential interventions, our estimates do not depend on assumptions about parental beliefs relating to 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}[12], 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.[13] Thus we have that

[12]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.

[13]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.

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

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

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 (excluding the δs and αs in the TFP terms A) 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 production functions are of the Cobb-Douglas type and the elasticity 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 life cycle 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.[14] 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

[14]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.

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

where v_t reflects random shocks, θ_{Yt} represents parental resources, and lnp_{It} represents log prices for child investment goods. All other variables are as defined in the production functions.[15]

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 parental investments in children. In our framework this implies that the shocks v_t in the investment function (6) may be correlated with those of the production functions, u_{ct} and u_{ht}, making investments endogenous. To allow for this potential endogeneity and thus obtain consistent estimates of the parameters of the production function, 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 allow 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.[16] Assuming that investments are exogenous amounts to

[15]Excluding other prices is effectively a restriction on preferences. Since we are not estimating a structural model the key assumption is that any omitted prices are not correlated with omitted inputs not the child production function.

[16]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)).

imposing $\kappa_c = 0$ and $\kappa_h = 0$, which 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 does not relate to the shocks or unobserved inputs in the human capital production functions.

Turning now to household resources as a determinant of investment and an excluded instrument, from an economic point of view we would not expect household resources to enter the production function directly. 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 parental health and cognition it is plausible that income is conditionally exogenous. Nevertheless, we explore whether our results are robust to the use of household resources as an instrument. Fortunately, the prices have sufficient power for us to estimate the model without relying on income as an excluded instrument. As we show below, our estimates are completely unaffected whether we use income as an excluded instrument or not, but using it does improve precision and importantly leads to a reduced from investment equation that is more interesting from an economic point of view. It is also interesting in terms of explaining the wealth gaps in child development.

3.4 The measurement system

We have rich data with multiple measurements for the variables that enter the 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 are just imperfect proxies of the underlying variables. 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 would lead to biases. And since the production functions are nonlinear we cannot even sign the bias (Griliches and Ringstad, 1970).

In our model, the latent factor k, which is observed with error, is denoted as θ_{kt}. The factors we consider include 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 extended to nonlinear models in Cunha, Heckman, and Schennach (2010).[17] Following this approach, 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.

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. While factors relating to parental background are assumed constant over time (and hence do not depend on t) those relating to health and cognition of the child and parental investments, vary with t. 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 non-separable 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

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

θ_{kt} and of each other.[18]

Since neither location nor scale of the latent factors can be identified we need normalization restrictions. For factors that are constant over time (such as parental cognition and health) or that are not explicitly linked through dynamic relationships, a natural and innocuous normalization is to set the mean of the log to zero. However, factors such as child cognition and health are linked dynamically over time and display average growth, which is an important part of the child's developmental outcomes. In particular cognition naturally grows with age over childhood and differences in this growth rate are a key developmental outcome. The health measure can grow relative to an international benchmark, as defined by the WHO.[19] For these it is important to normalize *only* the initial point. The mean of the factor in subsequent periods can then be identified relative to this initial point by assuming that the growth in the measurement is due only to the growth of the associated latent factor. Constraining the mean by not allowing for growth in the latent factor can lead to bias in the parameters of the production function (Agostinelli and Wiswall, 2016b) and misses part of the story for the overall developmental outcomes. We treat investments in the same way, allowing them to grow over time relative to the initial point.

The scale of the latent factor can be set to equal the units of one of the measurements, which is equivalent to setting the associated factor loading to 1. As also pointed out by Agostinelli and Wiswall (2016b), valid comparisons over time require that the scaling of the latent factors are comparable between periods. One way to meet this condition is to normalize each factor on the same measure every period, assuming that the mapping from measure to factor is invariant with respect to the age of the subject. Fortunately, 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

[18]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.

[19]World Health Organization

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 income.

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.[20] 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

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

the measurement system expressed here in matrix form

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

Where $\mathbf{A}$ is a vector of constant terms and $\mathbf{\Lambda}$ is the matrix of factor loadings in the measurement equations. These matrices incorporate the normalization and the zero restrictions (i.e. the restrictions that define the scale and metric of each factor, as well as what factors relate to what measures);[21] $\mathbf{\Sigma}$ 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:

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

where

$$\begin{aligned} \Psi_A &= \mathbf{\Lambda}^T \Omega_A \mathbf{\Lambda} + \mathbf{\Sigma}; \qquad \Psi_B = \mathbf{\Lambda}^T \Omega_B \mathbf{\Lambda} + \mathbf{\Sigma} \\ \Pi_A &= \mathbf{A} + \mathbf{\Lambda}\mu_A; \qquad \Pi_B = \mathbf{A} + \mathbf{\Lambda}\mu_B \end{aligned} \tag{11}$$

and where we impose the mean zero restriction in the first period[22]

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

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

[22] This normalization identifies the constant terms in the measurement equations in the first period. For those measurements, the expected value of the measure is simply equal to the constant. The age-invariant assumption on the constant can then be used to identify μ_A and μ_B in subsequent periods, since for the mea-

$$\tau\mu_{A,t=0} + (1-\tau)\,\mu_{B,t=0} = 0 \tag{12}$$

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

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 age-invariant assumptions, initial period normalizations and zero restrictions in $\mathbf{\Lambda}$ to recover $\mathbf{\Lambda}$, $\mathbf{A}$, $\mathbf{\Sigma}$, 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.[23] 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 additional variables as controls in the production function (such as number of children and gender) and instruments for investment (such as prices). Hence the joint distribution we estimate has to include them, so as to reflect all the relevant dependencies in the data. We treat the additional variables

---

surements which are age-invariant, $\mathbf{\Lambda} = 1$ and we have identified $\mathbf{A}$ from the first period. The remaining constant terms from the measurement equations can be identified once μ_A and μ_B are known.

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

as error free measures and we expand the distribution of latent factors to include them. Thus, in step 1 we expand the measurement system to include the control variables and the instruments with no measurement error; i.e. we set the corresponding standard deviation in Σ to zero and the corresponding factor loading 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.[24] 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. Equation 13 can be easily extended 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 without substantial bias for our sample size, 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 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 9. Next, we generate the output for the first and second periods using CES production functions specified in equations 14. We simulate with different values of the elasticity of substitution and we allow for growth in the

[24]While prices may be measured with error, what matters 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 when $log(A_1)= log(A_2)=1$

Coefficient	$log(A_1)$	δ_1	ρ_1	$log(A_2)$	δ_2	ρ_2
True	1	0.69	-1	1	0.82	-1
Mean Estimate	1.012	0.69	-1.05	0.993	0.819	-0.984
Standard Dev.	0.046	0.032	0.161	0.029	0.034	0.27
True	1	0.69	-0.5	1	0.82	-0.5
Mean Estimate	0.97	0.68	-0.46	0.99	0.81	-0.45
Standard Dev.	0.023	0.015	0.039	0.018	0.022	0.10
True	1	0.69	0	1	0.82	0
Mean Estimate	1.0	0.69	0.008	0.997	0.82	0.004
Standard Dev.	0.042	0.072	0.079	0.027	0.022	0.07
True	1	0.69	0.5	1	0.82	0.5
Mean Estimate	1.02	0.69	0.48	1.0	0.83	0.47
Standard Dev.	0.089	0.077	0.06	0.023	0.04	0.21
True	1	0.69	1	1	0.82	1
Mean Estimate	1.01	0.69	1.0	1.0	0.82	1.05
Standard Dev.	0.10	0.07	0.11	0.027	0.11	0.78

Monte Carlo simulations with 500 replications. Each sample used is 2000 individual observations.

latent factor, as is the case for cognition.

$$ln\theta_2 = log(A_1) + \frac{1}{\rho_1} ln\left(\delta_1 \theta_1^{\rho_1} + (1-\delta_1) X^{\rho_1}\right) + u_1 \tag{14}$$

$$ln\theta_3 = log(A_2) + \frac{1}{\rho_2} ln\left(\delta_2 \theta_2^{\rho_2} + (1-\delta_2) X^{\rho_2}\right) + u_2 \tag{15}$$

Once we generate the latent factors we use them to generate three measurements (m_j^{Θ}) for each (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:

$$m_j^{\Theta} = \lambda_j ln\left(\Theta\right) + \epsilon_j \tag{16}$$

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 simulation results are shown in Table 3.

Overall the parameters display little or no bias for this sample size and the standard deviations across Monte Carlo simulations are generally low implying a high degree of precision. The complementarity coefficient ρ_2 for the second period is a bit more noisy particularly at the extreme values of -1 and 1. However, at the other values the performance in terms of bias and precision is excellent.

5 Results

We start with a discussion of the measurement system properties. We then discuss the investment equations and production functions. We conclude 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:

$$s_j^{\ln \theta_{kt}} = \frac{(\lambda_{jkt})^2 \ Var(\ln \theta_{kt})}{(\lambda_{jkt})^2 \ Var(\ln \theta_{kt}) + Var(\epsilon_{jkt})} \tag{17}$$

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 consistent, as discussed in Agostinelli and Wiswall (2016b). The signal to noise ratios are all above 26%, 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		74%	26%	35%
Math			35%	60%
English				70%
Language				39%
EGRA (rasch)			53%	
CDA (rasch)		43%		
		Child Health		
Height Z-Score	57%	77%	68%	77%
Weight Z-Score	78%	70%	73%	
Weight in kg				66%
Health Status	7%	1%	5%	
		Investments		
Books		36%	26%	34%
Clothing		51%	35%	44%
Shoes		58%	42%	37%
Uniform		20%	15%	22%
Meals/day		4%	8%	2%
Food groups/day		21%	10%	0%
		Resources		
Income		30%	18%	20%
Wealth		63%	52%	49%
	Parental Cognition (fixed over age)			
Mother's education		79%		
Father's education		52%		
Literacy		45%		
	Parental Health (fixed over age)			
Mother's weight		62%		
Mother's height		13%		

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 per age and weight per age, computed according to WHO algorithms.[25] Height for age may capture longer term health and nutrition issues while weight for age likely reflects shorter term health status. Effectively, we are assuming that the position in the percentile distribution of height at each age is an indicator of health. The justification for this assumption is that disease and malnutrition are reflected in child growth deficits. This measure can change on average to the extent that the health of our specific sub population improves or worsens relative to the WHO standard, which is used as the basis of our measurement. The reason we use height for age (rather than just height) is because there is no sense by which an older child who is taller than a younger one is also healthier. The health measure relates to position in the distribution for that age. 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 take parental cognition to be 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

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

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 a measure that is standardized across rounds by Young Lives in a way that also captures mean growth. Although we can take this measure as cardinal, it would be better to be 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).[26] 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 estimated to be 0.56 (90% confidence interval [0.54,0.58]). This, together with the differences in the means and covariances across the mixtures, points to a substantial departure from the normal distribu-

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

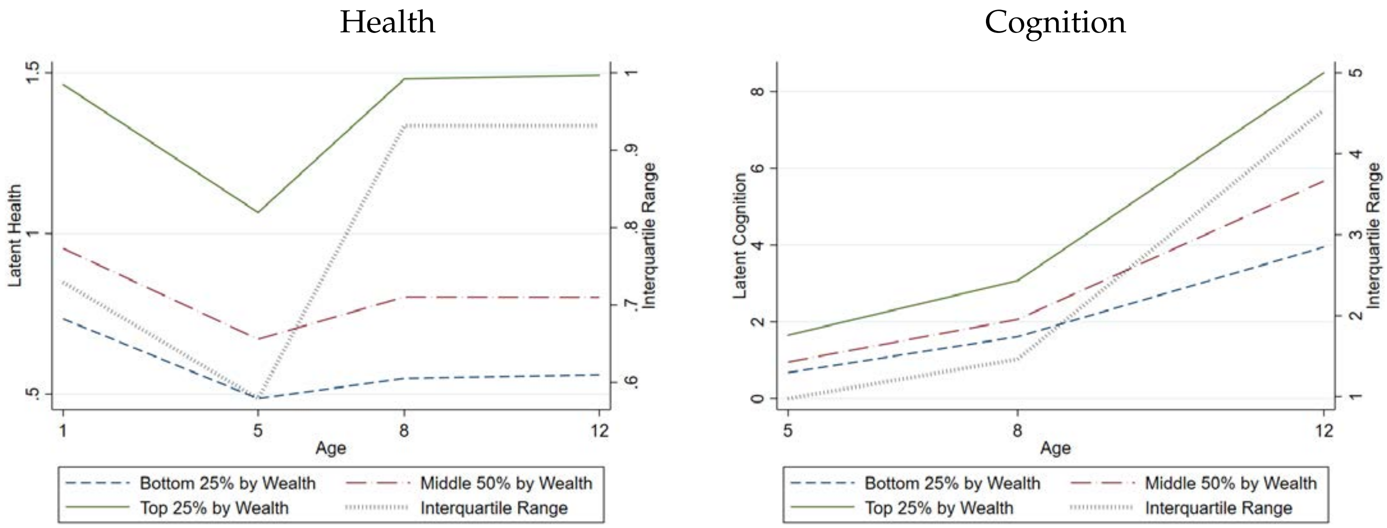
tion overall. The extent to which the overall distribution departs from normality depends on the extent to which the means and variances of the corresponding normal distributions being "mixed" are different.[27]

5.2 Using the latent factors: the evolution of cognition and health:

In Figure 2, we plot the mean of the health and cognitive factors against age for various wealth percentiles; we also plot the difference in cognition between the top and bottom quartile of wealth, which we show on the right axis. 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. As a result, it provides a more accurate picture and reveals growing gaps in the developmental measures across the wealth distribution. This evidence provides a much clearer picture, revealing substantial differences in child development across the wealth distribution, and substantial growth in cognition over time. 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, and seems to worsen vis a vis the international standard, catching up again fully only for the top quartile. The gap in cognition increases slowly at the start and then grows to a very large gap between ages 8 and 12. There is also significantly more overall growth in cognition between ages 8 and 12.

[27]The estimates of the mean of the two mixtures are presented in Appendix Table A.4. The variance-covariance matrices for the two mixtures are available upon request and will be published with the data replication files.

Figure 2: Wealth Gradient in latent Health and Cognition



Note: Interquartile range refers to the difference in the latent factors for health and cognition respectively, between the top and bottom quartile of wealth in our data. It is measured on the right axis, while the measures themselves are measured on the left axis.

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 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

Table 5: The Coefficients of the Investment Equations

	Age 5	Age 8	Age 12
		Child human capital	
Cognition		0.029 [−0.01,0.05]	0.436 [0.22,0.55]
Health	0.033 [0.02,0.04]	−0.001 [−0.03,0.03]	0.042 [−0.02,0.13]
Gender	−0.005 [−0.03,0.02]	−0.022 [−0.1,0.03]	0.029 [−0.09,0.16]
		Parental human capital	
Parental Cognition	0 [−0.02,0.03]	0.01 [−0.02,0.09]	−0.146 [−0.2,−0.03]
Parental Health	−0.014 [−0.04,0.01]	−0.021 [−0.06,0.04]	−0.073 [−0.23,−0.01]
		Prices	
Price Clothes	−0.022 [−0.05,0.01]	0.051 [−0.08,0.12]	0.189 [0.02,0.38]
Price Notebook	−0.11 [−0.16,−0.07]	−0.175 [−0.32,−0.05]	−0.414 [−0.56,−0.26]
Price Mebendazol	0.015 [0,0.03]	−0.117 [−0.2,−0.08]	0.032 [−0.06,0.09]
Price Food	−0.035 [−0.11,0.04]	−0.287 [−0.59,0.03]	−0.416 [−0.65,−0.17]
		Household Characteristics	
Resources	0.163 [0.1,0.2]	0.628 [0.43,0.69]	0.797 [0.58,0.97]
Older Siblings	0.013 [−0.01,0.03]	0.052 [−0.01,0.1]	−0.026 [−0.11,0.07]
Number of Children	−0.03 [−0.05,−0.01]	−0.044 [−0.09,0]	−0.073 [−0.16,0]
Urban	0.119 [0.08,0.19]	0.088 [0,0.23]	0.117 [−0.06,0.34]
Hindu	−0.001 [−0.01,0]	−0.013 [−0.02,0]	0.001 [−0.01,0.02]
Muslim	−0.029 [−0.1,0.03]	−0.224 [−0.35,−0.04]	−0.009 [−0.31,0.23]
Mother's Age	−0.001 [−0.05,0.04]	−0.096 [−0.21,0.08]	−0.039 [−0.23,0.19]
Scheduled Caste	−0.023 [−0.06,0.02]	−0.028 [−0.16,0.12]	−0.375 [−0.6,−0.13]
Scheduled Tribe	0.035 [−0.02,0.07]	−0.002 [−0.12,0.1]	−0.313 [−0.52,−0.07]
BC Caste	−0.008 [−0.05,0.03]	0.093 [0,0.21]	−0.205 [−0.4,−0.03]
Prices and Income (P-values)	0	0	0
Prices (P-values)	0	.017	0

Note: 90% confidence intervals based on 100 replications in square brackets are elasticities.

The coefficients on child cognition are positive and significantly so at age 12. Child health encourages investment in children at age 5, but the effect is not significant at later ages. Effectively the results suggest that parents invest more in healthier children at a young age and higher ability children when they are older. However, the impact of health is very small.

Parental cognition and health are never significant determinants of investments for this population, except at age 12 where parental cognition and health enter negatively. The number of children reduces investment. However, conditional on the number of children birth order does not seem to matter much. Contrary to Barcellos, Carvalho, and Lleras-Muney (2014) gender does not play much of a role in investments.

Turning now to resources, we find a large and significantly positive effect at all ages with an elasticity between 0.16-0.80.[28] At age 8, for example, a 10% increase in resources leads to a 6.3% 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, 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. How-

[28]Note that when we ran the model without using wealth indices as a second measurement on resources 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.

ever, 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. Generally, like for resources, the elasticities are larger for older children. 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 significant 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 zero at ages 5 and 12 and 1.7% at age 8. 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. Thus the identifying assumption is that these prices we include are not correlated with omitted inputs in the production function. Below we provide evidence that the exclusion restriction is acceptable and the results robust.

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

Cognition The estimated production function is close to being Cobb-Douglas. Indeed the substitution elasticity is very close to and not significantly different from one at all ages. This implies complementarity of the inputs, whose implications we will discuss below. It also implies that the coefficients of the inputs (parental cognition and health, investment, earlier child cognition and child health) can be interpreted as elasticities.[29]

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 much larger with age, implying a partial fade out of early experiences but eventually an increasing persistence of past human capital accumulation. This lower level of persistence may well underlie the partial fade out of early interventions.[30]

One of the most important results, which in large part motivates this paper, is the impact of health on cognition. Children in poor environments often suffer from various diseases, such as diarrhea or infection by worms, both of which undermine nutrition. In addition pre-birth maternal nutrition is also often deficient and gets reflected in our measures. All these factors can feed into cognitive development, particularly as they accumulate with age. Indeed our results show exactly this: health has an increasing and strong effect on cognitive development. By age 12 this no longer matters, but of course the earlier impacts have become embedded and persistent through the self-productivity of cognition. 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. Designing interventions that prevent ill health from an early

[29]We have also estimated the model allowing for departure from constant returns to scale (CRS). However, the scale coefficient was in all but one case estimated to be very close to one. The exception was for cognition at 8, where the point estimate displayed some decreasing returns. However, jointly there was no significant departure from CRS and all other returns to scale were estimated at almost exactly one. We thus stay with this specification.

[30]See Walker, Chang, Powell *et al.* (2005a) and Andrew, Attanasio, Fitzsimons *et al.* (2018) as examples.

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

	Cognition			Health		
Age	5	8	12	5	8	12
				Lagged Skills		
Cognition		0.15 [0.11,0.2]	0.77 [0.64,0.87]		0 [−0.04,0.02]	−0.01 [−0.05,0.14]
Health	0.05 [0.01,0.09]	0.14 [0.1,0.18]	0.03 [−0.01,0.09]	0.47 [0.44,0.52]	0.9 [0.84,0.93]	0.91 [0.85,0.97]
				Investment and Parental Skills		
Parental Cognition	0.34 [0.3,0.39]	0.11 [0.04,0.17]	0.04 [0,0.13]	0.02 [−0.04,0.05]	0.05 [0.03,0.09]	−0.05 [−0.09,0.01]
Parental Health	0.07 [0,0.18]	−0.07 [−0.1,0.01]	−0.02 [−0.06,0.04]	0.26 [0.18,0.38]	0.06 [0.02,0.1]	0.02 [−0.03,0.1]
Investment	0.53 [0.43,0.6]	0.66 [0.57,0.76]	0.19 [0.06,0.26]	0.25 [0.17,0.34]	0 [−0.05,0.08]	0.12 [−0.01,0.17]
				TFP - Demographic Characteristics		
Log TFP	−0.04 [−0.07,0.04]	0.57 [0.49,0.61]	1.08 [1.01,1.18]	−0.33 [−0.38,−0.27]	0.14 [0.08,0.2]	−0.09 [−0.14,−0.02]
Num Child	0 [−0.02,0.01]	−0.01 [−0.02,0.01]	−0.02 [−0.04,−0.01]	0.01 [−0.01,0.03]	0 [−0.01,0]	0 [−0.02,0.01]
Older Sibs	−0.01 [−0.03,0]	−0.01 [−0.03,0]	0.01 [−0.01,0.02]	−0.03 [−0.05,−0.01]	0 [−0.01,0.01]	0.01 [0,0.03]
Gender	0.01 [0,0.03]	0.03 [0.01,0.04]	−0.02 [−0.03,−0.01]	0 [−0.01,0.01]	0.01 [0,0.01]	0.01 [0,0.02]
Urban	0.01 [0,0.01]	−0.02 [−0.02,0]	−0.01 [−0.02,0]	0 [−0.01,0]	0.01 [0,0.01]	0 [−0.01,0]
Hindu	−0.01 [−0.02,0.01]	−0.01 [−0.02,0]	0.01 [0,0.03]	0.01 [0,0.02]	0 [−0.01,0.01]	−0.01 [−0.01,0.01]
Muslim	0 [0,0]	0 [0,0]	−0.01 [−0.01,0]	0 [−0.01,0]	0 [0,0]	0 [0,0]
Mother Age	0.01 [0,0.03]	0.02 [0,0.03]	−0.01 [−0.03,0]	0 [−0.01,0.02]	0 [−0.01,0.01]	−0.02 [−0.03,−0.01]
Sched Caste	−0.01 [−0.02,0]	0.02 [0.01,0.03]	0 [−0.01,0.01]	0 [−0.01,0.01]	0 [−0.01,0]	0 [−0.01,0.01]
Sched Tribe	0.03 [0.02,0.04]	0 [−0.01,0]	0 [−0.01,0.01]	0.01 [0,0.02]	−0.02 [−0.02,−0.01]	0.01 [0,0.01]
BC Caste	−0.01 [−0.03,0]	−0.01 [−0.02,0.01]	0.01 [0,0.02]	−0.02 [−0.03,−0.01]	0.01 [0,0.02]	−0.01 [−0.01,0.01]
				Production function structure and test of exogeneity for investment		
(ρ, ζ)	0.02 [−0.32,0.17]	0.04 [−0.06,0.15]	−0.09 [−0.33,0.11]	0 [−0.07,0.04]	0.36 [0.11,0.46]	−0.08 [−0.63,0.2]
Subst. Elast.	1.02 [0.76,1.21]	1.05 [0.94,1.18]	0.92 [0.75,1.12]	1 [0.93,1.04]	1.57 [1.12,1.84]	0.92 [0.61,1.24]
Inv. Res.	−0.84 [−1.26,−0.3]	−0.51 [−0.65,−0.37]	−0.28 [−0.39,−0.1]	−0.84 [−1.23,−0.51]	0.02 [−0.08,0.11]	−0.1 [−0.18,0.02]

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.

stage is likely to be important for the accumulation of human capital.

We find that parental cognition matters for all ages, but with a declining influence. In interpreting this result remember that we do not observe child cognition at age 1 and since the two are likely correlated, the effect of parental cognition is probably overstated. 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, but it is still there: an interpretation is that parental cognition improves the productivity of investments.

The next crucial parameter is that on investment itself. We find that investments have a very large influence, which declines substantially for age 12 children. At a young age the elasticity of cognition with respect to investments is 0.53, rises to 0.66 but at age 12 it is down to 0.19. This is consistent with the sensitivity of child development to investments at early ages as demonstrated by work on interventions and understood to be the case in the literature (Engle, Black, Behrman *et al.*, 2007).[31] 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 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. An interpretation of the negative coefficient is that parents increase investments to compensate for negative shocks to development. Ignoring this leads to an 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, particularly for ages 8 and 12.

[31] It is now understood that important aspects of child development takes place during adolescence. However the kind of inputs that may matter at that age are not clearly understood and may not be captured well by the kind of investment measures currently collected. This is an important area of current research.

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 for a young child. Being a boy has a positive impact on cognitive development (ages 5 and 8) but a negative one later on (age 12).

Health The estimates for the health production function are reported in the right hand side of Table 6. The production function again displays complementarity with a substitution elasticity at ages 5 and 12 that is not significantly different than 1. At age 8 the elasticity of substitution is 1.57 implying a bit less strong complementarity.

Health is highly self-productive, but cognition has no impact on health at any age. While parental cognition does not have much of an impact, parental health, which reflects mother's nutritional status, seems to matter for child health for all ages, but especially at age 5. Investments matter significantly only for age 8 children: in other words, the resources invested by parents can alter the health status of young children, but do little at later ages.

Of the variables that affect TFP the most notable impact is that of the number of older siblings, which reduce health substantially at an earlier age. In addition, fewer older siblings is associated with better health at age 5. Boys have marginally better health outcomes at ages 8 and 12.

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; indeed we have shown that is an important input in cognitive development. On the other hand, as implied by the results, the long-term health measure is highly persistent and hard to change past early childhood. Given this, and given the importance of health for cognitive development as we document here, it is important that interventions address health deficits as early as possible. Doing this for a very poor population is of course a challenge, given poor living conditions and the frequent lack of sanitation.

5.5 Robustness to the use of resources as an instrument

Our model includes resources in the investment equation, but not in the production function. This has various advantages: it allows us to estimate the sensitivity of investments to wealth, which explains in part the source of wealth disparities, and statistically it offers a strong instrument. However, if our resource measure is correlated with omitted variables affecting child development, this exclusion restriction may not be valid. The risk is small because we include parental background and various demographic characteristics that should capture the role of long term factors affecting child human capital. Nevertheless we can evaluate whether using resources as an instrument distorts the results in any substantive way, as the remaining price instruments are strong enough to identify the model (see table 5). Our analysis is based on the assumption that prices are exogenous for child development.

We first try a version of the model where we include resources in both the investment equation and the production functions. Estimates of this version of the production functions are presented in the Appendix Table 14. In Table 7, we compare the investment coefficients of our preferred specification and the one we obtain relaxing the exclusion restriction. The differences are very small, certainly not of any economic significance and in most cases statistically insignificant. Moreover, excluding income from the production function of cognition is only rejected at age 8 for cognition and marginally so for health. Importantly, whether income is included as an instrument or not leaves the results unaffected.[32]

In Appendix Table 15, we also present estimates of a version of the model that excludes resources from all equations. Again this does not change the coefficients on investment substantively. The only difference of note is that the investment coefficient for cognition

[32] All these tests are carried out using the bootstrap.

Table 7: Robustness to using resources as an excluded instrument

	Age 5		Age 8		Age 12	
	Child Cognition					
Coefficient on investment	0.53 [0.43,0.6]	0.55 [0.45,0.64]	0.66 [0.57,0.76]	0.62 [0.53,0.71]	0.19 [0.06,0.26]	0.18 [0.06,0.27]
P-value equality	0.43		0.01		0.87	
P-value excluding income		0.40		0.02		0.88
	Child Health					
Coefficient on investment	0.25 [0.17,0.34]	0.28 [0.17,0.38]	0 [−0.05,0.08]	0.01 [−0.03,0.08]	0.12 [−0.01,0.17]	0.12 [−0.02,0.18]
P-value equality	0.21		0.19		0.92	
P-value excluding income		0.22		0.05		0.93

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.

at age 12 becomes small and insignificant but the difference from the results where we include resources as an instrument is not significant. We conclude that using our resource measure as an instrument is acceptable and provides a better and more precise picture of the determinants of investment.

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 initial values. These graphs also incorporate the endogenous response of current period investments. The x-axis is the decile of cognition (top panel) and health (bottom). We do not report the effect of a change in cognition on health at any age as these effects are not significantly different from zero.

An important result here is that the persistence of cognition (top graph) is substantially higher for lower cognition levels, and the decline in persistence with initial levels is particularly pronounced at young ages. More generally, the persistence of cognition is lower at younger ages. This result indicates 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.[33]

The bottom left graph shows that health at younger ages affects the development of cognition; the impact is largest for the most unhealthy children. This result 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 potential. From the bottom right graph it is also evident that health is highly persistent, and slightly 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.

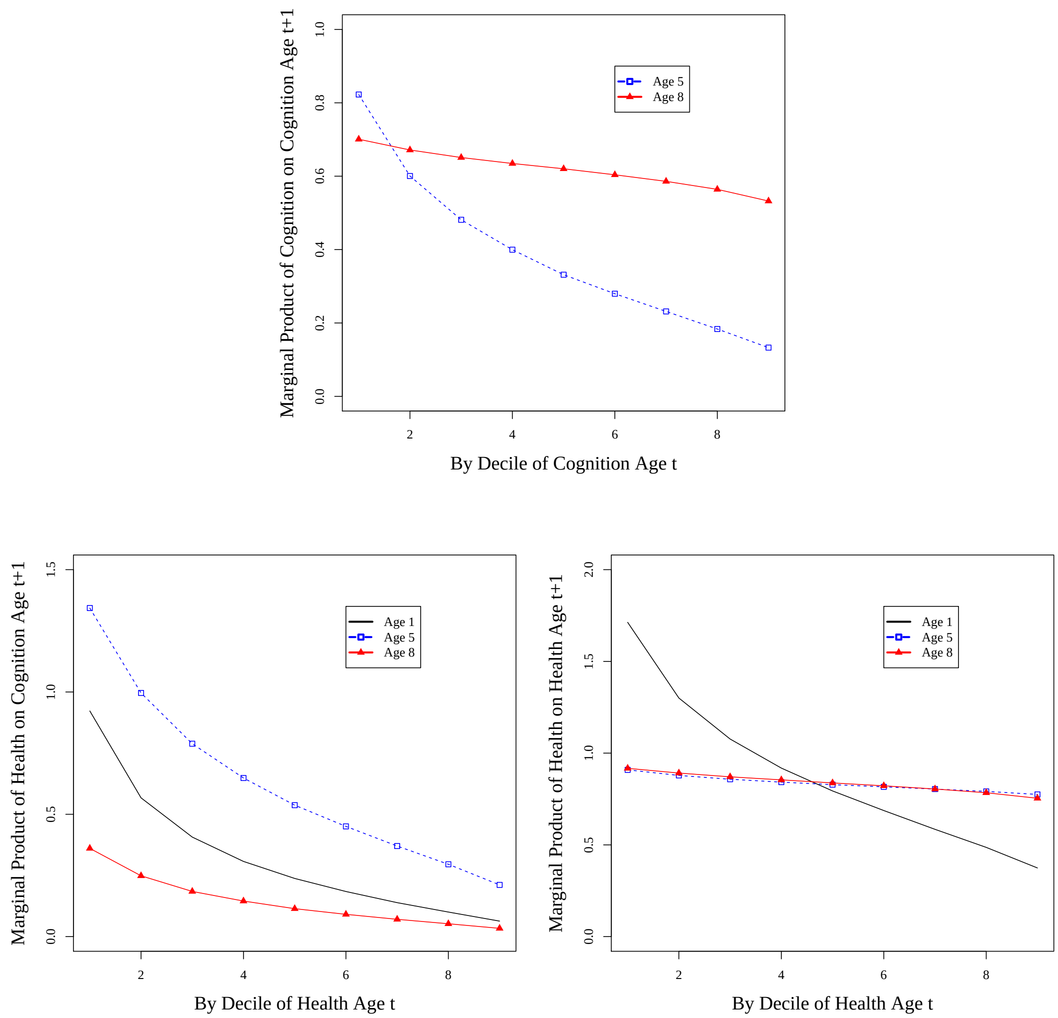
When considering the production of cognitive skills (left hand graph) we see that the productivity of investments is much higher at younger ages: investments are more able to affect cognition earlier on. The increasing slope of the marginal productivity graph is a reflection of complementarity between investments and the current level of cognition.[34]

The effect of investments on health is important both early on and at age 12; the complementarity with initial health as with initial cognition is evident, which raises the question of how best to reach those with bad initial conditions, or indeed how to prevent the worse beginnings. Affecting health may require specifically targeted approaches that perhaps parents do not engage in directly. It is of course an open question of how to deal with this important issue. Indeed the interaction between our health measure and cognition illustrates the importance of finding ways of improving long term health and nutritional status. This will require creative interventions both earlier on (possibly even during pregnancy) and addressing environmental issues that parental investments do not cover necessarily. The degree of persistence of cognitive development is central to

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

[34] We do not include the plot for age 1 because we do not observe initial cognitive levels for the children.

Figure 3: Marginal Product of Health and Cognition



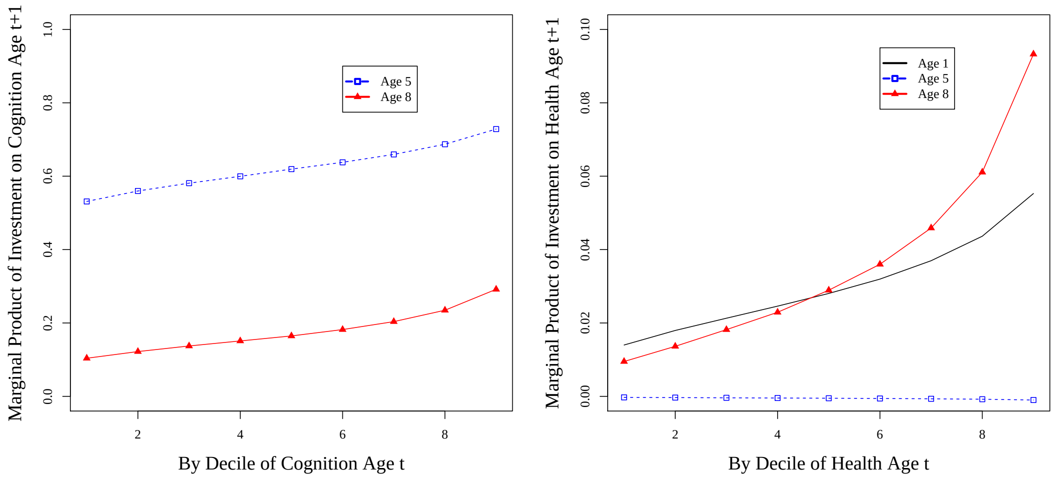
Note: The y-axis represents the impact on the outcome in question, in standard deviation units, of increasing cognition or health by one standard deviation. All other inputs are kept at their median value for the respective age group.

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 perform two counterfactual experiments using our model. These are meant to illustrate its implications and therefore we do not focus on how they would be implemented in practice.

Figure 4: Marginal Product of Investment on Health and Cognition



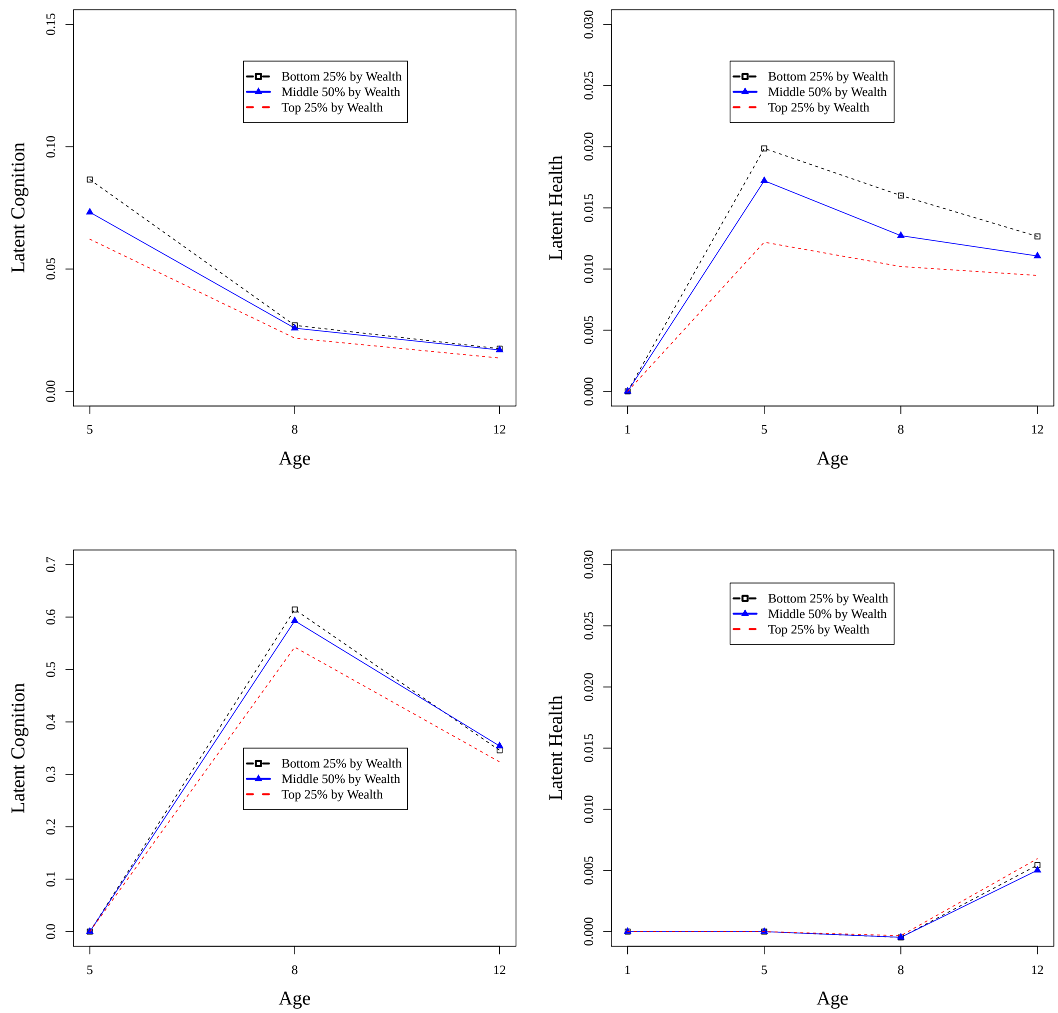
Note: The y-axis represents the impact on the outcome in question, in standard deviation units, of increasing investment by one standard deviation.

Income Transfer. 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, and the second row at age 8. Figure 5 depicts the resulting change in standard deviation units of cognition (left) and health (right) at each age relative to the baseline.

For this exercise assume that the income is spent entirely in the age at which it 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. In terms of timing, the largest impact is obtained if the transfer takes place when the children are between 5 and 8 for cognition, but before 5 for health. The result is driven by the combination of the coefficient on investment and the values of other inputs at each of the ages because of the complementarities we document.

Health Improvement. 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

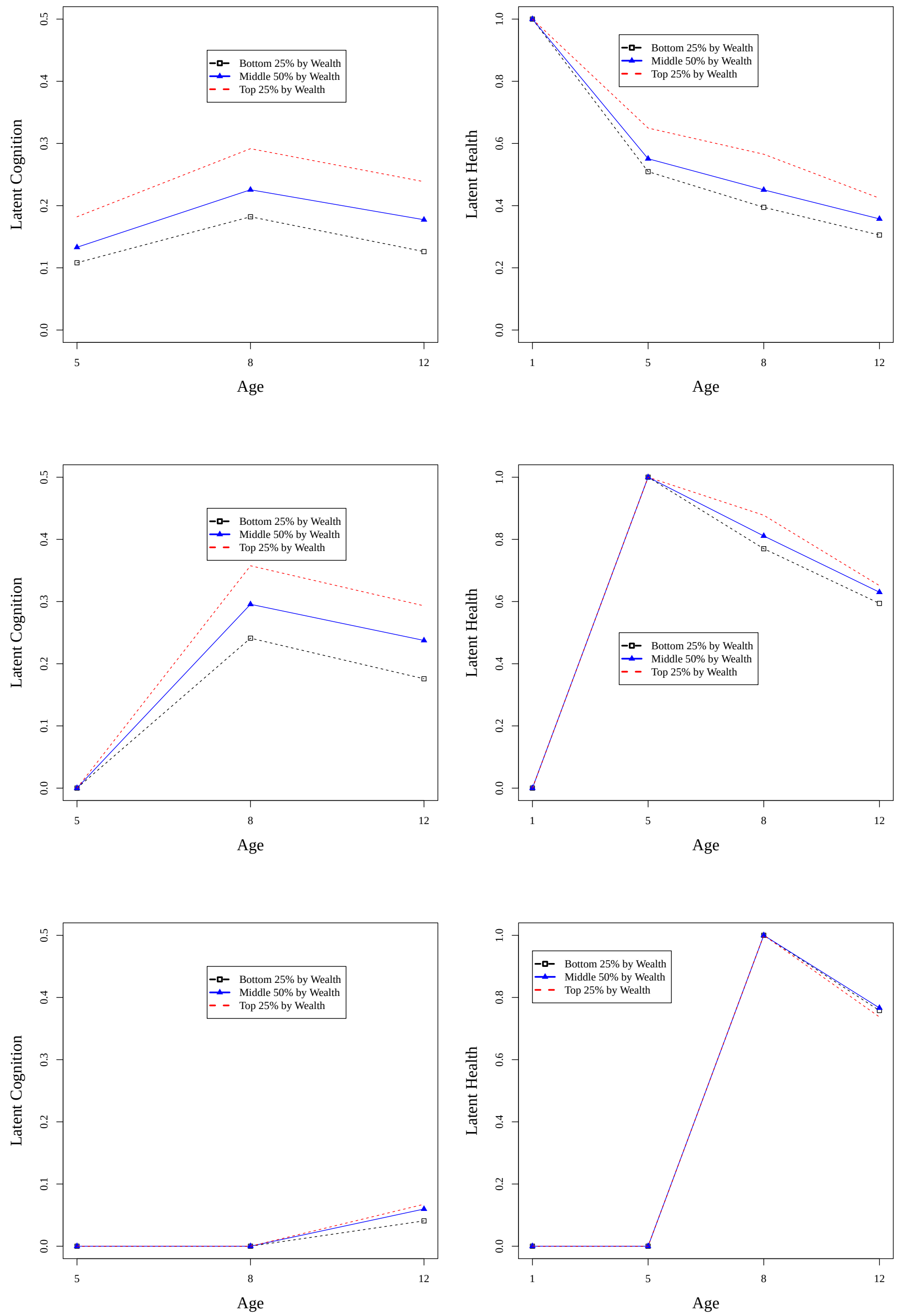
Figure 5: Dynamic Impact of Income Transfer



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.

our health measures, can affect cognitive development. Our estimates imply that they 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 1, 5 and 8 and show the resulting impacts in Figure 6.

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 increase in health takes place at age 1. In the middle two graphs it is made at age 5. In the lower two graphs it is made at age 8.

The effects on health itself are persistent as we could already predict based on the production function coefficients. The most interesting result here is the impact on cognition. In this setting it is clear that improving health has a strong impact on cognitive development. And because health is so persistent, early interventions do have long run persistent effects. The results show that if health increases at an early age this feeds into cognition, and the effect does not fade out. For example, a one standard deviation improvement in initial health leads to between 10% and 20% of a standard deviation improvement in cognition by age 12. However, interventions improving health and nutritional status are hard to design and are likely to be much more effective early on and can have important impacts on cognition. Starting during pregnancy may be they key to achieving the best results: the most effective design of health interventions is an important research question.

6.3 When is it best to invest

In our final experiment, we consider how overall investment should be distributed across ages to maximize child human capital as defined by equation (1). We assume that the function that defines human capital in this equation is a Cobb-Douglas function in cognition and health with constant returns to scale.

$$H_a = A(\theta_a^c)^{\alpha}(\theta_a^h)^{1-\alpha} \tag{18}$$

Since the parameter α in equation (18) is not known, we find the optimal investment paths for different assumptions about its value, starting with 25%. One of course could take the view that ultimately only cognition matters and that health (at least the way it is measured here) is important to the extent that it matters for cognitive development. In addition, we should take these results with some caution, as we have nothing to say about the role of non-cognitive skills that are not measured in our data. The appropriate definition of adult human capital is an empirical question to which we do not know the

Table 8: The optimal path of investment

Share of Cognition in Human Capital	Age 5	Age 8	Age 12
25%	0.405	0.281	0.314
50%	0.265	0.452	0.283
75%	0.175	0.563	0.262
100%	0.112	0.640	0.248

Notes: The numbers show how the average amount of life time investment in children is optimally allocated across ages based on the production function estimates and on the weight that cognition versus health has on final human capital.

answer, so we have opted for presenting the results under various alternatives.

The results are presented in Table 8. If cognition is assigned a low weight (25%) and thus health a large one, investments shift to a younger age because that is when they are most productive for health, which also is highly persistent from very early on. However, when cognition is given an increased weight more of the investment share is shifted to between ages 5 and 8 mainly because cognitive development becomes more persistent at that stage and investments are still very productive.

The early childhood literature has placed a lot of weight on the importance of investments at a very young age. These results are not inconsistent with that: much of the early stimulation activities that have been emphasized in the literature are not high cost in a financial sense.[35] The interventions focus on changing parenting behavior towards stimulating play activities, language development through interaction and play materials with greater educational content, such as picture books or simple stacking toys; these do not imply high levels of expenditure. Indeed most of the successful interventions are parenting ones, involving low costs in materials, including in developing countries.[36]

Compared to the optimal allocations based on the production function, parents in our data allocate 15.8%, 25.2% and 59% to each age group respectively given total resources

[35]See for example Attanasio, Fernández, Fitzsimons *et al.* (2014).

[36]See above reference and Walker, Chang, Powell *et al.* (2005b) as examples).

spent on children. These allocations may reflect distorted beliefs about child development as documented by Attanasio, Cunha, and Jervis (2015) and Cunha, Elo, and Culhane (2013). But they may in addition reflect liquidity constraints: as we show in Table 2 there is substantial parental income growth as the cohort ages, and the growth in child investments may just be tracking income if households cannot reallocate resources over the lifecycle.[37]

Thus improving child development may require a combination of parenting interventions that encourage stimulation (a low cost/high return activity) as well as well-targeted cash transfers ensuring improved expenditures on children at the appropriate times, as suggested by the results. Implementing such interventions can be challenging, both in terms of targeting resources to children and in terms of achieving appropriate parenting.

7 Conclusion

In this paper, we examine the human capital development of children from age 1 to 12 and we 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 for India. 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.

We obtain a number of important results. First, ill health at a young age causes permanent cognitive deficits. This result is crucial in understanding the developmental deficits of children growing up in poor environments characterized by high levels of morbidity, such as diarrhea, which are a cause of nutritional deficits. Here we are able to trace the effects throughout childhood. The key implication is that we need interventions that address health and malnutrition among the poor from a very early age and quite possibly during pregnancy (although our results do not speak directly to this). Second, invest-

[37]See Carneiro, Garcia, Salvanes *et al.* (2015) on this issue in a wealthier context.

ments 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 5 for health. In interpreting this it is important to remember that our health measure relates to longer-term malnutrition reflected in height for age and weight for age. Finally, we find that there are important complementarities in the production function, such that the marginal product of investments increases 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 its intergenerational transmission. 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 trade-off, 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 experiments addressing these issues combined with cohort studies such as this one are likely to be an important empirical tool for better understanding human capital development from an early age.

References

Agostinelli, F. and Wiswall, M. (2016a). 'Estimating the Technology of Children's Skill Formation.' *NBER Working Paper 22442*. 1

Agostinelli, F. and Wiswall, M. (2016b). 'Identification of dynamic latent factor models: The implications of re-normalization in a model of child development.' *NBER Working Paper 22441*. 1, 3.4, 5.1

Almond, D. (2006). 'Is the 1918 Influenza pandemic over? Long-term effects of in utero Influenza exposure in the post-1940 US population.' *Journal of Political Economy*, vol. 114(4):pages 672–712. 2

Almond, D., Edlund, L., and Palme, M. (2009). 'Chernobyl's Subclinical Legacy: Prenatal Exposure to Radioactive Fallout and School Outcomes in Sweden.' *The Quarterly Journal of Economics*, vol. 124(4):pages 1729–1772. 2

Andrew, A., Attanasio, O., Fitzsimons, E., Grantham-McGregor, S., Meghir, C., and Rubio-Codina, M. (2018). 'Impacts 2 years after a scalable early childhood development intervention to increase psychosocial stimulation in the home: A follow-up of a cluster randomised controlled trial in Colombia.' *PLoS Med*, vol. 15. 5, 30

Arcidiacono, P. and Jones, J. B. (2003). 'Finite mixture distributions, sequential likelihood and the EM algorithm.' *Econometrica*, vol. 71(3):pages 933–946. 4

Attanasio, O., Baker-Henningham, H., Bernal, R., Meghir, C., Pineda, D., and Rubio-Codina, M. (2018). 'Early Stimulation and Nutrition: The Impacts of a Scalable Intervention.' *NBER WP 25059*. 4

Attanasio, O., Cunha, F., and Jervis, P. (2015). 'Parental Beliefs and Investments in Human Capital.' Mimeo UCL. 3.2, 6.3

Attanasio, O., Fernández, C., Fitzsimons, E. O., Grantham-McGregor, S. M., Meghir, C., and Rubio-Codina, M. (2014). 'Using the infrastructure of a conditional cash transfer program to deliver a scalable integrated early child development program in Colombia: cluster randomized controlled trial.' *BMJ*, vol. 349. 35

Banerjee, A. V., Cole, S., Duflo, E., and Linden, L. (2007). 'Remedying Education: Evidence from Two Randomized Experiments in India.' *The Quarterly Journal of Economics*, vol. 122(3):pages 1235–1264. 4

Barcellos, S. H., Carvalho, L. S., and Lleras-Muney, A. (2014). 'Child Gender and Parental Investments in India: Are Boys and Girls Treated Differently?' *American Economic Journal: Applied Economics*, vol. 6(1):pages 157–189. 5.3

Behrman, J. R. (1996). 'The impact of health and nutrition on education.' *The World Bank Research Observer*, vol. 11(1):pages 23–37. 2

Bernal, R. (2008). 'The effect of maternal employment and child care on children's cognitive development.' *International Economic Review*, vol. 49(4):pages 1173–1209. 1

Bharadwaj, P., Løken, K. V., and Neilson, C. (2013). 'Early life health interventions and academic achievement.' *The American Economic Review*, vol. 103(5):pages 1862–1891. 2, 4

Black, M. M. (2003). 'Micronutrient deficiencies and cognitive functioning.' *The Journal of Nutrition*, vol. 133(11). 4

Bleakley, H. (2007). 'Disease and development: evidence from hookworm eradication in the American South.' *The Quarterly Journal of Economics*, vol. 122(1). 2

Bleakley, H. (2010). 'Malaria Eradication in the Americas: A retrospective Analysis of Childhood Exposure.' *American Economic Journal: Applied Economics*, vol. 2:pages 1–45. 4

Bond, T. N. and Lang, K. (2013). 'The evolution of the black-white test score gap in grades K–3: The fragility of results.' *Review of Economics and Statistics*, vol. 95(5):pages 1468–1479. 26

Boneva, T. and Rauh, C. (2015). 'Parental Beliefs about Returns to Educational Investments: The Later the Better?' Tech. rep., Human Capital and Economic Opportunity Global Working Group. 3.2

Campbell, F., Conti, G., Heckman, J. J., Moon, S. H., Pinto, R., Pungello, E., and Pan, Y. (2014). 'Early Childhood Investments Substantially Boost Adult Health.' *Science*, vol. 343:pages 1478–1485. 4

Carneiro, P., Garcia, I. L., Salvanes, K. G., and Tominey, E. (2015). 'Intergenerational Mobility and the Timing of Parental Income.' *mimeo, University College London*. 37

Carneiro, P., Lopez-Garcia, I., Salvanes, K., and Tominey, E. (2015). 'Intergenerational Mobility and the Timing of Parental Income.' Mimeo UCL. 3

Case, A., Lubotsky, D., and Paxson, C. (2002). 'Economic Status and Health in Childhood: The Origins of the Gradient.' *American Economic Review*, vol. 92(5):pages 1308–1334. 1

Chay, K. Y. and Greenstone, M. (2003). 'Air quality, infant mortality, and the Clean Air Act of 1970.' *NBER Working Paper 10053*. 2

Chong, A., Cohen, I., Field, E., Nakasone, E., and Torero, M. (2016). 'Are there nutrient-based poverty traps? Evidence on iron deficiency and schooling attainment in Peru.' *American Economic Journal: Applied Economics*. 4

Clark, S. E., Jukes, M. C., Njagi, J. K., Khasakhala, L., Cundill, B., Otido, J., Crudder, C., Estambale, B. B., and Brookera, S. (2008). 'Effect of intermittent preventive treatment of malaria on health and education in schoolchildren: a cluster-randomised, double-blind, placebo-controlled trial.' *Lancet*, vol. 372:pages 127–138. 4

Cunha, F., Elo, I., and Culhane, J. (2013). 'Eliciting Maternal Expectations about the Technology of Cognitive Skill Formation.' *NBER Working Paper 19144*. 1, 3.2, 6.3

Cunha, F. and Heckman, J. (2007). 'The Technology of Skill Formation.' *American Economic Review*, vol. 97(2):pages 31–47. 3, 1

Cunha, F. and Heckman, J. J. (2008). 'Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation.' *Journal of Human Resources*, vol. 43(4):pages 738–782. 1

Cunha, F., Heckman, J. J., and Schennach, S. M. (2010). 'Estimating the technology of cognitive and noncognitive skill formation.' *Econometrica*, vol. 78(3):pages 883 – 931. 1, 3, 3, 3.1, 3.4, 3.4, 5.1, 5.4, 7, A.1

Currie, J. (2009). 'Healthy, wealthy, and wise: Socioeconomic status, poor health in childhood, and human capital development.' *Journal of Economic Literature*, vol. 47(1):pages 87–122. 26

Currie, J. (2011). 'Inequality at birth: Some causes and consequences.' *NBER Working Paper 16798*. 1

Currie, J. and Almond, D. (2011). 'Human capital development before age five.' *Handbook of Labor Economics*, vol. 4:pages 1315–1486. 3

Currie, J. and Hyson, R. (1999). 'Is the Impact of Health Shocks Cushioned by Socioeconomic Status? The Case of Low Birthweight.' *American Economic Review*, vol. 89(2):pages 245–250. 1

Currie, J. and Neidell, M. (2005). 'Air Pollution and Infant Health: What Can We Learn from California's Recent Experience?' *The Quarterly Journal of Economics*, vol. 120(3):pages 1003–1030. 2

Currie, J., Neidell, M., and Schmieder, J. F. (2009). 'Air pollution and infant health: Lessons from New Jersey.' *Journal of Health Economics*, vol. 28(3):pages 688–703. 2

Currie, J. and Stabile, M. (2003). 'Socioeconomic Status and Child Health: Why Is the Relationship Stronger for Older Children?' *American Economic Review*, vol. 93(5):pages 1813–1823. 1

Del Boca, D., Flinn, C., and Wiswall, M. (2014). 'Household choices and child development.' *The Review of Economic Studies*, vol. 81(1):pages 137–185. 3, 1, 11, 3, 38

Dempster, A. P., Laird, N. M., and Rubin, D. B. (1977). 'Maximum likelihood from incomplete data via the EM algorithm.' *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 1–38. 4

Engle, P. L., Black, M. M., Behrman, J. R., Cabral de Mello, M., Gertler, P. J., Kapiriri, L., Martorell, R., Eming, M., Young, and Group", T. I. C. D. S. (2007). 'Strategies to avoid the loss of developmental potential in more than 200 million children in the developing world.' *The Lancet*, vol. 369 (9557):pages 229–242. 5.4

Fernald, L. C., Weber, A., Galasso, E., and Ratsifandrihamanana, L. (2011). 'Socioeconomic gradients and child development in a very low income population: evidence from Madagascar.' *Developmental Science*, vol. 14(4):pages 832–847. 1

Field, E., Robles, O., and Torero, M. (2009). 'Iodine deficiency and schooling attainment in Tanzania.' *American Economic Journal: Applied Economics*, pages 140–169. 2

Figlio, D., Guryan, J., Karbownik, K., and Roth, J. (2014). 'The effects of poor neonatal health on children's cognitive development.' *The American Economic Review*, vol. 104(12):pages 3921–3955. 4

Florens, J. P., Heckman, J. J., Meghir, C., and Vytlacil, E. (2008). 'Identification of Treatment Effects Using Control Functions in Models with Continuous, Endogenous Treatment and Heterogeneous Effects.' *Econometrica*, vol. 76(5):pages 1191–1206. 16

Galab, S., Kumar, S. V., Reddy, P. P., Singh, R., and Vennam, U. (2011). *The Impact of Growth on Childhood Poverty in Andhra Pradesh: Initial Findings from India: Round 3 Survey Report*. Young Lives, Department of International Development, University of Oxford. 8

Gertler, P., Heckman, J., Pinto, R., Zanolini, A., Vermeersch, C., Walker, S., Chang-Lopez, S., and Grantham-McGregor, S. (2013). 'Labor Market Returns to Early Childhood Stimulation: A 20-year Followup to an Experimental Intervention in Jamaica.' *NBER Working Paper 19185*. 1

Glewwe, P. and Jacoby, H. G. (1995). 'An economic analysis of delayed primary school enrollment in a low income country: the role of early childhood nutrition.' *The Review of Economic Statistics*, pages 156–169. 4

Glewwe, P., Jacoby, H. G., and King, E. M. (2001). 'Early childhood nutrition and academic achievement: a longitudinal analysis.' *Journal of Public Economics*, vol. 81(3):pages 345–368. 4

Glewwe, P. and King, E. M. (2001). 'The impact of early childhood nutritional status on cognitive development: Does the timing of malnutrition matter?' *The World Bank Economic Review*, vol. 15(1):pages 81–113. 4

Glewwe, P. and Miguel, E. A. (2007). 'The impact of child health and nutrition on education in less developed countries.' *Handbook of Development Economics*, vol. 4:pages 3561–3606. 4

Grantham-McGregor, S., Cheung, Y. B., Cueto, S., Glewwe, P., Richter, L., and Strupp, B. (2007). 'Developmental potential in the first 5 years for children in developing countries.' *The Lancet*, vol. 369(9555):pages 60 – 70. ISSN 0140-6736. 1

Grantham-McGregor, S. M., Powell, C. A., Walker, S. P., and Himes, J. H. (1991). 'Nutritional supplementation, psychosocial stimulation, and mental development of stunted children: The Jamaican Study.' *The Lancet*, vol. 338(8758):pages 1–5. 4

Griliches, Z. and Ringstad, V. (1970). 'Error-in-the-variables bias in nonlinear contexts.' *Econometrica: Journal of the Econometric Society*, pages 368–370. 3.4

Gronau, R. (1974). 'Wage Comparisons–A Selectivity Bias.' *Journal of Political Economy*, vol. 82(6):pages 1119–1143. 16

Hamadani, J. D., Tofail, F., Huda, S. N., Alam, D. S., Ridout, D. A., Attanasio, O., and Grantham-McGregor, S. M. (2014). 'Cognitive deficit and poverty in the first 5 years of childhood in Bangladesh.' *Pediatrics*, vol. 134(4):pages e1001–e1008. 1

Heckman, J. J. (1979). 'Sample Selection Bias as Specification Error.' *Econometrica*, vol. 47(1):pages 153–161. 16

Heckman, J. J. (2007). 'The economics, technology, and neuroscience of human capability formation.' *Proceedings of the National Academy of Sciences*, vol. 104(33):pages 13250–13255. 3

Heckman, J. J., Moon, S. H., Pinto, R., Savelyev, P. A., and Yavitz, A. (2010). 'The rate of return to the HighScope Perry Preschool Program.' *Journal of Public Economics*, vol. 94(1):pages 114–128. 4

Heckman, J. J., Schennach, S., and Williams, B. (2010). 'Matching with error-laden covariates.' *Unpublished manuscript, Department of Economics, University of Chicago*. 1

Hoddinott, J., Maluccio, J., Behrman, J., Flores, R., and Martorell, R. (2008). 'Effect of a nutrition intervention during early childhood on economic productivity in Guatemalan adults.' *Lancet*, vol. 371(9610). 4

Hu, Y. and Schennach, S. M. (2008). 'Instrumental variable treatment of nonclassical measurement error models.' *Econometrica*, vol. 76(1):pages 195–216. 7, 17

Jayachandran, S. and Kuziemko, I. (2011). 'Why Do Mothers Breastfeed Girls Less Than Boys: Evidence and Implications for Child Health in India.' *Quarterly Journal of Economics*, vol. 126(3):pages 1485–1538. 3.1

Kippler, M., Tofail, F., Hamadani, J. D., Gardner, R. M., Grantham-McGregor, S. M., Bottai, M., and Vahter, M. (2012). 'Early-life cadmium exposure and child development in 5-year-old girls and boys: A cohort study in rural Bangladesh.' *Environmental Health Perspectives*, vol. 120(10):pages 1462–1468. 4

Kumra, N. (2008). 'An assessment of the Young Lives sampling approach in Andhra Pradesh, India.' *Young Lives*. 10

Lu, C., Black, M. M., and Richter, L. M. (2016). 'Risk of poor development in young children in low-income and middle-income countries: an estimation and analysis at the global, regional, and country level.' *The Lancet Global Health*, vol. 4(12):pages e916–e922. 1

Lucas, A., Morley, R., and Cole, T. J. (1998). 'Randomised trial of early diet in preterm babies and later intelligence quotient.' *BMJ*, vol. 317(7171):pages 1481–1487. 4

Ludwig, J. and Miller, D. L. (2007). 'Does Head Start Improve Children's Life Chances? Evidence from a Regression Discontinuity Design.' *The Quarterly Journal of Economics*, vol. 122(1):pages 159–208. 4

Miguel, E. and Kremer, M. (2004). 'Worms: identifying impacts on education and health in the presence of treatment externalities.' *Econometrica*, vol. 72(1):pages 159–217. 4

Newey, W. K., Powell, J. L., and Vella, F. (1999). 'Nonparametric Estimation of Triangular Simultaneous Equations Models.' *Econometrica*, vol. 76(3):pages 565–603. 16

Nielsen, E. R. (2015a). 'Achievement Gap Estimates and Deviations from Cardinal Comparability.' *FEDS Working Paper No. FEDGFE2015-40*. 26

Nielsen, E. R. (2015b). 'The Income-Achievement Gap and Adult Outcome Inequality.' *FEDS Working Paper*. 26

Rubio-Codina, M., Attanasio, O., Meghir, C., Varela, N., and Grantham-McGregor, S. (2015). 'The socioeconomic gradient of child development: Cross-sectional evidence from children 6–42 months in Bogota.' *Journal of Human Resources*, vol. 50(2):pages 464–483. 1

Sakti, H., Nokes, C., Hertanto, W., Hendratno, S., Hall, A., and Bundy, D. A. (1999). 'Evidence for an association between hookworm infection and cognitive function in Indonesian school children.' *Tropical Medicine & International Health*, vol. 4(5):pages 322–334. 4

Sazawal, S., Bentley, M., Black, R. E., Dhingra, P., George, S., and Bhan, M. K. (1996). 'Effect of zinc supplementation on observed activity in low socioeconomic Indian preschool children.' *Pediatrics*, vol. 98(6):pages 1132–1137. 4

Schennach, S. M. (2004). 'Estimation of nonlinear models with measurement error.' *Econometrica*, vol. 72(1):pages 33–75. 7, 17

Todd, P. E. and Wolpin, K. I. (2007). 'The production of cognitive achievement in children: Home, school, and racial test score gaps.' *Journal of Human Capital*, vol. 1(1):pages 91–136. 1

Walker, S. P., Chang, S. M., Powell, C. A., and Grantham-McGregor, S. M. (2005a). 'Effects of early childhood psychosocial stimulation and nutritional supplementation on cognition and education in growth-stunted Jamaican children: prospective cohort study.' *Lancet*, vol. 366. 5, 30

Walker, S. P., Chang, S. M., Powell, C. A., and Grantham-McGregor, S. M. (2005b). 'Effects of early childhood psychosocial stimulation and nutritional supplementation on cognition and education in growth-stunted Jamaican children: Prospective cohort study.' *The Lancet*, vol. 366:pages 1804 – 1807. 36

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

$$U = \Sigma_{t=1}^{T} \beta^t u_t(c_t) + \beta^a \mu v(H_a) \tag{19}$$

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

$$H_a = H(\theta_a^c, \theta_a^h) \tag{20}$$

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.

$$\begin{aligned} \theta_{t+1}^c &= G\left(\theta_t^c, \theta_t^h, \theta_t^I, Z_t\right) && (21) \\ \theta_{t+1}^h &= F\left(\theta_t^c, \theta_t^h, \theta_t^I, Z_t\right) && (22) \end{aligned}$$

where θ_t^I is an investment good that parents can buy in the market.[38]. 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

$$A_{t+1} = (1+r)(A_t - c_t - p_t^I \theta_t^I + y_t) \tag{23}$$

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 (20, 21, 22) and the budget constraint (23). 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

$$\begin{aligned}
V_t(A_t, \theta_t^c, \theta_t^h) &= max_{c_t, A_{t+1}, I_t} u(c_t) + \beta E_t V_{t+1}(A_{t+1}, \theta_{t+1}^c, \theta_{t+1}^h) \text{ for } t < a && (24) \\
V_t(A_t, \theta_t^c, \theta_t^h) &= max_{c_t, A_{t+1}} u(c_t) + \mu v(H_a) + \beta E_t V_{t+1}(A_{t+1}) \text{ for } t = a && (25) \\
V_t(A_t) &= max_{c_t, A_{t+1}} u(c_t) + \beta E_t V_{t+1}(A_{t+1}) \text{ for } t > a && (26)
\end{aligned}$$

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

[38] 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.

$$p_t^I = \frac{E_t V'_{\theta^c_{t+1}} G'_{\theta^c_{t+1}} + E_t V'_{\theta^h_{t+1}} F'_{\theta^h_{t+1}}}{V'_{A_{t+1}} + \lambda_t} \tag{27}$$

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 cognition at ages 5, 8, and 12 respectively. Note that we also introduce some error when generating the production functions.

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 normalized to 1 (presented in Table 2 in the main text). Note that amount spent on child

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	(-4,-2)
μ_B	Mean vector of mixture B	(6,3)
Σ_A	Var-cov of mixture A	$\begin{pmatrix} .62 & .035 \\ .035 & .056 \end{pmatrix}$
Σ_B	Var-cov of mixture B	$\begin{pmatrix} .83 & .17 \\ .17 & 1.28 \end{pmatrix}$
τ	Mixture weight	0.62
1st stage production function		
$log(A_1)$	TFP	1
δ_1	Share parameter	0.69
ρ_1	Complementarity parameter	$\{-1, -0.5, 0, 0.5, 1\}^*$
2nd stage production function		
$log(A_2)$	TFP	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	0.36
Σ_{u_2}	SD of u_2	0.42
Measurement Equations		
λ_X	Measurement loadings for X	(1,0.84,0.79)
λ_{θ_1}	Measurement loadings for θ_1	(1,0.36,0.56)
λ_{θ_2}	Measurement loadings for θ_2	(1,0.66,1.18)
λ_{θ_3}	Measurement loadings for θ_3	(1,0.19,0.5)
σ_X	Measurement error SD for X	(.15,.39,.47)
σ_{θ_1}	Measurement error SD for θ_1	(.68,.03,.08)
σ_{θ_2}	Measurement error SD for θ_2	(.51, .12,.19)
σ_{θ_3}	Measurement error SD for θ_3	(.14,.03,.15)

*These are the values we will assume in alternative simulations. When ρ is 0, we simulate a Cobb Douglas.

investment goods is in Rhupees, not USD.

A.4 Additional results

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	.	.	10.29	12.76
	.	.	5.31	6.61
English test	.	.	.	13.61
	.	.	.	4.39
Language test	.	.	.	13.39
	.	.	.	4.47
CDA test	.	9.40	.	.
	.	2.59	.	.
Egra test	.	.	2.45	.
	.	.	2.08	.
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: Descriptive statistics for prices

	Age 5			Age 8			Age 12		
	Mean	SD	IQR	Mean	SD	IQR	Mean	SD	IQR
Price Food	2.48	0.15	0.22	2.95	0.18	0.26	3.54	0.21	0.28
Price Clothes	4.40	0.41	0.54	4.85	0.40	0.70	5.24	0.28	0.37
Price Notebook	1.65	0.27	0.29	1.75	0.31	0.29	2.31	0.34	0.45
Price Mebendazol	1.66	0.77	1.38	2.46	0.54	0.18	2.04	0.69	0.77

All prices are in logs

Table 12: Mixture Weights and Means

	Mixture A	Mixture B
Weights	0.56 [0.54,0.58]	0.44 [0.42,0.46]
Mean Cognition Age 12	1.569 [1.53,1.61]	1.954 [1.9,2]
Mean Cognition Age 8	0.591 [0.55,0.63]	0.99 [0.95,1.04]
Mean Cognition Age 5	-0.203 [-0.24,-0.17]	0.259 [0.22,0.3]
Mean Health Age 12	-0.383 [-0.42,-0.33]	0.146 [0.08,0.2]
Mean Health Age 8	-0.415 [-0.46,-0.36]	0.171 [0.12,0.23]
Mean Health Age 5	-0.549 [-0.59,-0.5]	-0.116 [-0.17,-0.05]
Mean Health Age 1	-0.203 [-0.24,-0.15]	0.259 [0.21,0.3]
Mean Investment Age 12	0.495 [0.43,0.57]	1.279 [1.15,1.4]
Mean Investment Age 8	0.16 [0.11,0.2]	0.628 [0.56,0.72]
Mean Investment Age 5	-0.082 [-0.1,-0.06]	0.104 [0.08,0.12]
Mean Parental Cognition	-0.438 [-0.48,-0.39]	0.557 [0.52,0.61]
Mean Parental Health	-0.283 [-0.32,-0.22]	0.36 [0.28,0.41]
Mean Income Age 12	-0.304 [-0.34,-0.26]	0.387 [0.34,0.43]
Mean Income Age 8	-0.298 [-0.34,-0.25]	0.379 [0.32,0.43]
Mean Income Age 5	-0.349 [-0.38,-0.31]	0.444 [0.41,0.48]

Table 13: Production of Cognitive Skills and Health - Exogenous Investment

	Cognition			Health		
Age	5	8	12	5	8	12
			Lagged Skills			
Cognition		0.18 [0.13,0.25]	0.89 [0.76,0.96]		-0.01 [-0.04,0.01]	0.06 [-0.01,0.15]
Health	0.06 [0.01,0.1]	0.17 [0.11,0.2]	0.05 [0,0.12]	0.48 [0.44,0.53]	0.9 [0.84,0.93]	0.9 [0.85,0.97]
			Investment and Parental Skills			
Investment	0.48 [0.38,0.55]	0.49 [0.4,0.55]	-0.04 [-0.08,0.03]	0.2 [0.12,0.28]	0 [-0.03,0.07]	0.04 [-0.02,0.06]
Parent Cog	0.36 [0.32,0.41]	0.17 [0.11,0.22]	0.09 [0.03,0.18]	0.04 [-0.02,0.07]	0.05 [0.03,0.09]	-0.03 [-0.07,0.01]
Parent Health	0.1 [0.02,0.2]	-0.01 [-0.04,0.08]	0.01 [-0.05,0.07]	0.28 [0.2,0.42]	0.05 [0.01,0.1]	0.03 [-0.02,0.1]
			TFP - Demographic Characteristics			
Log TFP	-0.06 [-0.09,0.03]	0.61 [0.54,0.66]	1.15 [1.05,1.25]	-0.34 [-0.39,-0.28]	0.14 [0.09,0.19]	-0.06 [-0.12,-0.01]
Num Child	0.01 [-0.01,0.01]	0 [-0.02,0.01]	-0.01 [-0.04,0]	0.02 [0,0.03]	0 [-0.02,0]	0 [-0.02,0.01]
Older Sibs	-0.01 [-0.03,0]	-0.01 [-0.02,0.01]	0 [-0.01,0.02]	-0.03 [-0.05,-0.01]	0 [-0.01,0.01]	0.01 [0,0.03]
Gender	0.01 [0,0.03]	0.03 [0.01,0.04]	-0.02 [-0.03,0]	0 [-0.01,0.01]	0.01 [0,0.01]	0.01 [0,0.02]
Urban	0 [-0.01,0.01]	-0.02 [-0.02,-0.01]	-0.01 [-0.01,0]	0 [-0.01,0]	0.01 [0,0.01]	0 [-0.01,0]
Hindu	-0.01 [-0.02,0.01]	-0.01 [-0.02,0.01]	0.02 [0,0.04]	0.01 [0,0.02]	0 [-0.01,0.01]	0 [-0.01,0.01]
Muslim	0 [0,0]	0 [-0.01,0]	-0.01 [-0.01,0]	-0.01 [-0.01,0]	0 [0,0]	0 [0,0]
Mother Age	0.01 [0,0.03]	0.01 [0,0.03]	-0.01 [-0.03,0]	0 [-0.01,0.02]	0 [-0.01,0.01]	-0.02 [-0.03,-0.01]
Sched. Caste	0 [-0.02,0.01]	0.02 [0.01,0.03]	0 [-0.02,0.01]	0 [-0.01,0.01]	0 [-0.01,0]	0 [-0.01,0.01]
Sched. Tribe	0.03 [0.02,0.04]	0 [-0.01,0]	0 [-0.01,0.01]	0.01 [0.01,0.02]	-0.02 [-0.02,-0.01]	0 [0,0.01]
BC Caste	-0.01 [-0.03,0]	0 [-0.01,0.01]	0.01 [0,0.02]	-0.02 [-0.03,0]	0.01 [0,0.02]	0 [-0.01,0.01]
			Production function structure and test of exogeneity for investment			
(ρ, ζ)	0.05 [-0.25,0.19]	0.04 [-0.11,0.11]	0.18 [-0.31,0.43]	-0.01 [-0.08,0.04]	0.37 [0.12,0.44]	-0.49 [-0.8,0.24]
Subst. Elast.	1.05 [0.8,1.23]	1.04 [0.9,1.12]	1.21 [0.76,1.74]	0.99 [0.93,1.04]	1.58 [1.14,1.8]	0.67 [0.56,1.31]

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

	Cognition			Health		
Age	5	8	12	5	8	12
				Lagged Skills		
Cognition		0.14 [0.11,0.2]	0.77 [0.66,0.89]		0 [−0.04,0.02]	0 [−0.06,0.15]
Health	0.05 [0.01,0.1]	0.14 [0.09,0.17]	0.03 [−0.01,0.1]	0.48 [0.44,0.52]	0.91 [0.84,0.94]	0.91 [0.84,0.97]
				Investment and Parental Skills		
Investment	0.55 [0.45,0.64]	0.62 [0.53,0.71]	0.18 [0.06,0.27]	0.28 [0.17,0.38]	0.01 [−0.03,0.08]	0.12 [−0.02,0.18]
Parent Cog	0.33 [0.27,0.39]	0.15 [0.08,0.2]	0.03 [0,0.14]	0 [−0.06,0.04]	0.04 [0.02,0.08]	−0.05 [−0.1,0]
Parent Health	0.07 [0,0.17]	−0.05 [−0.09,0.01]	−0.02 [−0.06,0.04]	0.24 [0.16,0.37]	0.05 [0.01,0.09]	0.02 [−0.03,0.1]
				TFP - Demographic Characteristics		
Log TFP	−0.07 [−0.14,0.03]	0.69 [0.54,0.76]	1.08 [0.99,1.22]	−0.38 [−0.45,−0.28]	0.08 [0.04,0.17]	−0.09 [−0.2,0]
Numb Child	0 [−0.02,0.01]	−0.01 [−0.02,0.01]	−0.02 [−0.04,−0.01]	0.01 [−0.01,0.03]	0 [−0.02,0]	0 [−0.02,0.01]
Older Sibs	−0.01 [−0.03,0.01]	−0.01 [−0.03,0]	0.01 [−0.01,0.02]	−0.02 [−0.05,−0.01]	0 [−0.01,0.01]	0.01 [0,0.03]
Gender	0.01 [0,0.03]	0.03 [0.01,0.04]	−0.02 [−0.03,−0.01]	0 [−0.01,0.01]	0.01 [0,0.01]	0.01 [0,0.02]
Income	0.03 [−0.02,0.09]	−0.1 [−0.15,−0.01]	0.01 [−0.08,0.05]	0.04 [−0.02,0.07]	0.05 [−0.01,0.07]	0 [−0.05,0.06]
Urban	0 [−0.01,0.01]	−0.01 [−0.02,0]	−0.01 [−0.02,0]	0 [−0.01,0]	0.01 [0,0.01]	0 [−0.01,0]
Hindu	−0.01 [−0.02,0.01]	−0.01 [−0.02,0]	0.01 [0,0.03]	0.01 [0,0.02]	0 [−0.01,0.01]	−0.01 [−0.01,0.01]
Muslim	0 [0,0]	0 [0,0]	−0.01 [−0.01,0]	0 [−0.01,0]	0 [0,0]	0 [0,0]
Mother Age	0.01 [0,0.03]	0.02 [0.01,0.03]	−0.01 [−0.03,0]	0 [−0.01,0.01]	0 [−0.01,0.01]	−0.02 [−0.03,−0.01]
Sched. Caste	−0.01 [−0.02,0]	0.01 [0.01,0.02]	0 [−0.01,0.01]	0 [−0.01,0.01]	0 [−0.01,0]	0 [−0.01,0.01]
Sched. Tribe	0.03 [0.02,0.04]	−0.01 [−0.01,0]	0 [−0.01,0.01]	0.01 [0,0.02]	−0.01 [−0.02,−0.01]	0.01 [0,0.01]
BC Caste	−0.01 [−0.03,0]	−0.01 [−0.02,0.01]	0.01 [0,0.02]	−0.02 [−0.03,−0.01]	0.01 [0,0.02]	0 [−0.01,0.01]
				Production function structure and test of exogeneity for investment		
(ρ, ζ)	−0.02 [−0.37,0.16]	0.12 [0,0.21]	−0.1 [−0.36,0.1]	0 [−0.07,0.05]	0.34 [0.07,0.43]	−0.09 [−0.59,0.12]
Elasticity of Subst.	0.98 [0.73,1.19]	1.13 [1,1.27]	0.91 [0.74,1.11]	1 [0.94,1.05]	1.52 [1.07,1.76]	0.92 [0.63,1.14]
Inv. Res	−0.86 [−1.27,−0.31]	−0.47 [−0.62,−0.34]	−0.28 [−0.41,−0.09]	−0.86 [−1.23,−0.53]	0 [−0.09,0.09]	−0.09 [−0.17,0.04]

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 15: Production of Cognitive Skills and Health without Income as Instrument for Investment or Control Variable

	Cognition			Health		
Age	5	8	12	5	8	12
				Lagged Skills		
Cognition		0.13 [0.09,0.19]	0.9 [0.74,1.02]		0 [−0.04,0.02]	0.07 [−0.05,0.16]
Health	0.05 [0.01,0.1]	0.13 [0.08,0.17]	0.05 [0,0.12]	0.48 [0.44,0.52]	0.9 [0.84,0.93]	0.9 [0.85,0.97]
				Investment and Parental Skills		
Investment	0.52 [0.42,0.59]	0.77 [0.61,0.89]	−0.05 [−0.23,0.15]	0.24 [0.16,0.33]	−0.03 [−0.08,0.05]	0.03 [−0.09,0.17]
Parental Cognition	0.35 [0.3,0.4]	0.08 [−0.02,0.15]	0.09 [0.03,0.19]	0.02 [−0.04,0.06]	0.06 [0.04,0.1]	−0.03 [−0.09,0.02]
Parental Health	0.08 [0.01,0.19]	−0.1 [−0.15,−0.02]	0.01 [−0.05,0.07]	0.26 [0.18,0.38]	0.07 [0.03,0.11]	0.03 [−0.02,0.1]
				TFP - Demographic Characteristics		
Log TFP	−0.05 [−0.07,0.04]	0.54 [0.47,0.6]	1.15 [1.04,1.26]	−0.33 [−0.38,−0.27]	0.15 [0.09,0.21]	−0.06 [−0.13,0]
Numb Child	0 [−0.01,0.01]	−0.01 [−0.02,0.01]	−0.01 [−0.03,0]	0.01 [−0.01,0.03]	0 [−0.01,0]	0 [−0.02,0.01]
Older Siblings	−0.01 [−0.03,0]	−0.01 [−0.03,0]	0 [−0.01,0.02]	−0.03 [−0.05,−0.01]	0 [−0.01,0.01]	0.01 [0,0.03]
Gender	0.01 [0,0.03]	0.03 [0.01,0.04]	−0.02 [−0.03,0]	0 [−0.01,0.01]	0.01 [0,0.02]	0.01 [0,0.02]
Urban	0 [0,0.01]	−0.01 [−0.02,0]	−0.01 [−0.01,0]	0 [−0.01,0]	0.01 [0,0.01]	0 [−0.01,0]
Hindu	−0.01 [−0.02,0.01]	−0.01 [−0.02,0]	0.02 [0,0.04]	0.01 [0,0.02]	0 [−0.01,0.01]	0 [−0.01,0.01]
Muslim	0 [0,0]	0 [0,0]	−0.01 [−0.01,0]	0 [−0.01,0]	0 [0,0]	0 [0,0]
Mother Age	0.01 [0,0.03]	0.02 [0.01,0.03]	−0.01 [−0.03,0]	0 [−0.01,0.01]	0 [−0.01,0.01]	−0.02 [−0.03,−0.01]
Sched. Caste	−0.01 [−0.02,0]	0.01 [0,0.02]	0 [−0.01,0.01]	0 [−0.01,0.01]	0 [−0.01,0]	0 [−0.01,0.01]
Sched. Tribe	0.03 [0.02,0.04]	−0.01 [−0.01,0]	0 [−0.01,0.01]	0.01 [0,0.02]	−0.02 [−0.02,−0.01]	0 [0,0.01]
BC Caste	−0.01 [−0.03,0]	−0.01 [−0.02,0.01]	0.01 [0,0.02]	−0.02 [−0.03,−0.01]	0.01 [0,0.02]	0 [−0.01,0.01]
				Production function structure and test of exogeneity for investment		
(ρ,ζ)	0.04 [−0.28,0.18]	0.05 [−0.06,0.17]	0.17 [−0.37,0.36]	−0.01 [−0.07,0.04]	0.29 [0.07,0.41]	−0.55 [−0.71,0.19]
Elasticity of Subst.	1.04 [0.78,1.23]	1.05 [0.94,1.21]	1.21 [0.73,1.57]	0.99 [0.93,1.04]	1.41 [1.08,1.7]	0.65 [0.58,1.23]
Inv. Res.	−0.58 [−1.01,−0.07]	−0.59 [−0.74,−0.43]	0.01 [−0.23,0.24]	−0.59 [−0.98,−0.35]	0.1 [−0.03,0.18]	0.01 [−0.16,0.11]

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.