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ABSTRACT

In this paper we estimate production functions for cognition and health throughout four stages of childhood from 5-15 years of age using two cohorts of children drawn from the Young Lives Survey for India. The inputs into the production function include parental background, prior child cognition and health and child investments. We allow investments to be endogenous and they depend on local prices and household income, as well as on the exogenous determinants of cognition and health. We find that investments are very important determinants of child cognition and of health at an earlier age. We also find that inputs are complementary and crucially that health is very important in determining cognition. Our paper contributes in understanding how early health outcomes are important in child development.

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1 Introduction

In emerging and rapidly developing countries such as India, a high level of human capital may offer a way to escape poverty and take advantage of the new opportunities that arise. However, soon after birth (if not before), children from poorer backgrounds fall behind in every aspect of human capital development, including health and cognition, potentially depriving them of such opportunities.[1] It is thus important to understand how human capital is formed. In particular, what role can investment in children play and what is the relative importance of family background, family composition and parental behavior in driving children's development.

There is strong evidence showing that children's early experiences have long lasting effects, with implications for adult outcomes and even inter-generational transmission of human capital. Yet we still do not fully understand the mechanisms through which the many components of human capital develop and how different inputs interact in a dynamic fashion to shape the overall development of a child. There is growing consensus on the presence of important dynamic complementarities and interactions among different inputs and factors, but very few studies have quantified the importance of these interactions.[2]

This paucity of evidence is partly explained by the small number of longitudinal data following children over time; by the intrinsic difficulty of obtaining high quality measures of development in different domains; by the difficulty in measuring

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

[2]See Currie and Almond (2011), Cunha, Heckman, and Schennach (2010), Cunha and Heckman (2007), and Heckman (2007). We discuss this literature in more detail below

inputs for children; and by the fact that these inputs are not assigned exogenously but determined by individual choices. As a result, our understanding of how the components of human capital are formed is relatively limited. And yet, if we are to design interventions that will increase human capital and thereby improve individual productivity, this is critical, particularly in the context of rapidly growing economies like India.

In this paper, we study the dynamic production of cognition and health - two important constituents of human capital- throughout childhood. We focus on these dimensions of human capital because both are likely to be key determinants of productivity and the ability to acquire future skills through more advanced education. Furthermore, there are likely to be important interactions between these two factors that we cannot understand by examining one or the other in isolation.

Studying the development of the constituents of human capital is particularly important given the evidence regarding their sensitivity to environmental factors, positive or negative. For example, cognition and health are both vulnerable to environmental risks that range from the presence of pollutants and sources of infection, to insufficient nutritional resources, to micronutrient deficiencies, to the lack of affection and stimulation.[3] Poverty has been shown to be an important determinant of the exposure to such risk factors. There is evidence that poorer children are more vulnerable to early life shocks and that they experience more frequent and larger

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

early life shocks (see Case, Lubotsky, and Paxson (2002), Currie and Hyson (1999) and Currie and Stabile (2003)).

Fortunately, a number of studies have shown that some of the deficits acquired through poverty can be reversed by well designed interventions. This is particularly true for cognition, often via improvements in health. An important example is the Jamaica home visiting intervention whose long term effect on cognition is described in Walker, Chang, Powell *et al.* (2005) and has also been shown to have labour market impacts by Gertler, Heckman, Pinto *et al.* (2013).[4] The Jamaica intervention has been replicated in various modified forms: for example Attanasio, Fernández, Fitzsimons *et al.* (2014) report that their scaleable intervention produced 26% of a standard deviation improvement in cognition. Other interventions on nutrition have also had spectacular positive results on poor populations as shown in Hoddinott, Maluccio, Behrman *et al.* (2008).[5] A number of authors have pointed to this link between health and child development. For example, Figlio, Guryan, Karbownik *et al.* (2013) find that in the U.S. context, early health effects on cognition are constant throughout children's school careers and invariant to school quality and

[4]A relatively comprehensive description of the state of knowledge for ECD interventions is given in Engle, Black, Behrman *et al.* (2007).

[5]Bharadwaj, Løken, and Neilson (2013) find that low birth weight infants effectively randomized to receive extra medical care have lower mortality rates and better test scores and grades. Banerjee, Cole, Duflo *et al.* (2007) show that lagging children improve test scores following a remedial education intervention. Miguel and Kremer (2004) find that a deworming intervention improves health and school attendance, but does not affect test scores. Grantham-McGregor, Powell, Walker *et al.* (1991) find that early life nutritional supplementation and stimulation have independent beneficial effects on children's development. Lucas, Morley, and Cole (1998) find that preterm infants fed standard versus nutrient enriched formulas had reduced IQ scores at 7.5-8 years old, particularly among boys. Sazawal, Bentley, Black *et al.* (1996) find that zinc supplementation improved observed activity levels among low income children in India. Heckman, Moon, Pinto *et al.* (2010) find substantial economic benefits from preschool education programs. All of these studies utilized randomized experiments.

family background.[6]

The implication of this literature is that appropriate policy can play a key role in fighting poverty in the long term. This naturally brings us to the role of health and cognition in driving investments in children. For example it may well be the case that parents invest less in unhealthy children with low cognitive skills because they perceive the returns to be low. On the other hand, parents may compensate for the effect of transitory shocks, particularly if they believe that by investing more they can overcome the resulting disadvantage, in which case the return is very high. Delivering interventions and ensuring they are sustained through time involves understanding how parents make investment decisions, how these decisions are affected by their own and their child's background, and how effective investments are in changing the course of development of these children. Underlying parental decisions will be the technology of human capital formation as well as the overall opportunities offered by the economic environment. In this sense India is a particularly interesting country because the growing economic opportunities, at least in urban areas, may offer the right incentives for parents to invest, while at the same time poor children suffer huge amounts of deprivation as we document later in the paper.

Our aim in this paper is to explore the link between cognition and health and to provide a better understanding on how both these constituents of human capital are determined during childhood. We pay particular attention to modeling investments in children based both on child and family background as well as exogenous cost

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

shifters, such as prices of relevant goods.

Our approach consists of estimating a joint model for the production of cognition, health, and parental investment decisions for four different stages of life. In our model, cognition and health are produced by parental background, the past levels of cognition and health for the child, and investments by parents. Importantly the production functions allow for complementarity between the various background variables and investments, generating heterogeneity in responses and allowing for the possibility that the timing of investments for children matters in a crucial way. The importance of such complementarities has been stressed in the seminal paper by Cunha, Heckman, and Schennach (2010) on whose approach we build.

Our data is drawn from the Young Lives Survey for India. The Young Lives project has collected a unique data set focusing on child development in four different countries: India, Vietnam, Ethiopia and Peru. It covers children from age one to age fifteen in two different cohorts. The younger cohort includes children surveyed at ages 1, 5 and 8, while the older cohort includes children surveyed at 8, 12 and 15.[7] The first survey for each cohort occurred in 2002. Information in the data covers household and parental characteristics as well as numerous measures of child cognitive and health outcomes. This is important since the method we use relies on having multiple measures for each underlying latent factor.

Our approach advances the existing literature in a number of ways. First, we consider the interaction of health and cognition over the entirety of childhood, from

[7]More specifically, at the start of the first round the younger cohort is between 6 and 18 months and the older cohort is between ages 7.5 and 8.5. This implies that the younger cohort was born between 2000-2002 and the older cohort was born between 1994-1996.

birth up to age 15. This allows us to identify the ages that are most sensitive to health and cognition interventions and how health and cognition may feed into each other. Second, we look at investments over many ages, the way investments relate to family background and family structure, and we are able to account for the endogeneity of investments. These issues have been central to the literature, but our dynamic framework allows for a better understanding of the process over ages.[8]

Last, we contribute to the literature on nonlinear factor models, building on the framework of Cunha, Heckman, and Schennach (2010). We develop an estimation approach that combines maximum likelihood estimation using the EM algorithm (see Dempster, Laird, and Rubin (1977) and Arcidiacono and Jones (2003)) with simulation methods and the control function approach to account for the endogeneity of investments. The advantage of our approach is that it is both flexible and easy to use, even when we allow for complex distributions of the underlying latent factors.

In the remainder of the paper we first present our model for the production of cognitive skills and health over the child's life-cycle in Section 2, discussing in detail our model for parental investments. In Section 3 we discuss the main econometric challenges: the endogeneity of investments and the unobservability of our main variables of interest. We also introduce and describe a relatively simple computational approach to deal with estimating the model. In Section 4 we describe the data and in Section 5 we present the results. In Section 6 we conclude.

[8]In China, Rosenzweig and Zhang (2009) find evidence for a modest effect of family size on later educational outcomes. Rosenzweig and Wolpin (1988) show the importance of accounting for endogenous parental investment behavior to obtain unbiased estimates of the effects of parental investments. Dunbar, Lewbel, and Pendakur (2013) show that in Malawi resources toward children depend on family structure.

2 The Development of Child Cognitive Skill and Health: A Conceptual Framework

In this section, we define the conceptual framework we use to study the cognitive and health development of children, their interaction, and how they are effected at different ages by environmental factors and parental choices. We define the child life cycle as consisting of distinct periods indexed by t. At birth, each child is endowed with a stock of health and cognitive skills denoted by $\{\theta_{c,0}, \theta_{h,0}\}$.

Between any two periods, the child's cognitive skills and health stock will change as a result of five main inputs: the previous period stock of health and cognitive skills $\{\theta_{c,t}, \theta_{h,t}\}$, the amount of investments $\theta_{I,t}$, the parental stock of health θ_{ph}, and the parental stock of cognitive skills θ_{pc}. We assume that parental health and cognitive skills are fixed at their current levels. 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.

We avoid the assumption that these five inputs enter the production of cognitive skills and health stock in a separable fashion. Instead, we allow for the possibility of complementarities between the various factors. While more flexible functional forms are possible, we assume a Constant Elasticity of Substitution (CES) where the degree of complementarity between the different inputs is governed by a single parameter. In addition, we let the total factor productivity be a function of a number of observable variables as well as an unobservable shock. We let all the parameters of the production functions vary with the age of the child. In particular, we consider the following specification for cognitive skills ($\theta_{c,t+1}$) and health ($\theta_{h,t+1}$) respectively at age $t+1$:

$$\theta_{c,t+1} = \left(\delta_{c,t}\theta_{c,t}^{\rho_t} + \delta_{h,t}\theta_{h,t}^{\rho_t} + \delta_{pc,t}\theta_{pc}^{\rho_t} + \delta_{ph,t}\theta_{ph}^{\rho_t} + \delta_{I,t}\theta_{I,t}^{\rho_t}\right)^{\frac{1}{\rho_t}} A_{c,t} \tag{1}$$

$$A_{c,t} = exp\left(\delta_{0,t} + \delta_{X,t}X_t + u_{c,t}\right)$$

$$\theta_{h,t+1} = \left(\alpha_{c,t}\theta_{c,t}^{\zeta_t} + \alpha_{h,t}\theta_{h,t}^{\zeta_t} + \alpha_{pc,t}\theta_{pc}^{\zeta_t} + \alpha_{ph,t}\theta_{ph}^{\zeta_t} + \alpha_{I,t}\theta_{I,t}^{\zeta_t}\right)^{\frac{1}{\zeta_t}} A_{h,t} \tag{2}$$

where

$$A_{h,t} = exp\left(\alpha_{0,t} + \alpha_{X,t}X_t + u_{h,t}\right)$$

The parameters of the prodution function (the $\delta_t's$ the $\alpha_t's$, ρ_t and ζ_t), all vary with age t. ρ_t and ζ_t control the elasticity of substitution between the various inputs in the cognition and health production function respectively. u_{ct} and u_{ht} are shocks to child cognition and health respectively. Total factor productivity depends on X_t, which includes family composition, birth order, and gender.

The specification has a number of important features. First, the cognitive and health background of parents, as well as the investment choices they make, are assumed to be determinants of child development. Second, past levels of the child's cognition and health affect the outcomes in the next stage: this is important because it allows for long term persistence of past investments. Third, the marginal product of each input depends on the value of the others depending on the value of the substitution elasticity, implying the possibility of important complementarities, both among different inputs and, given the presence of lagged levels of development, over time. The fact that parameters are allowed to change over time also implies that this structure can capture the presence of critical periods in child development.

The CES specification, while potentially restrictive in some dimensions, also has important advantages. In particular, it allows as special cases a linear specification in which the marginal product of different inputs does not depend on the level of other inputs (separability) and the Cobb-Douglas case of unit elasticity (which applies when ρ and ζ converge to zero).

Notice that within this framework, policy can impact child development in different ways. Most obviously, it can directly increase investment in children $\theta_{I,t}$. Policy could also change the parameters of the production function and make some or all inputs more productive. Furthermore, policy can induce parents to change their investment behavior by relaxing some resource constraints, changing parents' beliefs about the production function, or by affecting their tastes.

2.1 Parental investments

While at any point in time current health and cognition of the children and parental characteristics are predetermined, future outcomes may change as a result of investments, given by θ_I. More generally, we can think of this factor as the conduit of possible interventions. In our framework, θ_I is a composite of time and resources that parents need to decide to allocate to children.

We assume parents derive utility from their own consumption and from the future well-being of their children. This combination makes their problem inherently dynamic. In each period, parents need to decide how much to invest, trading current investments off against future investments and own consumption. When making these decisions, parents take into account the entire sequence of production functions we specified above. The resulting investment at a given point in time will depend on the current information set, including the child's current ability and, importantly, shocks to the production function u_{ht} and u_{ct} as well as variables determining the budget constraint of the household. These include prices q and income Y. Thus the investment function at any point in time will take the following general form, in which the effects of current information are mediated by individual tastes, the parameters of the production function, and the budget constraint:

$$\theta_{I,t} = \theta_{I,t}\left(q_t, Y_t \,|\, \theta_{c,t}, \theta_{h,t}, \theta_{pc}, \theta_{ph}, u_{h,t}, u_{c,t}, X_t\right)$$

Rather than making specific assumptions about parental tastes and deriving the investment function that such preferences (and information sets) would imply, we approximate it using a log-linear specification which takes the form:

$$ln\theta_{I,t} = \gamma_0 + \gamma_{c,t} ln\theta_{c,t} + \gamma_{h,t} ln\theta_{h,t} + \gamma_{pc,t}\theta_{pc} + \gamma_{ph,t} ln\theta_{ph} + \gamma^{'}_{X,t} X_t + \gamma^{'}_{q,t} lnq_t + \gamma_Y lnY + v_{I,t} \tag{3}$$

where v_{It} is an error term. Importantly, we allow this to be correlated with the shocks to health and to cognitive human capital. The interpretation is that when parents decide upon investments they take into account both the observables summarized above as well as the unobserved shocks.

In addition to all the background variables, investments also depend on prices and parental resources which together determine the budget constraint. These variables play an important role in the identification of the production function, as we assume they do not affect production of health and cognition directly. Especially in the case of prices, it is not unreasonable to assume that households take them as given when choosing investments. For this approach to work, we also need to assume that the technology of child development and household preferences remain constant across markets that we are comparing. Finally, note that all the coefficients of equation (3) depend on the life-cycle stage (t), since the investment decision may change with the age of the child both because the productivity of investments may vary and because parental preferences may change.

3 Econometric issues and estimation

There are two key econometric challenges in estimating the model we sketched above. First, investments are endogenous: that is, when choosing investments, households may react to the production function shocks $u_{h,t}$ and $u_{c,t}$. Second, many of the variables we have considered in the model (all those denoted by θ) are not directly observable.

In this section, we first discuss how we deal with the endogeneity of investments. We then discuss how we adapt and use the nonlinear factor model approach, introduced by Cunha, Heckman, and Schennach (2010), to identify our underlying variables of interest using observable measurements in the data. Last, we present a new estimation approach to estimate the entire problem.

3.1 Endogenous investments: A control function approach

We re-write the production functions in a log linear fashion. Equations (1) and (2) become:

$$ln\theta_{c,t+1} = \frac{1}{\rho_t} ln\left(\delta_{c,t}\theta_{ct}^{\rho_t} + \delta_{h,t}\theta_{h,t}^{\rho_t} + \delta_{pc,t}\theta_{pc}^{\rho_t} + \delta_{ph,t}\theta_{ph}^{\rho_t} + \delta_{I,t}\theta_{I,t}^{\rho_t}\right) + \delta_{c,t} + \delta_{X,t}X_t + u_{c,t}$$

$$ln\theta_{h,t+1} = \frac{1}{\zeta_t} ln\left(\alpha_{c,t}\theta_{c,t}^{\zeta_t} + \alpha_{h,t}\theta_{h,t}^{\zeta_t} + \alpha_{pc,t}\theta_{pc}^{\zeta_t} + \alpha_{ph,t}\theta_{ph}^{\zeta_t} + \alpha_{I,t}\theta_{I,t}^{\zeta_t}\right) + \alpha_{h,t} + \alpha_{X,t}X_t + u_{h,t}$$

Denote the vector of factors dated t (excluding investment $\theta_{I,t}$) by θ_t^*. Then our identifying assumption is:

$$\begin{aligned} E\left(u_{c,t}|\theta_t^*, \theta_{I,t}, X, q, Y\right) &= \kappa_c v_{I,t} \\ E\left(u_{h,t}|\theta_t^*, \theta_{I,t}, X, q, Y\right) &= \kappa_h v_{I,t} \end{aligned} \tag{4}$$

Equation (4) says that the expectation of the production function residuals, conditional on the arguments of the production function (including investment), are a linear function of the residuals of the investment equations. The κ parameters can depend on conditioning variables such as θ_t^*, X, q and Y. The residual v_I is known as a control function and underlies the work of Gronau (1974), and Heckman (1979) and the vast literature that followed. A sufficient condition for this linear conditional expectation to be true is joint normality of the shocks. However, the linearity is not an essential part of the argument: allowing the conditional expectation to be a general function of the residuals is equivalent to allowing for any joint distribution of the unobservables.[9]

Given the control function assumption, if all factors and the instruments were observable with no measurement error, estimation would be a relatively simple non-linear least squares problem where a consistent estimate of $v_{I,t}$ is added as a regressor on the right hand side of the (log-linearized) production functions. A consistent estimate of $v_{I,t}$ can be obtained in a first step, estimating the investment function in equation (3). The problem with such a simple strategy, however, is that we do not observe the factors θ, but only proxies thereof. We now discuss how to deal with this second challenge.

3.2 A factor structure for the measurements of skills and investments

The various factors we discussed above (cognition, health, parental background, and investments) are not directly observable. Instead, in our data we have a large number of measurements that can be thought of as imperfectly reflecting cognition and health of parents and children as well as parental investments. We use a framework that explicitly recognizes the difference between the theoretical concepts in the context of the production functions and the available measurements. This framework allows us

[9]See Newey, Powell, and Vella (1999) and Florens, Heckman, Meghir *et al.* (2008).

to think of the large number of measurements in the data as proxying more or less well our factors, rather than assuming that any one of them reflects exactly what we understand to be the entire stock of health, cognition, or investments. We thus follow a factor analytic approach as recently extended to nonlinear models by Cunha, Heckman, and Schennach (2010). This approach is a useful way of summarizing a variety of measures available in the data under the umbrella of the factors in which we are interested.

In what follows, let $m_{j,k,t}$ denote the jth available measurement relating to latent factor k in time t. We assume a semi-log relationship between measurements and factors

$$m_{j,k,t} = a_{j,k,t} + \lambda_{j,k,t} ln\left(\theta_{k,t}\right) + \epsilon_{j,k,t} \tag{5}$$

where $\lambda_{j,k,t}$ is a factor loading which converts the scale of the factor to be consistent with that of the measure. We set the scale of each factor by normalizing the factor loading on one of the measurements to one, so that $\lambda_{1,k,t} = 1$. All log-factors are normalized to have mean zero and thus the coefficients $a_{j,k,t}$ will be estimated by the mean of the measurement. Finally, $\epsilon_{j,k,t}$ are zero mean measurement errors, which capture the fact that the ms are imperfect proxies of the underlying factors. A fundamental identification assumption is that the measurement error is independent of the latent factors. In addition, we also assume measurement errors to be independent of each other. This latter assumption can be relaxed to allow for some correlation among certain measures. However, for each factor, it is necessary to have two measures with independent measurement errors.

In equation (5), we assume that each measurement is affected by only one factor.

This assumption can also be somewhat relaxed. It will be necessary, however, to have some measures that are affected by only one factor. These restrictions are analogous to exclusion restrictions. Under these assumptions, if we denote with K is the number of factors, the availability of at least $2K + 1$ measurements (with at least 2 per factor) is sufficient for the non-parametric identification of the joint distribution of the factors and of measurement error. However, it is computationally simpler to use a parametric approximation.

Our goal is to estimate the eight production functions represented in equations (1) and (2) across all stages of childhood, allowing for endogenous investments. If we observed the set of factors, θ, for each child in our data, this would be a totally straightforward problem. We would first estimate the control function to deal with endogeneity of investments outlined in Section 3.1, and then estimate the CES production functions using nonlinear least squares.

Without observing θ directly, estimation is more complicated. As outlined in this section, this is no longer quite as straightforward, given that we do not observe the factors directly. The only alternative estimation approach that has previously been used to estimate a problem at this level of complexity in the literature is the Unscented Kalman Filter applied in Cunha, Heckman, and Schennach (2010). In the next section, we propose and outline an alternative estimation approach.

3.3 Estimation

Recall that the set of factors we are interested in consist of investment, health and cognition at each stage $(\{\theta_{c,t}\}_{t=2}^{T}, \{\theta_{h,t}\}_{t=1}^{T}, \{\theta_{I,t}\}_{t=1}^{T})$, and parental characteristics

$(\theta_{pc}, \theta_{ph})$. We denote the set of factors θ. Our approach to the estimation of the production function parameters consists of two steps. First, given the measurement system and the observed data, we identify the joint distribution of $ln\theta$, which we denote $f(ln\theta)$. Second, given $f(ln\theta)$, we use it to draw a synthetic dataset of factors, θ, which we can treat as observed and easily estimate the parameters of the production functions using nonlinear least squares.

However, given the specification of the production function, a synthetic set of the unobserved factors is not sufficient for this exercise. The production functions' inputs include, in addition to the unobserved factors, several other variables, such as conditioning variables X and the control function. Therefore, we need the joint distribution of the factors, conditioning variables, and the instruments.

Thus, we augment the set of latent factors with the instruments $(q,\ Y)$ and the conditioning variables X. With the exception of income, these variables are treated as "latent" factors that are measured without error. If additional measurements were available, we could relax this assumption and assume measurements of instruments and conditioning variables are observed with error, as with the latent factors. We are only able to do this with income. We therefore define the following vector of factors, some of which do not have measurement error

$$\theta = \left(\{\theta_{c,t}\}_{t=2}^{T}, \{\theta_{h,t}\}_{t=1}^{T}, \{\theta_{I,t}\}_{t=1}^{T}, \theta_{pc}, \theta_{ph}, X, q, Y\right)$$

Note that the deterministic component of the loglinearized production functions is the conditional mean of the log-cognitive and log-health factors $\theta_{c,t+1}$ and $\theta_{h,t+1}$ respectively, given the other latent factors and the control functions discussed earlier.

When inputs are complementary (as in the case of the CES production function) these conditional means are non-linear, which precludes assuming that the joint distribution of the factors is a multivariate normal distribution, as joint normality implies linear conditional means. Flexibility in the specification of the production functions requires flexibility in the parametric assumptions about the joint distribution of factors observed at different points in time. The goal is to estimate the joint distribution of $ln\theta$, denoted by $f\left(ln\theta\right)$, in a way consistent with the specification of our production functions.

The specification of our measurement system and our assumptions about the nature of measurement error imply a joint distribution of measurements and factors. We demean the set of measurements represented in equation (5) and rewrite it in matrix notation. Define

$$\widetilde{M} = M - A = \Lambda ln\left(\theta\right) + \varepsilon \tag{6}$$

where M is the vector of all measurements for each child, A is the vector of all the measurement means for each child, Λ is the matrix of all of the loadings, and ε is the vector of measurement error terms for each child.

In order to use a flexible joint distribution for the factor capable of allowing for different types of complementarities in the production function, we assume that the joint distribution of the log-factors is a mixture of two normals, $f^A\left(ln\theta\right)$ and $f^B\left(ln\theta\right)$, with mean vectors and variance covariance matrices μ^A, Σ^A and μ^B, Σ^B, respectively and with mixture weight τ. This implies that

$$f\left(ln\theta\right) = \tau f^A\left(ln\theta\right) + \left(1-\tau\right) f^B\left(ln\theta\right)$$

where the $f^A(\cdot)$ and $f^B(\cdot)$ are Normal distributions. Since the measures have all been demeaned we also standardize the log-factors to have mean zero, so that $\tau\mu^A + (1-\tau)\,\mu^B = 0$. One can theoretically obtain even more general distributions by adding further components to this mixture, approximating a wide class of distributions. However, sample sizes will limit the amount of flexibility that is actually empirically possible.

The distribution of the observed measurements is given by

$$f\,(m) = \tau \int g(\tilde{M} - \Lambda\theta) f^A\,(ln\theta)\,d\theta + (1-\tau) \int g(\tilde{M} - \Lambda\theta) f^B\,(ln\theta)\,d\theta$$

which is a mixture of normals itself if the distribution of measurement errors $g(\cdot)$ is normal ($\varepsilon \sim N\,(0, \Sigma^{\varepsilon})$).

This set up allows us to break estimation of the distribution $f\,(ln\theta)$ down into two simple steps: first, we estimate an unconstrained mixture of normals for the distribution of the measurements. In particular, we use we use the Expectation Maximization (EM) algorithm of Dempster, Laird, and Rubin (1977) as further adapted for the mixture of normals by Arcidiacono and Jones (2003)). Further details are provided in the Appendix.

We then use minimum distance to impose the restrictions implicit in the measurement structure above and therefore will identify the distribution of the measurement errors as well as the parameters of the factors' distribution: the mixing parameter τ and the vector of means and covariance matrices for $f^A\,(ln\theta)$ and $f^B\,(ln\theta)$. We provide the equations that link the parameters of the measurement and distribution of factors in the Appendix.

The final stage of our procedure is to estimate the two production functions and the investment equation at each stage of life. We do this by drawing a large sample of observations of all latent factors, including the X, Y and q, from the joint distribution that we have estimated in the first and second steps.

Given this synthetic data set, a simple OLS regression based on equation 3 provides estimates of the determinants of investment. We then construct the residual $\hat{v}_{I,t}$ from this equation to be included as an extra regressor in the production function, allowing us to control for the endogeneity of investments. Last, we apply nonlinear least squares to each of the following two equations, separately for each stage of life:

$$
\begin{aligned}
ln\theta_{c,t+1} &= \frac{1}{\rho_t} ln\left(\delta_{c,t}\theta_{c,t}^{\rho_t} + \delta_{h,t}\theta_{h,t}^{\rho_t} + \delta_{pc,t}\theta_{pc}^{\rho_t} + \delta_{ph,t}\theta_{ph}^{\rho_t} + \delta_{I,t}\theta_{I,t}^{\rho_t}\right) + \\
&\quad + \delta_{c,t} + \delta_{X,t}X_t + \kappa_c \hat{v}_{I,t} + u_{c,t}^{*} \\
ln\theta_{h,t+1} &= \frac{1}{\zeta_t} ln\left(\alpha_{c,t}\theta_{c,t}^{\zeta_t} + \alpha_{h,t}\theta_{h,t}^{\zeta_t} + \alpha_{pc,t}\theta_{pc}^{\zeta_t} + \alpha_{ph,t}\theta_{ph}^{\zeta_t} + \alpha_{I,t}\theta_{I,t}^{\zeta_t}\right) + \\
&\quad \alpha_{h,t} + \alpha_{X,t}X_t + \kappa_h \hat{v}_{I,t} + u_{h,t}^{*}
\end{aligned}
$$

Assuming that investments are exogenous amounts to imposing $\kappa_c = 0$ and $\kappa_h = 0$. This hypotheses can be tested. The results we present below indicate that investment is indeed endogenous. In the Appendix, for completeness, we present Results obtained assuming exogeneity of investment.

To compute the standard errors of our estimates, we need to take into account the entire sequence of estimation steps as well as the noise from the simulation. We do this by using 1000 bootstrap replications.[10]

[10] Using simulated data introduces error that vanishes with the size of the simulated data.

4 Data

We estimate the production functions using data from India drawn from the Young Lives Survey. The Young Lives longitudinal survey, covers 12,000 children in four countries: Ethiopia, India, Peru, and Vietnam. Each survey includes a child questionnaire, a household questionnaire, and a community questionnaire.

The survey began in 2002 with two cohorts of children in each of these countries. In 2002 the younger cohort was between 6 and 18 months and the older cohort was 7.5 to 8.5 years old. The second wave of the survey took place in 2006-2007, and the third wave took place in 2009. The survey is scheduled to continue, following the same children, every three years through 2016.

The surveys are extremely detailed, yielding a wealth of measurements relating to child health and cognition as well as to family background and parental investments in children. We use information from household questionnaires, child questionnaires, and community questionnaires. Through the dynamic latent factor approach that we discussed above, we are able to take full advantage of the level of detail in these surveys in a parsimonious fashion.

In this paper, we focus exclusively on India. In India the younger cohort is composed of 2,000 children from the state of Andhra Pradesh, observed at ages 1, 5, and 8. The older cohort consists of 1,000 children observed at ages 8, 12, and 15. By combining the two cohorts we are able to estimate the production function for cognitive skills and health for the following age periods: 1-5, 5-8, 8-12, and 12-15.

The sampling selected children 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, the Young Lives sample included 98 separate communities. Since Young Lives aims to document child poverty, it deliberately over sampled poor communities. The sample, therefore, is not a representative one. However, households from different socio-economic backgrounds are included.

To give an idea of the main features of our sample, in Table 1, we present descriptive statistics on household characteristics. Among both cohorts, around 75% live in rural communities. On average, household size is about 5.5 for both cohorts. The children in both cohorts, have around 1 additional. The total number of children for the older cohort is about 3 by the time they are 15.

These families are poor. Income is computed by summing over income from all possible sources, including but not limited to income from wages, income from agricultural work, income from trade, income from self-employment, and income from transfers. Mean income is around US$850 per year, for both cohorts in the second round, and rises to around $1450 for both cohorts in the third round (income was not measured in the first round). Note that this increase is consistent with the per capita GDP increase that occurred in Andhra Pradesh from 2006 to 2009. The fraction of households with levels of income less than US$1 per day declines from around 60% in the second wave to around 40% in the third wave. 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 the simple average of three separately computed indices which measure housing quality, consumer durables, and access to services.[11] In the Table, we report the average of this index and its standard deviation. While the mean is not easy to interpret, the evidence on the standard deviation indicates that within our sample there is a considerable degree of heterogeneity in socio-economic background. In what follows, we show how this diversity is associated with diversity in child development.

Table 1: Summary Statistics: Demograph Variables

	Younger Cohort			Older Cohort		
	Age 1	Age 5	Age 8	Age 8	Age 12	Age 15
Demographics						
Number of Children	1.89	2.54	2.54	2.89	3.12	3.12
	1.00	1.08	1.08	1.21	1.39	1.39
Number Older Siblings	0.69	0.98	.	1.55	1.31	.
	1.03	1.12	.	1.72	1.39	.
Household Size	5.42	5.52	.	5.55	5.20	.
	2.37	2.23	.	2.04	1.83	.
Urban Dummy	0.24	0.26	0.26	0.24	0.25	0.26
Measures of Economic Well Being						
Annual Income	.	882	1,576	.	846	1,351
	.	1,241	3,689	.	934	1,845
Wealth Index	0.41	0.46	0.51	0.41	0.47	0.52
(st.dev)	(0.20)	(0.20)	(0.18)	(0.21)	(0.20)	(0.18)
Percent Below $2 Per Day	.	0.63	0.44	.	0.62	0.42
Observations		1950			994	

NOTE.- For all categorical variables, higher values are better. Income is annual income in the past 12 months in USD. At ages 5 and 12, 1USD≅45INR. At ages 8 and 15, 1USD≅49INR. Income consists of earnings from all sources, including but not limited to wage work, agricultural work, self-employment and other transfers. Standard errors are reported below the estimates, as applicable.

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

In Table 2, we report information on the children. In the younger cohort, 54% of children are male while in the older cohort, 49% of the children are male. These children exhibit high levels of malnutrition at baseline. The picture that emerges considering height per age z-scores, which are considered good markers of the nutritional status of children, revealing information about the 'stock' of nutrition, is revealing. While at age 1, the average height per age z-score for the younger cohort is -1.30 (that is 1.3 standard deviations below the median of a healthy population), at age 5 it is as low as -1.65, to improve slightly at age 8 to -1.45. Among the older cohort, at age 5 the average younger cohort, aged 1 at baseline, 33% were underweight, and 31% were stunted. Among the older cohort, aged approximately 8 at baseline, the average z-score for height per age is -1.56, which becomes -1.64 by age 15. For the younger cohort, 36% of the children at stunted at age 5, while for the older cohort 33% are stunted at age 8.

Table 2 also reports information on questions about the general health status of the cohorts' children, as reported by their parents. In the first two waves, this was on a scale from 0 to 2, while in the third wave on a scale from 1 to 5, with a lower number signifying worse health.

The last part of Table 2 reports information on the children's cognitive development. In particular, in the Table, we report information on the Raven Progressive Matrices Tests and on (self reported) reading and writing levels, with the former being on a scale from 1 to 4 and the latter on a scale from 0 to 2. Once again, we notice a certain level of heterogeneity among the cohorts' children. In addition to this information, the survey also contains information on PPVT tests of language

Table 2: Summary Statistics: Child Measurements

	Younger Cohort			Older Cohort		
	Age 1	Age 5	Age 8	Age 8	Age 12	Age 15
Gender (male)	0.54	0.54	0.54	0.49	0.49	0.49
Health Measures						
Height for Age Z-Score	-1.30	-1.65	-1.45	-1.56	-1.53	-1.64
	(1.48)	(0.99)	(1.04)	(1.03)	(1.04)	(1.00)
Weight for Age Z-Score	-1.52	-1.86	-1.87	-1.96	.	.
	(1.09)	(0.93)	(1.06)	(1.03)	.	.
Weight in kg	7.88	15.02	19.67	19.44	31.70	41.33
	(1.16)	(1.93)	(3.06)	(2.97)	(6.72)	(7.98)
Fraction Stunted						
Fraction Underweight						
Fraction Wasted						
How is Child's Health? (0-2)	1.24	1.26	.	1.30	1.25	.
	(0.67)	(0.65)	.	(0.62)	(0.68)	.
How is Child's Health? (1-5)	.	.	3.93	.	.	4.01
	.	.	(0.68)	.	.	(0.60)
Cognitive Measures						
Rasch Score PPVT Test	.	300.00	300.01	.	300.00	300.00
	.	(50.00)	(15.00)	.	(50.00)	(15.00)
Rasch Score Math Test	.	.	300.02	.	300.00	300.00
	.	.	(14.98)	.	(50.00)	(14.99)
Rasch Score CDA Test	.	300.00	.	.	.	.
	.	(49.99)	.	.	.	.
Rasch Score Egra Test	.	.	300.00	.	.	.
	.	.	(15.00)	.	.	.
Rasch Score Cloze Test	.	.	.	.	.	300.00
	.	.	.	.	.	(15.00)
Ravens Total Correct (0-36)	.	.	.	22.97	.	.
	.	.	.	(5.30)	.	.
Child's Reading Level (1-4)	.	.	.	3.08	3.66	.
	.	.	.	(1.05)	(0.79)	.
Child's Writing Level (0-2)	.	.	.	1.34	1.19	.
	.	.	.	(0.78)	(0.51)	.
What is 2x4? (1 if correct)	.	.	.	0.90	.	.
Observations		1950			994	

NOTE.- For all categorical variables, higher values are better. Z-scores are computed relative to WHO international standards, Rasch scores are internally standardized. Standard deviations are reported in parentheses.

development. As these tests are internally standardized, we do not comment on them but do report them to summarize in the Table what is available. However, in what follows, we relate these measures to the wealth index.

Figure 1: Wealth Gradients in Height

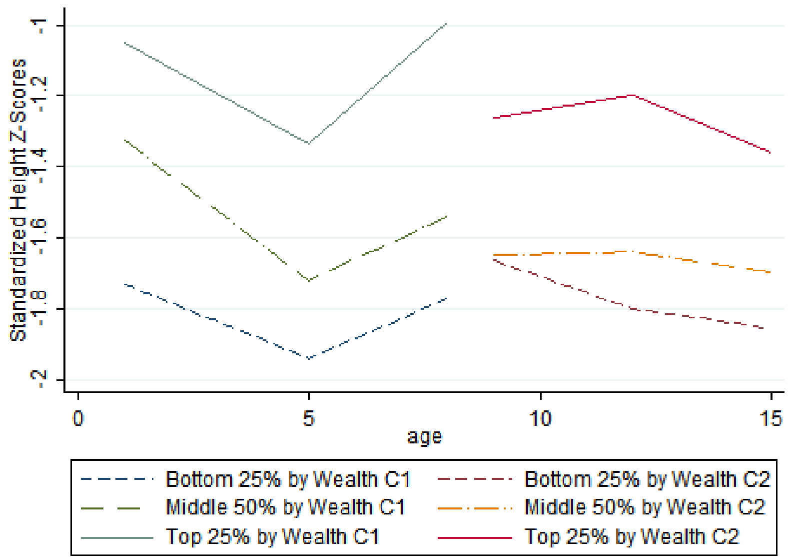
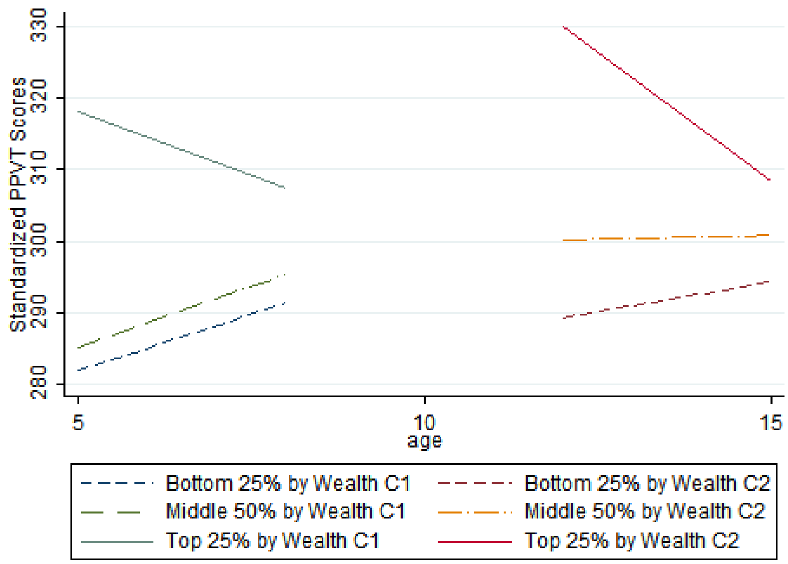


Figure 2: Wealth Gradients in PPVT Score



In Figures 1 and 2, we plot z-scores for height per age and standardized PPVT scores against age for three groups of children: those living in families in the bottom 25% of the wealth index, those around the median wealth index and those in the top 75% of the wealth index. In the case of the first cohort, the differences between the bottom 25% and the top 75% of the wealth distribution in height per age is about 0.8 of a standard deviation of the z-score at age 1, with the score of the median, slightly closer to the top 75% than to the 25%. These scores get worse at age 5, in particular for the median wealth index, which is closer to the bottom 25%. Finally, by age 8, the difference between the top 75% and the other two groups increases again. The picture for the older cohort is very different. At age 8, there are no large differences between children in the bottom 25% and the median. On the other hand, the top 75% has a score which is .4 of a standard deviation higher. This picture does not change much at subsequent waves.

Moving to differences in language development, we find that, for the younger cohort, at age 5 there are very large differences between the top 75% of the wealth index and the other two groups. The differences decline slightly by age 8. In the old cohorts, the differences at age 12 (again in particular between the top group and the other two groups) are very large and decline considerably by age 15.

This evidence indicates the presence of important differences in child development (as measured by indicators of health status or language development) by socio-economic background. In what follows, we will repeat this exercise using the latent factors we will identify, rather than arbitrary measures of development that are just noisy proxies of underlying human capital. Such an exercise can be seen as a useful way to summarize information from a variety of different indicators as well as a reality check for the latent factor model we will be estimating.

5 Results

In this section, we discuss our empirical results. We start with the assignment of measurements to factors, how well these measurements proxy their assigned factors, and the estimation results for the joint distribution of factors, $f\left(ln\theta\right)$. Next, we discuss the results from estimating the investment functions. Finally, we present our estimates of the parameters of the production functions for cognitive skills and health and discuss their implications.

5.1 The measurement system

A first important step in our exercise is the assignment of measurements to latent factors. For each available measurement in the data, we must decide which (if any) factor it proxies. Depending on age, we have at our disposal different measures of cognition and health. In general not all measurements are available at all ages. However, this is not a concern: the underlying assumption that drives our results is that for each latent factor at each age there should be at least three measures and only two are needed it the factor loading can be taken as known, or equated to a load factor from another age.

For the younger cohort's cognitive skills, we use the Peabody Picture Vocabulary Test (PPVT), a math test, a reading comprehension test (EGRA), and the Cognitive Development Assessment (CDA). For the older cohort's cognitive skills, we use the PPVT, a math test, a verbal test (the cloze test), reading level, the Ravens test, writing level, and a numeracy test. For health we use the z-score for height per age, which captures longer term health and nutrition issues and that for weight per age, which can also reflect shorter term health status. We also use the parental rating of health status, although at age 8 for the younger cohort and age 15 for the older cohort we use the child's rating of health status. For the older cohort we simply use weight at ages 12 and 15, as the WHO does not provide z-score computation algorithms for weight at these ages.

To capture investments, we use a variety of measurements: some examples are amount spent on school fees, books, and clothing for the child, number of meals provided daily, and number of food groups consumed daily. Summary statistics for investment, parental cognition and parental health measurements for both cohorts can be found in Tables A.1 and A.2 in the Appendix.

Given the assignment of measurements to factors, it is important to establish the extent to which the measures we use are informative. This can be examined by computing, for each measurement, the signal to noise ratios, that is the ratio of the variance of the latent factor (as estimated within the specification of our model) to the variance of each measurement. These ratios give an indication of the amount of information included in each measure, given the structure imposed by our measurement model. We report these statistics in Tables 3 for cognition, health, and income at each age for both cohorts, as well as parental health and cognition for each cohort. The signal to noise for the investment measures are reported in Table 4.

From Table 3 it is evident that the measures we use for cognition are highly informative. For instance, with the exception of reading level, writing level, and numeracy, all measures at all ages have signal to noise ratios greater than 40%. A third of the measures have signal to noise ratios greater than 50%. For the health factors, both height and weight z-scores (or in the case of ages 12 and 15, child weight) are very informative at all ages, while the rating of child's health status does not contain much information, except at age 1.

Turning to the investment measurements our main information relates to various expenditures made for the children. Amount spent on fees, shoes, clothing and books play a central role. Perhaps one disadvantage of the Young Lives survey is the absence of sufficiently detailed time use data[12], which restricts us to consider only one type

[12]The survey does ask about time the child spent on a set of activities, but there is not enough information on time spent with parents to use for our purposes.

Table 3: Signal to Noise Ratios for Health, Cognition and Income Measures

Younger Cohort			Older Cohort		
Factor	Measures	% Signal	Factor	Measures	% Signal
Child's Cognitive Skills (Age 8)	PPVT Test	40%	Child's Cognitive Skills (Age 15)	PPVT Test	59%
	Math Test	68%		Math Test	44%
	Egra Test	47%		Cloze Test	44%
Child's Cognitive Skills (Age 5)	PPVT Test	59%	Child's Cognitive Skills (Age 12)	PPVT Test	60%
	CDA Test	43%		Math Test	53%
				Reading Level	17%
Child's Cognitive Skills (Age 1)	.	.	Child's Cognitive Skills (Age 8)	Ravens Test	45%
	.	.		Reading Level	32%
	.	.		Writing Level	13%
	.	.		Numeracy	13%
Child's Health (Age 8)	Height Z-Score	55%	Child's Health (Age 15)	Height Z-Score	49%
	Weight Z-Score	72%		Weight	70%
	Healthy? (1-5)	7%		Healthy? (1-5)	1%
Child's Health (Age 5)	Height Z-Score	69%	Child's Health (Age 12)	Height Z-Score	66%
	Weight Z-Score	76%		Weight	68%
	Healthy? (0-2)	2%		Healthy? (0-2)	4%
Child's Health (Age 1)	Height Z-Score	54%	Child's Health (Age 8)	Height Z-Score	69%
	Weight Z-Score	78%		Weight Z-Score	82%
	Healthy? (0-2)	11%		Healthy? (0-2)	1%
Parental Cognition	Mom Education	82%	Parental Cognition	Mom Education	90%
	Dad Education	53%		Dad Education	43%
	Literacy	43%		Literacy	47%
Parental Health	Mom Weight	44%	Parental Health	Mom Weight	98%
	Mom Height	14%		Mom Height	9%
Income (Age 8)	Income	19%	Income (Age 15)	Income	21%
	Wealth Index	36%		Wealth Index	35%
Income (Age 5)	Income	36%	Income (Age 12)	Income	33%
	Wealth Index	55%		Wealth Index	55%

of investment. However, the measures we do use are sufficiently informative.

Before proceeding with the main set of results, Tables 5 presents the parameters characterizing the form of the distribution of the the two cohorts we observe. In both Tables the first row reflects the mixture weights and the remaining rows are the means of the two normal distributions being mixed - their weighted mean is normalized to zero. From these it is evident that the distributions of the latent factors is not normal.

In Figures 3 and 4, we plot the mean of the health and cognitive factors against age for various percentiles, for both cohorts. This is similar to the descriptive exercise in Figures 1 and 2, except that now, instead of using a specific measure (such as height or the PPVT) we aggregate all the available information in our two factors and, by doing so, control for measurement error. One feature of these figures that should be noticed is that, as in Figures 1 and 2, the main difference seems to be between the children living in households in the top 75% of the wealth index distribution and the other two groups. Second, the graphs for the two cohorts seem to 'line up' more closely than those in Figures 1 and 2 in that the distribution of the latent factors for older cohort in the first wave does not seem as dissimilar from the distribution of the same factors in the third wave for the younger cohort. The interpretation is that a large part of the differences across cohorts was due to measurement error.

Table 4: Signal to Noise Ratios for Investment Measures

Younger Cohort			Older Cohort		
Factor	Measures	% Signal	Factor	Measures	% Signal
				Amount Spent on Fees	24%
	Amount Spent on Books	18%		Amount Spent on Books	14%
	Amount Spent on Clothing	29%		Amount Spent on Clothing	25%
Investment (Age 8)	Amount Spent on Shoes	35%	Investment (Age 15)	Amount Spent on Shoes	13%
	Amount Spent on Uniform	15%		Amount Spent on Uniform	7%
	Meals in Day	3%		Meals in Day	1%
	Food Groups in Day	6%		Food Groups in Day	1%
				Amount Spent on Fees	36%
	Can Help Sick Child? (1-5)	3%		Can Help Sick Child? (1-5)	0.07%
	Can Help Chld in Schl? (1-5)	0.22%		Can Help Chld in Schl? (1-5)	0.07%
	Amount Spent on Books	16%		Amount Spent on Books	13%
Investment (Age 5)	Amount Spent on Clothing	41%	Investment (Age 12)	Amount Spent on Clothing	22%
	Amount Spent on Shoes	39%		Amount Spent on Shoes	35%
	Amount Spent on Uniform	7%		Amount Spent on Uniform	15%
	Meals in Day	2%		Meals in Day	2%
	Food Groups in Day	4%		Food Groups in Day	2%

Table 5: Mixture Weights and Means

Younger Factors	Mixture A	Mixture B	Older Factors	Mixture A	Mixture B
Weights	0.726	0.274	Weights	0.351	0.649
Cognition 8	0.243	-0.198	Cognition 15	0.355	-0.192
Cognition 5	0.325	-0.264	Cognition 12	0.407	-0.22
.	.	.	Cognition 8	0.379	-0.205
Health 8	0.281	-0.229	Health 15	0.293	-0.159
Health 5	0.236	-0.192	Health 12	0.29	-0.157
Health 1	0.19	-0.154	Health 8	0.243	-0.131
Investment 8	0.246	-0.2	Investment 15	0.512	-0.277
Investment 5	0.24	-0.195	Investment 12	0.496	-0.268
Parental Cognition	0.528	-0.429	Parental Cognition	0.738	-0.399
Parental Health	0.414	-0.337	Parental Health	0.497	-0.268
Income 8	0.288	-0.234	Income 15	0.56	-0.303
Income 5	0.421	-0.343	Income 12	0.603	-0.326

Figure 3: Wealth Gradients in Latent Health

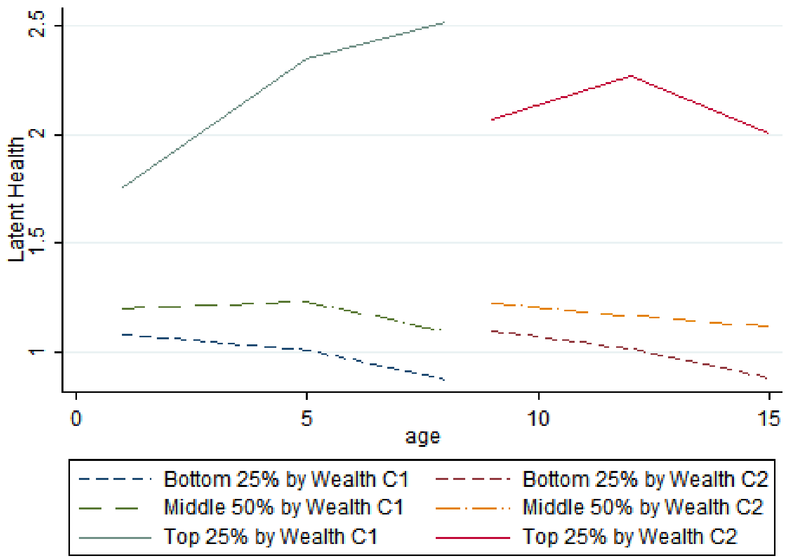
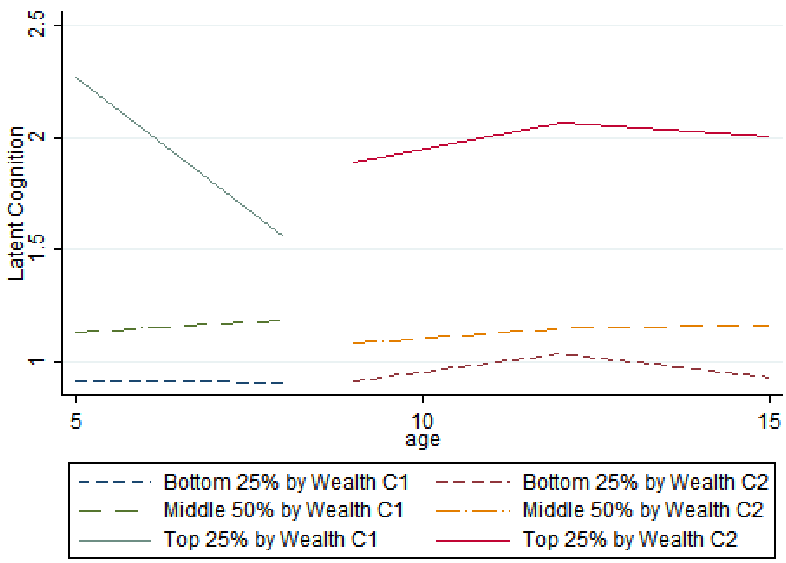


Figure 4: Wealth Gradients in Latent Cognitive Skill



5.2 The determinants of parental investments in children

The determinants of parental investments are interesting in their own right, as their characterization is informative about the factors that lead parents to invest in their children. Furthermore, these parameters provide information regarding the scope for policy to change investments by shifting the determinants of investment, rather than increasing investment directly.

The investment function we estimate is given by the following equation:

$$log(\theta_{I,t}) = \beta_{0t}+\beta_{1t}log(\theta_{c,t})+\beta_{2t}log(\theta_{h,t})+\beta_{3t}log(\theta_{pc,t})+\beta_{4t}log(\theta_{ph,t})+\beta_{5t}Z_t+\beta_{6t}X_t+v_t$$

This investment equation reflects an approximation to an endogenous parental decision rule. It is a log linear function of child cognition and health in the previous period of childhood, parental health and cognition, and a set of household and locality-specific variables X and Z respectively. Parental cognition and health reflect both tastes and long term capabilities of parents. They can affect investments both because they reflect tastes, but also because they can affect returns to investment. Child health and cognition may be relevant because they may also affect the return to investments. We include prices and income to capture the household budget constraint focussing on goods that are relevant for children, i.e. food, clothing, notebooks and Mebendazol (used for the treatment of worms). Household composition variables may be important determinants of investment as resources are shared and because of potential gender preference by parents (see Becker (1993)). Finally, parents in urban areas may have stronger incentives to invest in child human capital because of the possible increased returns in the city. The coefficients of this equation are allowed to be age specific to reflect the varying importance of such factors in determining investments.

In Table 6, we report the coefficient estimates and the 95% bootstrap confidence intervals for the four age groups. Note that in the investment equation for five year olds we do not include the lagged cognition factor as we do not have any measurements for such a variable, since the younger cohort of children were all two or less at the time of the first survey. All coefficients (apart from the coefficient on “Male” and “Urban”), are interpreted as the effect of a log change. Finally note that the number of observations for the younger cohort are much larger than those for the older one.

Parental cognition has a positive effect on investments at ages 5 and 12. At its peak at age 12, a 10% increase in parent cognition leads to 1.6% increase in child investments. This effect indicates investments as one of the important channels through which better parental background leads to improved intergenerational outcomes, and may justify interventions. Parental health never impacts significantly investments. The coefficient on child health and cognition are positive for all ages, but only significantly so at age 12 for health and age 8 for cognition- this implies that parents do not compensate for long term ill-health or low cognitive skills. Perhaps surprisingly, the number of children and birth order do not affect investments at all. However, male children receive significantly higher investments at age 15. Thus by the time children are 15 males receive 25% more investments than females. This adds up to a substantially lower investment for girls.

Turning now to income, we find, perhaps unsurprisingly, a large and significant

Table 6: The Coefficients of the Investment Equations

	Age 5		Age 8		Age 12		Age 15	
Cognitive Skills			0.06	[0,0.14]	0	[-0.07,0.09]	0.07	[-0.01,0.19]
Health	0.01	[-0.03,0.03]	0.02	[-0.05,0.07]	0.07	[0.01,0.13]	0.01	[-0.06,0.09]
Parental Cognition	0.04	[0.01,0.07]	0	[-0.05,0.11]	0.16	[0.05,0.26]	-0.01	[-0.09,0.16]
Parental Health	0.02	[-0.01,0.08]	-0.05	[-0.12,0.12]	-0.04	[-0.15,0.02]	-0.04	[-0.14,0.05]
Price Food	-0.27	[-0.52,-0.01]	-0.34	[-0.81,0.2]	0.11	[-0.16,0.42]	-0.73	[-1.36,0.05]
Price Clothing	0.18	[0.08,0.28]	-0.03	[-0.13,0.07]	-0.06	[-0.17,0.08]	0.02	[-0.1,0.12]
Price Notebook	0	[-0.16,0.17]	-0.35	[-0.54,-0.14]	0.25	[-0.02,0.42]	-0.59	[-0.86,-0.27]
Price Mebendazol	-0.06	[-0.11,-0.01]	-0.19	[-0.3,-0.04]	0.02	[-0.05,0.1]	-0.29	[-0.47,-0.07]
Income	0.12	[0.06,0.22]	0.77	[0.43,0.99]	0.36	[0.17,0.6]	0.78	[0.3,1.11]
Birth Order	0.03	[-0.04,0.09]	0.06	[-0.01,0.11]	-0.07	[-0.13,0]	-0.01	[-0.07,0.08]
Number of Children	0	[-0.07,0.07]	-0.09	[-0.14,0]	0	[-0.08,0.07]	-0.08	[-0.15,0]
Male	0.01	[-0.03,0.05]	-0.03	[-0.11,0.08]	0.11	[-0.02,0.24]	0.25	[0.09,0.39]
Urban	-0.04	[-0.26,0.03]	-0.04	[-0.17,0.24]	0	[-0.32,0.23]	-0.07	[-0.34,0.21]
Prices and Income (P-values)	0		0		0.005		0.006	
Prices (P-values)	0.005		0		0.25		0.004	

Note: 95% confidence intervals based on 1000 replications in square brackets positive effect at all ages. At age 15, for example, a 10% increase in income leads to a 8% increase in child investments. Note that when we ran the model without using wealth indices as a second measurement on income, the effect of income was much lower. This suggests that attenuation due to measurement error is an important problem to be dealt with in these settings whenever possible.

Prices of child goods may well affect investments. We explore this possibility by exploiting the spatial variation in prices at the community level. In most cases, the effect of prices is indeed quite strong and negative, with some anomalies for age 12. The food elasticity is small at young ages and becomes large at age 15, always below one though.[13] The price of the deworming drug Mebendazol also has a negative elasticity, but it only becomes economically sizable for older ages, particularly at 15. Finally, the price of a notebook, relevant for schooling, also has a negative impact, which is strongest at 15. Thus, overall prices matter, as we would expect. This is of substantive economic importance and also supports the value of our instruments in the control function approach for accounting for the endogeneity of investments. The p-value for the test that they can be excluded from the investment equation is zero for 8 year olds, and under 0.5% for 5 and 15 year olds. Prices are not significant at age 12, with a p-value of 25%.[14]

The excluded instruments for estimating the effect of investment in the production

[13]In the second round, prices were collected in local units while in the third round they are reported in units standardized across communities. We converted second round prices to standardized units as much as possible, to make them comparable across communities, but we believe this issue might be behind the higher p-values we observe for prices at age 5 and age 12.

[14]Generally, we had some problems with the data on the 12 year olds. We have not been able to identify a specific problem with that round of data collection, although it is half the sample size than for the younger cohort.

function are the prices and income. While income is always highly significant prices are not so for age 12. In this case income becomes an identifying instrument. The key justification for using income 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 permanent income, allowing us to take income as representing a random liquidity shock. In what follows we test whether income is excludable from the production function in the cases where prices alone are sufficient for identification - that is for all ages but age 12.

5.3 Production function estimates

We now turn to the estimation of the production functions, which define the way that human capital is produced. For convenience, we restate here, in log form, the production functions we estimate.

$$
\begin{aligned}
ln\theta_{c,t+1} &= \tfrac{1}{\rho_t} ln\left(\delta_{c,t}\theta_{c,t}^{\rho_t} + \delta_{h,t}\theta_{h,t}^{\rho_t} + \delta_{pc,t}\theta_{pc}^{\rho_t} + \delta_{ph,t}\theta_{ph}^{\rho_t} + \delta_{I,t}\theta_{I,t}^{\rho_t}\right) + \\
&\quad + \delta_{c,t} + \delta_{X,t}X_t + \kappa_c v_{I,t} + u_{c,t}^* \\
ln\theta_{h,t+1} &= \tfrac{1}{\zeta_t} ln\left(\alpha_{c,t}\theta_{c,t}^{\zeta_t} + \alpha_{h,t}\theta_{h,t}^{\zeta_t} + \alpha_{pc,t}\theta_{pc}^{\zeta_t} + \alpha_{ph,t}\theta_{ph}^{\zeta_t} + \alpha_{I,t}\theta_{I,t}^{\zeta_t}\right) + \\
&\quad \alpha_{h,t} + \alpha_{X,t}X_t + \kappa_h v_{I,t} + u_{h,t}^*
\end{aligned}
$$

The characteristics X_t include birth order, the number of children, and a male dummy variable. v_{It} is the residual from the investment equation and controls for its endogeneity (control function). The remaining random shock, $u_{jt},\ j = c,\ h$, is orthogonal to all included variables (once the control function has been included).

There is very limited evidence on the joint development of health and cognition, important components of overall human capital, particularly over the entire course of childhood. Our estimates characterize the process of child development and how it varies during childhood; they allow for complementarities of different inputs and take into account explicitly the endogeneity of investment. [15] We start with the estimates for cognition, presented in Table 7.

Cognition Starting with the Xs, which affect total factor productivity, we notice that neither the number of children, nor the number of older siblings are significant in the production function, which means that, conditional on investments, they do not affect outcomes of the child in question. However, male children have higher on cognition, over and above the effects of investment, for ages 8 and 15. A possible interpretation is that parents apply different parenting practices to boys and girls, not captured by our investment measure.

The parameter that affects the elasticity of substitution between the various inputs of the production function, ρ, is estimated to be small and is never significantly different from zero. Hence, the production function has an elasticity of substitution close to 1 (i.e. is a Cobb Douglas) and the inputs are complementary. We strongly reject the hypothesis that $\rho = 1$, which would imply linearity of the production function and additive separability of the various inputs. In other words the returns to investment vary depending on the other inputs, such as parental background and prior levels of achievement of the child.

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

Table 7: Production of Cognitive Skill with Endogenous Investments

	Age 5	Age 8	Age 12	Age 15
Cognitive Skills		0.283	0.697	0.605
		[0.17,0.4]	[0.48,0.87]	[0.49,0.79]
Health	0.158	0.223	-0.054	0.018
	[0.06,0.24]	[0.13,0.32]	[-0.11,0.06]	[-0.06,0.1]
Parent Cognition	0.322	0.013	0.073	-0.014
	[0.27,0.44]	[-0.06,0.15]	[-0.03,0.19]	[-0.11,0.09]
Parent Health	0.036	-0.128	0.028	-0.013
	[-0.04,0.24]	[-0.33,0.04]	[-0.04,0.14]	[-0.07,0.08]
Investments	0.483	0.609	0.255	0.403
	[0.29,0.56]	[0.39,0.8]	[-0.02,0.54]	[0.15,0.55]
Complementarity (ρ)	-0.024	-0.148	-0.101	-0.051
	[-0.16,0.37]	[-0.47,0.06]	[-0.32,0.13]	[-0.28,0.17]
Elasticity of substitution	0.976	0.871	0.909	0.952
	[0.86,1.59]	[0.68,1.07]	[0.76,1.15]	[0.78,1.2]
logTFP ($\log(A_t)$)	0.008	-0.037	0.027	-0.053
	[-0.06,0.04]	[-0.08,0.01]	[-0.03,0.08]	[-0.11,-0.01]
Investment Residual (v_t)	-0.257	-0.782	-0.185	-0.297
	[-0.59,0.18]	[-1.07,-0.42]	[-0.52,0.13]	[-0.61,0.03]
Number of Children	-0.008	0.002	-0.007	-0.019
	[-0.03,0.01]	[-0.02,0.02]	[-0.03,0.02]	[-0.04,0.01]
Older Siblings	-0.001	-0.007	-0.002	0.003
	[-0.02,0.02]	[-0.03,0.02]	[-0.03,0.02]	[-0.02,0.03]
Gender	0.006	0.037	-0.003	0.054
	[-0.01,0.02]	[0.02,0.06]	[-0.02,0.02]	[0.03,0.08]

Notes: 95% confidence intervals based on 1000 bootstrap replications in square brackets.

As might be expected, child cognition is highly self-productive: child cognition from an earlier stage in childhood induces better outcomes in the next stage. In addition, child health leads to better cognitive outcomes when children are young, but becomes unimportant at 12 and 15. This is consistent with the body of research demonstrating a link between health and cognition discussed in the Introduction. What is perhaps more surprising is the size of this impact, relative to the impact of previous period cognitive skills. Child health at age 5 is just as important as child cognition at age 5 in terms of producing child cognition at age 8. This is a potentially important result, because it highlights the potential returns of interventions that improve health outcomes in early life, such as prevention of Malaria and diarrhea. Parental cognition matters for child cognition at age 5, while parental health is never important for child cognition.

Investments are very important determinants of the production function at all ages with an elasticity of cognition with respect to investment ranging from 0.25 to 0.6. The coefficients on investments are always significantly positive, except at age 12, where the estimate is very imprecise (but still positive). Furthermore, the coefficients are large, as we show graphically below, when we examine the impact of shifting investments on long and short term cognitive and health development.

The coefficient on the control function is negative and significant at age 8, implying that investment is endogenous. An interpretation of this negative correlation between investment and productivity shocks is that parents increase investments when adverse events cause a decline in child cognitive outcomes. Furthermore, when comparing the coefficients on investments in Table 7 and the coefficients on investments inTable B.1 in the Appendix, we see that for ages 8-15, the coefficient on investments almost doubles.

Health We turn now to the health production function, reported in Table 8. Given the relative weakness of the instruments at age 12 it is also worth considering the results with investments taken as exogenous and reported in the Appendix in Table B.2. Looking at Table 8, some of the main conclusions are similar to those drawn from Table 7. The demographic characteristics included in X have no impact: they all have very small and insignificant coefficients, with the exception of gender at age 12 (perhaps a result of girls going through puberty around this age) and number of older siblings at age 15. Moreover, as with the cognition production function, the elasticity of substitution is estimated to be close to one.

Investments are only significant at age 8. The coefficients do increase compared to when we treat investment as exogenous in Table B.2. However, the coefficient on the investment residual is never significant.

Health is strongly self-productive. However, cognitive skills do not have any effect on health, except very marginally at age 15. This is in contrast to the result for cognition where health does impact cognition significantly at younger ages.

Parental health is positive and significant at ages 5 and 12, but similarly to the results for the effect of parental cognition on child cognition, the most substantial impact occurs at the youngest age. Given how close the coefficient for age 12 is to 0, it is fair to say that beyond age 5, parental health and cognition only matter insomuch as they determine parental levels of income, which impacts future cognition and health through the investment equation.

Table 8: Production of Health with Endogenous Investments

	Age 5	Age 8	Age 12	Age 15
Cognitive Skills		-0.045	-0.054	0.061
		[-0.08,0.03]	[-0.12,0.03]	[0.01,0.12]
Health	0.671	0.763	0.861	0.785
	[0.58,0.78]	[0.74,0.92]	[0.76,0.93]	[0.72,0.85]
Parent Cognition	0.008	0.042	-0.016	-0.001
	[-0.05,0.07]	[0,0.09]	[-0.1,0.05]	[-0.06,0.06]
Parent Health	0.393	0.075	0.084	0.028
	[0.19,0.6]	[-0.04,0.11]	[0.03,0.19]	[0,0.16)
Investments	-0.072	0.165	0.125	0.129
	[-0.21,0.08)	[0.04,0.21)	[-0.01,0.28)	[-0.03,0.21)
Complementarity (ρ)	-0.165	0.172	-0.029	-0.067
	[-0.45,0.12)	[0.02,0.44)	[-0.2,0.19)	[-0.24,0.11)
Elasticity of substitution	0.859	1.208	0.972	0.938
	[0.69,1.13)	[1.02,1.8)	[0.84,1.23)	[0.81,1.12)
logTFP ($\log(A_t)$)	0.041	0.267	-0.021	0.031
	[0,0.08)	[-0.03,0.02)	[-0.05,0.01)	[-0.02,0.07)
Investment Residual (v_t)	0.273	-0.105	-0.051	-0.053
	[-0.1,0.62]	[-0.21,0.07]	[-0.25,0.14]	[-0.16,0.24]
Number of Children	0.007	-0.003	-0.012	-0.015
	[-0.01,0.02]	[-0.02,0.01]	[-0.03,0.01]	[-0.04,0.01]
Older Siblings	-0.024	-0.004	0	0.018
	[-0.04,0]	[-0.02,0.01]	[-0.02,0.01]	[0,0.04]
Gender	0	0.002	0.025	-0.016
	[-0.02,0.01]	[-0.01,0.01]	[0.01,0.04]	[-0.03,0]

Notes: 95% confidence intervals based on 1000 bootstrap replications in square brackets.

5.4 Robustness

As already noted the exclusion restrictions in the model are prices and income, which reflect the budget constraint. However, income may also reflect permanent household characteristics that in turn affect child development. Of course by controlling for parental background and household demographic composition we expect to have already taken this into account. Hence our assumption is that income reflects variation of resources, given the quality of the home environment. Nevertheless, some robustness analysis is called for.

We have already shown that the model is identified at ages 5, 8 and 15 with just the prices as exclusion restrictions. This allows us to re-estimate the model at these ages, while including income among the X characteristics in the production function and test whether it is significant and whether results change much.

The results are presented in the Appendix Tables **??** for cognition and B.6 for health, while in Table 9 we present relevant specification tests. For cognition we find that income is not significant at ages 5 and 15 and is marginally significant at age 8. The p-value that income does not enter in any of the three ages is 4.2%. For health income is marginally significant in the production function for age 15, but not at other ages. The joint test has a p-value of 6.9%. More importantly, when we use just prices as excluded instruments the coefficient on investment does not change much (and certainly not significantly) in either of the production functions. The p-values for the equality of the investment coefficient across specifications that include and exclude income in the production function range from 68% to 91% and thus the differences are completely insignificant.

Table 9: Test Statistics

Hypothesis	Cognition	Health
Income excluded from the Production function	0.042	0.069
Investment coefficients equal across specification including and excluding income		
Age 5	0.917	0.77
Investment Age 8	0.734	0.877
Investment Age 15	0.672	0.751

Notes: P-values for the tests computed using the bootstrap

5.5 Implication for Human Capital Accumulation

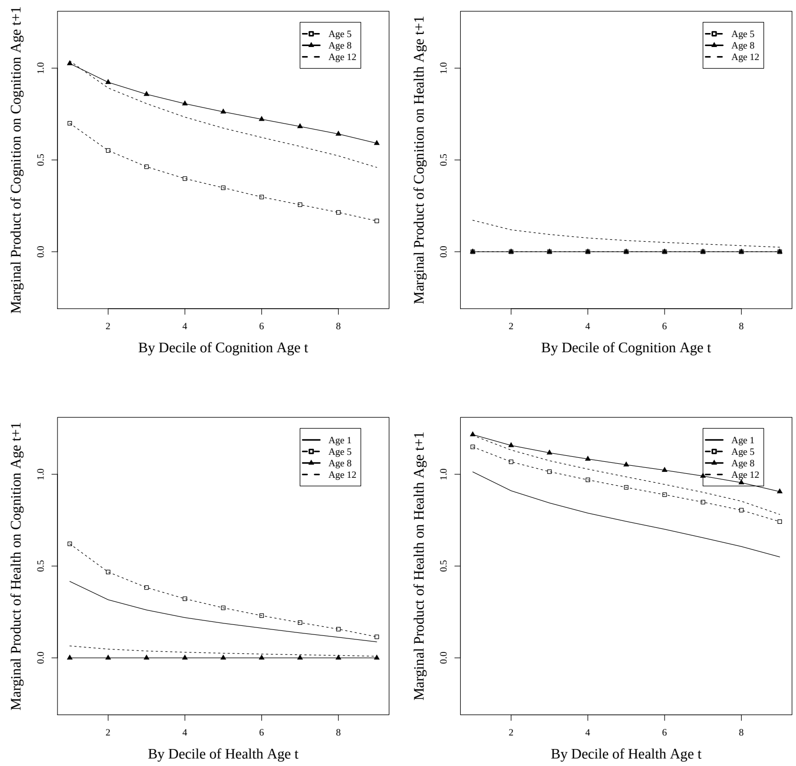
In figure 5, we show the marginal product (MP) of cognition (top panels) and health (bottom panels) on cognition (left panels) and health. On the horizontal axis we vary cognition and health respectively (keeping all other factors at their mean values). We show the MP at different ages. An important result here is that the persistence of cognition (top left graph) is substantially lower at younger ages and moreover, is higher for lower cognition levels. This points both to the fact that other external factors are more at play early on and that such external factors (positive or negative) are more important for children with higher levels of initial cognition.[16] The lower level of persistence is consistent with experimental evidence that shows that early interventions (such as the Perry Pre-School Program), while effective in raising cognition on impact, often fade out substantially.

Cognition seems to have no effect on health early on. However, there is a small but positive effect of cognition on health at later ages; as we know from Table 8 only

[16]Remember we do not observe cognition at age 1 so it is not possible to consider all ages. We also do not have measures that would allow us to model an additional factor of human capital, namely, socio-emotional skills.

the one relating to age 15 is significant. Interestingly the MP is highest at lower levels of cognition.

Figure 5: Marginal Product of Health and Cognition



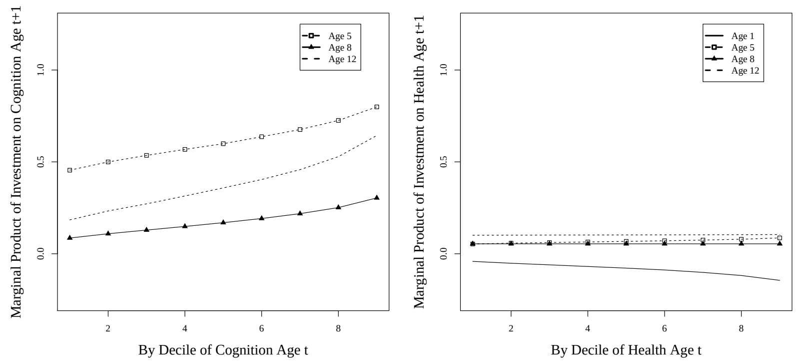
Note: Other than cognition and health respectively all other values are set equal to the mean value for the sample.

The bottom left graph implies that health at lower ages affects the development of cognition and the impact is largest for the lowest health children. This demonstrates the role of endemic diseases such as diarrhea, malaria, parasitic worms and others, as well as nutritional status in inhibiting children in developing countries from reaching their full potential. From the bottom right graph it is also evident that health is highly persistent, particularly at higher ages and even more so for lower health children.

An issue of central importance is the extent to which investments in children can actually change the course of their development. The parameter estimates suggest they can, since investments are significant in producing cognitive skills and less so health. However, the degree of persistence of cognitive development is central to propagating the effects of successful investments. We explore the marginal productivity of these investments on cognition and health by age along different levels of prior cognition and health in Figure 6.

When considering the production of cognitive skills (left hand graph) we see that investments are complementary to cognition: the marginal product increases as baseline cognition increases. Overall the productivity of investments is higher at the younger age: investments are more able to affect cognition earlier on. Finally, investments have no effect on health at the youngest age, but a positive and small impact at higher ages; there seems to be no complementarity of these investments with the level of health.

Figure 6: Marginal Product of Investment on Health and Cognition



Excluding health or cognition, which are computed at each decile, the figures above are produced holding all other values equal to the mean value for the sample.

5.6 When is it best to invest

The fact that the marginal product is highest at a younger age does not imply that it is also optimal to invest most when young. This depends on an array of factors, including the marginal product of investment, the persistence of cognition and the level of other factors. We now explore the implied optimal paths of investment.

Ultimately we are interested in human capital formation, which here we view as a function of health and cognition. Thus the objective is to find an optimal way of allocating an increment to overall investment across childhood stages that maximizes final human capital. Considering the dynamics of health and cognition in tandem is important because we already saw that health deficiencies lead to cognitive deficits. Moreover, child investments can improve both health and cognition, contributing to overall increases in human capital and potentially reinforcing each other.

We start by assuming a Cobb-Douglas function for human capital W as function

Table 10: The optimal path of increments to investment

	Distribution of investment by age			
Cognition Weight (α)	Age 5	Age 8	Age 12	Age 15
0	0	0.45	0.25	0.30
0.25	0	0.38	0.17	0.45
0.50	0	0.33	0.11	0.56
0.75	0	0.30	0.07	0.63
1	0	0.28	0.05	0.67

Notes the numbers show how one standard deviation of increase in investment is distributed across childhood stages

of health H and cognition C.

$$W = C^{\alpha} H^{1-\alpha}$$

The object of the exercise is to allocate incremental investment to maximize W. Unfortunately we do not have data that allows us to estimate α. This could achieved if our data included wages for adults. We thus present results for various values of α, giving different relative weight to health and cognition.

In Table 10 we show how one standard deviation increase in overall investment should be optimally distributed over childhood stages according to our estimates. The exercise is performed for four values of α ranging from full weight on health ($\alpha = 0$) to all the weight being placed on cognition. First we find that investment at 5 is not increased in any of the scenaria, in spite of the relatively high productivity of investments at an early age. This is because investment does not increase health at age 5[17] and because cognition is not persistent enough. Depending on the relative importance of health on final human capital the investment path emphasizes

[17] we have set the negative point estimate to zero in the simulations.

early investments differently. In the extreme case of cognition being the only factor most incremental investments are optimally allocated in the last stage of childhood, shifting away mainly from the middle stage of 12 years.

These results are surprising and counter to much of the discussion on the importance of ECD so we need to qualify these a bit. First, our result do not imply that investments at an early age are ineffective for final human capital, but just that given our parameter estimates they are better made later because of the lower level of persistence. Second and more importantly, the investments we measure relate closely to resources spent on children. However, most ECD interventions can best be described as providing and encouraging quality time. So a richer data set would allow us to distinguish between time and money investments. Even with the amount of persistence that we now estimate it may well be the case that early on time investments work best, while resource investments are more important at a final age. Third, we consider ages (past 5) when, at least for some authors in the literature, it is difficult to affect cognition and intelligence. Finally, and related to the previous point, human capital may also depend on socio-emotional skills , which have also been shown to be sensitive to early investments, as shown in Cunha, Heckman, and Schennach (2010) and Cunha and Heckman (2007) and elsewhere. This component could well change the picture of the optimal profile of investment increments by intervention. Thus our approach establishes the importance of investment at all ages and crucially the cross productivity with health, but may not provide the complete picture.

6 Conclusion

In this paper, we estimate production functions for health and cognition over a number of child ages spanning most of childhood. We use nonlinear factor models combined with a flexible parametric approach. Our data is drawn for the Young Lives Survey for India, a two-cohort study covering ages of 1, 5 and 8 and 8, 12 and 15 respectively.

In our approach the production function is CES and includes as inputs the child's past level of achievement and health as well as parental health and cognition and household composition. Importantly we also estimate investment equations, which depend on local prices allowing us to explicitly take into account of endogeneity of investment and its potential correlation with shocks to cognition and health. We show that not allowing for such endogeneity severely biases downwards the estimate of the effectiveness of investment on the production of cognition. Our results also imply that cognition becomes more persistent with age, implying that some of the effectiveness of earlier investment is lost in the long run.

Two key results stand out from our work: first resource investment is effective in improving cognition at all stages of childhood; second health is particularly important fro the production of cognition. These two facts together can go a long way towards explaining underperformance of children in poor environments, with a number of endemic diseases.

Our results emphasize the importance of investments at all stages of the lifecycle. However, we cannot claim that the picture is complete. First, we are not able to take into account of socio-emotional skills. These may be an important element of human capital and a conduit for the impact of interventions on later outcomes. Second, we are not able to capture the impact of quality-time investments because we do not have time-use data. This may be important to better capture the effect of inputs at a young age. Finally, we are not able to link the human capital measures to final economic outcomes of interest, such as wages and employment. Ultimately this is the metric that we need to use to evaluate the effectiveness of investments and of interventions at various ages.

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Appendix

A Using the Expectation Maximization algorithm to estimate the joint distribution of the measurements

There are a variety of approaches that can be used to estimate a joint distribution of variables, and any method can be used in the first step of our estimation approach. In this paper, we use the Expectation Maximization (EM) algorithm of Dempster, Laird, and Rubin (1977) as further adapted for the mixture of normals by Arcidiacono and Jones (2003)).

To summarize the procedure, we begin by guessing starting parameters for vectors of means, covariance matrices, and mixture weights. In practice, we use k-means clustering to obtain initial guesses for the means.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. We then iterate until convergence is reached.

B Estimating the distribution of the latent factors

The following equations link the implied moments of the joint distribution of measurements to the moments of the distribution of actors and of the measurement error:

$$
\begin{aligned}
\tau \Lambda \mu^{A} + (1-\tau)\,\Lambda \mu^{B} &= 0 \\
\Lambda \mu^{A} &= E\left[\widetilde{M}^{A}\right] \\
\Lambda \mu^{B} &= E\left[\widetilde{M}^{B}\right] \\
\Lambda \Sigma^{A} \Lambda' + \Sigma^{\varepsilon} &= cov\left[\widetilde{M}^{A}\right] \\
\Lambda \Sigma^{B} \Lambda' + \Sigma^{\varepsilon} &= cov\left[\widetilde{M}^{B}\right]
\end{aligned}
$$

where the A and B superscripts denote the first and the second element of the mixture of normal. Since these as well as the mixture weight τ have been estimated in the earlier step, estimating μ^A, μ^B, Σ^A, and Σ^B is a straightforward application of minimum distance.[18]

C Discrete measurements

Many measurements are discrete, which of course implies they cannot be continuously distributed. In principle we can deal with this by thinking of it as a censoring problem with a corresponding underlying latent measurement being continuously distributed. Denoting by m^l the continuous measurements, which are latent when there is no censoring, and by m the actual measures (some of which will be discrete and some of which continuous) the distribution of observed measurements conditional on the measurements we actually observe is

[18] See Rothenberg (1971).

$$f^o(m) = Ef(m^l|m)$$

For example, if $m_1 = 1(m_1^l > 0)$ and m_2 is observed as a continuous measurement the observed distribution of measurements will be

$$f^o(m_1, m_2) = \begin{cases} \int_0^\infty f(m_1, m_2) dm_1 \; if \; m_1 = 1 \\ \\ \int_{-\infty}^0 f(m_1, m_2) dm_1 \; if \; m_1 = 0 \end{cases}$$

While this is mathematically straightforward, when a measurement system includes many discrete variables this involves multidimensional integration making the problem quickly intractable from a computational point of view, particularly because the measurements are interdependent random variables. In this paper we have ignored the problem of discrete measurements. However in a Monte Carlo study presented in the appendix we show that this may not necessarily cause much bias. In future work we are intending to look into efficient ways of getting round this problem.

D Assignment of measures to latent factors

In Table A.1, we present the descriptive statistics from the sample for the measurements that are assigned to the investment factor at each age. These measurements consist of amount spent on fees, books, clothing, shoes, and uniform for the child. In addition, we have variables on how often and what food groups the child ate in the last 24 hours and whether the parent thinks they are able to help their child with school or when the child is sick. Next, Table A.2 reports descriptive statistics for the measurements assigned to the parental health and parental investment factors. These measurements include mother's weight, mother's height, mother's and father's years of education, and whether the primary caregiver is literate.

Table A.1: Investment Measures Summary Statistics

	Age 5	Age 8	Age 12	Age 15
Amount Spent on Fees for Child	1,214	1,718	1,290	2,447
	3643	2,758	2,572	5,426
Amount Spent on Books for Child	157	440	338	630
	243	637	484	672
Amount Spent on Clothing for Child	412	754	543	1,031
	392	688	470	880
Amount Spent on Shoes for Child	75	135	100	189
	89	145	102	172
Amount Spent on Uniform for Child	227	378	301	501
	223	295	226	386
Times Child Ate in Last 24 Hours	4.99	4.85	4.47	4.59
	1.07	1.10	1.23	1.07
Food Groups in Last 24 Hours	5.78	6.43	5.66	5.64
	1.55	1.63	1.66	1.33
Cannot Help Child when Sick (1-4)	3.77	.	3.73	.
	0.67	.	0.74	.
Cannot Help Child in School (1-4)	3.60	.	3.60	.
	0.80	.	0.85	.
Observations	1950		994	

Table A.2: Parental Measures Summary Statistics

	Younger Cohort	Older Cohort
Mother Years of Education	3.63	2.67
	4.43	4.01
Father Years of Education	5.54	4.59
	4.93	4.85
Caregiver is Literate? (0-2)	0.78	0.60
	0.94	0.88
Mother's Weight (kg)	46.41	48.40
	9.41	10.75
Mother's Height (cm)	151.43	151.08
	6.53	7.08
Observations	1950	994

E Production functions with exogenous investments

In this section we present parameter estimates for the production functions for cognition and health across all ages where we assume that investments are exogenous. Table B.1 gives parameter estimates for the production functions for cognition while Table B.2 shows the results for the production functions for health across all ages. These estimates are discussed in more detail in Section 5.3.

Table B.1: Production of Cognitive Skills - Exogenous Investment

	Age 5	Age 8	Age 12	Age 15
Cognitive Skills		0.347	0.739	0.65
		[0.22,0.47]	[0.55,0.86]	[0.54,0.81]
Health	0.168	0.237	-0.022	0.057
	[0.07,0.24]	[0.15,0.34]	[-0.08,0.08]	[-0.02,0.14]
Parent Cognition	0.329	0.093	0.119	0.034
	[0.28,0.44]	[0.04,0.23]	[0.05,0.21]	[-0.04,0.12]
Parent Health	0.048	-0.004	0.037	0.001
	[-0.03,0.26]	[-0.18,0.16]	[-0.02,0.16]	[-0.05,0.11]
Investments	0.456	0.327	0.127	0.258
	[0.28,0.54]	[0.15,0.49]	[0.02,0.26]	[0.11,0.36]
Complementarity (ρ)	-0.032	-0.404	-0.225	-0.177
	[-0.16,0.36]	[-0.63,-0.05]	[-0.44,0.11]	[-0.38,0.2]
Elasticity of substitution	0.969	0.713	0.816	0.85
	[0.86,1.56]	[0.61,0.95]	[0.69,1.13]	[0.72,1.23]
TFP (A_0)	0.006	-0.016	0.036	-0.055
	[-0.06,0.04]	[-0.08,0.03]	[-0.03,0.09]	[-0.12,-0.01]
Number of Children	-0.007	0.009	-0.005	-0.017
	[-0.03,0.02]	[-0.01,0.03]	[-0.04,0.02]	[-0.04,0.01]
Older Siblings	0	-0.006	-0.002	0.007
	[-0.02,0.02]	[-0.03,0.02]	[-0.03,0.03]	[-0.02,0.03]
Gender	0.006	0.039	-0.003	0.057
	[-0.01,0.02]	[0.02,0.06]	[-0.02,0.02]	[0.04,0.08]

Notes: 95% Confidence intervals in square brackets

Table B.2: Production of Health - Exogenous Investment

	Age 5	Age 8	Age 12	Age 15
Cognitive Skills		-0.039	-0.043	0.068
		[-0.07,0.04]	[-0.1,0.04]	[0.01,0.12]
Health	0.661	0.803	0.87	0.792
	[0.57,0.77]	[0.74,0.92]	[0.78,0.93]	[0.72,0.84]
Parent Cognition	0.001	0.055	-0.003	0.007
	[-0.06,0.06]	[0.02,0.09]	[-0.07,0.06]	[-0.06,0.06]
Parent Health	0.381	0.093	0.086	0.03
	[0.19,0.57]	[-0.03,0.12]	[0.03,0.19]	[0,0.16]
Investments	-0.043	0.089	0.09	0.103
	[-0.18,0.09]	[0.03,0.16]	[0,0.17]	[0.01,0.19]
Complementarity (ρ)	-0.139	0.156	-0.072	-0.099
	[-0.45,0.14]	[-0.01,0.44]	[-0.27,0.2]	[-0.25,0.12]
Elasticity of substitution	0.878	1.185	0.933	0.91
	[0.69,1.16]	[0.99,1.79]	[0.79,1.25]	[0.8,1.13]
TFP (A_0)	0.043	-0.003	-0.019	0.031
	[0,0.08]	[-0.03,0.02]	[-0.05,0.02]	[-0.02,0.07]
Number of Children	0.006	-0.002	-0.012	-0.015
	[-0.01,0.02]	[-0.02,0.01]	[-0.03,0.01]	[-0.04,0.01]
Older Siblings	-0.024	-0.003	0	0.018
	[-0.04,0]	[-0.02,0.01]	[-0.02,0.01]	[0,0.04]
Gender	0	0.002	0.025	-0.016
	[-0.02,0.01]	[-0.01,0.01]	[0.01,0.04]	[-0.03,0]

Notes: 95% Confidence intervals in square brackets

F Production functions with Income Included

Table B.3: Production of Cognitive Skills with Income - Endogenous Investment

	Age 5	Age 8	Age 12	Age 15
Cognitive Skills		0.239	0.697	0.595
		[0.15,0.68]	[0.49,0.87]	[0.48,0.77]
Health	0.148	0.197	-0.054	0.014
	[0.04,0.23]	[0.11,0.3]	[-0.12,0.05]	[-0.06,0.09]
Parent Cognition	0.38	0.1	0.073	0.013
	[0.29,0.5]	[-0.05,0.18]	[-0.03,0.19]	[-0.08,0.11]
Parent Health	0.078	-0.113	0.028	-0.01
	[-0.04,0.3]	[-0.34,0.01]	[-0.03,0.17]	[-0.08,0.08]
Investments	0.395	0.577	0.255	0.388
	[0.19,0.55]	[0.29,0.76]	[-0.05,0.51]	[0.16,0.56]
Complementarity (ρ)	0.125	-0.012	-0.101	-0.059
	[-0.1,0.39]	[-0.18,0.12]	[-0.33,0.15]	[-0.21,0.14]
Elasticity of substitution	1.143	0.988	0.909	0.944
	[0.91,1.64]	[0.84,1.14]	[0.75,1.18]	[0.83,1.16]
TFP (A_t)	0.089	0.188	0.027	-0.002
	[-0.03,0.19]	[-0.02,0.26]	[-0.03,0.07]	[-0.13,0.11]
Investment Residual (v_t)	-0.113	-0.701	-0.185	-0.279
	[-0.46,0.41]	[-1.01,-0.31]	[-0.5,0.17]	[-0.59,0]
Number of Children	-0.007	0.001	-0.007	-0.019
	[-0.03,0.02]	[-0.03,0.02]	[-0.03,0.03]	[-0.04,0.01]
Older Siblings	-0.001	-0.01	-0.002	0.004
	[-0.02,0.02]	[-0.04,0.02]	[-0.04,0.02]	[-0.02,0.02]
Gender	0.008	0.037	-0.003	0.054
	[-0.01,0.03]	[0.02,0.06]	[-0.02,0.02]	[0.03,0.07]
Income	-0.08	-0.192		-0.04
	[-0.17,0.01]	[-0.26,-0.02]		[-0.12,0.05]

Notes: 95% Confidence intervals in square brackets

Table B.4: Production of Cognitive Skills with Income - Exogenous Investment

	Age 5	Age 8	Age 12	Age 15
Current Period Cognitive Skills	0	0.29	0.739	0.633
	0	[0.21,0.43]	[0.54,0.86]	[0.52,0.8]
Current Period Health	0.15	0.212	-0.022	0.049
	[0.05,0.23]	[0.14,0.32]	[-0.09,0.08]	[-0.02,0.13]
Parental Cognitive Skills	0.388	0.187	0.119	0.064
	[0.31,0.49]	[0.11,0.27]	[0.04,0.2]	[-0.02,0.15]
Parental Health	0.085	-0.008	0.037	0.004
	[-0.02,0.28]	[-0.17,0.13]	[-0.01,0.19]	[-0.06,0.11]
Current Period Investments	0.377	0.319	0.127	0.25
	[0.2,0.51]	[0.16,0.44]	[0.01,0.26]	[0.11,0.34]
Complementarity Parameter	0.132	-0.126	-0.225	-0.154
	[-0.06,0.46]	[-0.32,0.01]	[-0.4,0.12]	[-0.34,0.14]
Implied Elasticity of Substitution	1.152	0.888	0.816	0.867
	[0.95,1.84]	[0.76,1.01]	[0.71,1.13]	[0.74,1.16]
TFP	0.096	0.227	0.036	0.011
	[-0.05,0.14]	[0.03,0.27]	[-0.03,0.08]	[-0.11,0.1]
Number of Children	-0.006	0.007	-0.005	-0.018
	[-0.03,0.02]	[-0.02,0.03]	[-0.03,0.02]	[-0.04,0.01]
Older Siblings	-0.001	-0.009	-0.002	0.007
	[-0.02,0.02]	[-0.03,0.02]	[-0.03,0.02]	[-0.02,0.03]
Gender	0.008	0.039	-0.003	0.057
	[-0.01,0.03]	[0.02,0.06]	[-0.02,0.02]	[0.04,0.08]
Income	-0.086	-0.224		-0.053
	[-0.13,0.02]	[-0.26,-0.06]		[-0.11,0.03]

Notes: 95% Confidence intervals in square brackets

Table B.5: Production of Health with Income - Exogenous Investment

	Age 5	Age 8	Age 12	Age 15
Cognitive Skills		-0.033	-0.043	0.046
		[-0.08,0.04]	[-0.1,0.04]	[-0.01,0.11]
Health	0.662	0.806	0.87	0.78
	[0.58,0.78]	[0.73,0.9]	[0.78,0.93]	[0.71,0.83]
Parent Cognition	-0.004	0.046	-0.003	0.049
	[-0.08,0.05]	[0.01,0.09]	[-0.07,0.06]	[-0.03,0.09]
Parent Health	0.378	0.092	0.086	0.034
	[0.18,0.57]	[-0.01,0.15]	[0.03,0.19]	[0,0.16]
Investments	-0.036	0.089	0.09	0.091
	[-0.16,0.13]	[0.02,0.16]	[0,0.17]	[0.02,0.16]
Complementarity (ρ)	-0.142	0.107	-0.072	0.013
	[-0.49,0.23]	[-0.08,0.38]	[-0.27,0.2]	[-0.12,0.2]
Elasticity of substitution	0.876	1.12	0.933	1.013
	[0.67,1.3]	[0.92,1.63]	[0.79,1.25]	[0.89,1.25]
TFP (A_0)	0.034	-0.031	-0.019	0.115
	[-0.08,0.11]	[-0.1,0.06]	[-0.05,0.02]	[0.02,0.17]
Number of Children	0.006	-0.002	-0.012	-0.015
	[-0.01,0.03]	[-0.02,0.01]	[-0.03,0.01]	[-0.04,0.01]
Older Siblings	-0.024	-0.003	0	0.018
	[-0.05,0]	[-0.02,0.01]	[-0.02,0.01]	[0,0.04]
Gender	0	0.002	0.025	-0.016
	[-0.02,0.01]	[-0.01,0.01]	[0.01,0.04]	[-0.03,0]
Income	0.007	0.025		-0.074
	[-0.05,0.09]	[-0.04,0.07]		[-0.11,-0.01]

Notes: 95% Confidence intervals in square brackets

Table B.6: Production of Health with Income - Endogenous Investment

	Age 5	Age 8	Age 12	Age 15
Cognitive Skills		-0.041	-0.054	0.042
		[-0.08,0.04]	[-0.12,0.03]	[-0.01,0.11]
Health	0.67	0.803	0.861	0.777
	[0.58,0.79]	[0.73,0.9]	[0.76,0.93]	[0.71,0.84]
Parent Cognition	0.014	0.031	-0.016	0.045
	[-0.07,0.07]	[-0.03,0.06]	[-0.1,0.05]	[-0.04,0.11]
Parent Health	0.398	0.075	0.084	0.033
	[0.18,0.58]	[-0.04,0.14]	[0.03,0.19]	[0,0.16]
Investments	-0.082	0.132	0.125	0.103
	[-0.21,0.12]	[0.05,0.24]	[-0.01,0.28)	[-0.05,0.18]
Complementarity (ρ)	-0.161	0.117	-0.029	0.024
	[-0.49,0.17]	[-0.07,0.33]	[-0.2,0.19)	[-0.14,0.18]
Elasticity of substitution	0.862	1.133	0.972	1.025
	[0.67,1.21]	[0.94,1.5]	[0.84,1.23)	[0.88,1.22]
TFP (A_t)	0.052	-0.036	-0.021	0.114
	[-0.09,0.12]	[-0.12,0.03]	[-0.05,0.01)	[0.02,0.17]
Investment Residual (v_t)	0.289	-0.118	-0.051	-0.024
	[-0.14,0.6]	[-0.25,0.03]	[-0.25,0.14]	[-0.15,0.26]
Number of Children	0.007	-0.003	-0.012	-0.016
	[-0.01,0.03]	[-0.02,0.01]	[-0.03,0.01]	[-0.04,0.01]
Older Siblings	-0.024	-0.003	0	0.018
	[-0.05,0]	[-0.02,0.01]	[-0.02,0.01]	[0,0.04]
Gender	0	0.002	0.025	-0.016
	[-0.02,0.02]	[-0.01,0.01]	[0.01,0.04]	[-0.03,0]
Income	-0.009	0.03		-0.073
	[-0.06,0.1]	[-0.01,0.09]		[-0.12,-0.01]

Notes: 95% Confidence intervals in square brackets

Table B.7: The Coefficients of the Investment Equations without Income

	Age 5		Age 8		Age 12		Age 15	
Cognitive Skills	0	0	0.05	[0,0.14]	0.04	[-0.03,0.13]	0.06	[-0.01,0.15]
Health	0	[-0.03,0.03]	0.02	[-0.04,0.07]	0.08	[0.02,0.14]	0.06	[-0.01,0.14]
Parental Cognition	0.09	[0.06,0.13]	0.27	[-0.06,0.11]	0.29	[0.16,0.42]	0.26	[0.11,0.47]
Parental Health	0.05	[0.01,0.12]	0.13	[-0.12,0.11]	-0.01	[-0.09,0.06]	0.03	[-0.05,0.14]
Price Food	-0.33	[-0.55,-0.08]	0.08	[-0.81,0.13]	0.07	[-0.17,0.37]	0.05	[-0.44,0.53]
Price Clothing	0.18	[0.08,0.28]	-0.14	[-0.12,0.07]	-0.06	[-0.17,0.07]	-0.05	[-0.15,0.05]
Price Notebook	-0.02	[-0.21,0.16]	-0.1	[-0.53,-0.14]	0.2	[-0.05,0.38]	-0.33	[-0.59,-0.07]
Price Mebendazol	-0.07	[-0.12,-0.02]	-0.19	[-0.31,-0.05]	-0.01	[-0.08,0.06]	-0.2	[-0.37,-0.02]
Birth Order	0.02	[-0.05,0.08]	0.04	[0.36,0.85]	-0.03	[-0.09,0.03]	0.02	[-0.05,0.11]
Number of Children	0.01	[-0.06,0.08]	-0.05	[-0.01,0.12]	-0.01	[-0.08,0.06]	-0.03	[-0.09,0.03]
Male	0.04	[-0.06,0.12]	0	[-0.27,-0.01]	0.06	[-0.05,0.16]	0.2	[0.06,0.35]
Urban	0	[-0.28,0.07]	0.08	[-0.13,0.08]	0.16	[-0.08,0.36]	0.05	(-0.18,0.3]
Prices (P-values)	0.001		0		0.493		0.016	

Notes: 95% Confidence intervals in square brackets