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Human Capital Development and Parental Investment in India

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

Key words: Child development, Human capital, Poverty, Inequality, Equal opportunity, Cognitive skills, Health, Human capital production functions, Nonlinear factor models, Measurement error, Development

JEL Codes: I14, I15, I25, I32, J13, J24, O15

1. INTRODUCTION

In emerging and rapidly developing countries such as India, human capital may offer a way of escaping poverty and taking advantage of new opportunities. However, soon after birth (if not before) children from poorer backgrounds fall behind in every aspect of human capital development, including health and cognition, potentially depriving them of such opportunities. Indeed 52% of the 137 million children aged 0–5 in India are at risk of developmental deficits.[1] Therefore, policies addressing such deficits in child development are important. However, their design, implementation, and targeting require a good understanding of the determinants of human capital formation throughout childhood.

1. See, for instance, Lu *et al.* (2016). On the link between poverty and child development delays see Fernald *et al.* (2011), Grantham-McGregor *et al.* (2007), Hamadani *et al.* (2014), Rubio-Codina *et al.* (2015), and Currie (2011).

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There is strong evidence showing that children's early experiences have long lasting effects, with implications for adult outcomes and even inter-generational transmission of human capital.[2] There is also evidence that poorer children are more vulnerable to early life shocks and that they experience adverse events more frequently (Currie and Hyson, 1999; Case *et al.*, 2002; Currie and Stabile, 2003). There is growing consensus on the presence of important dynamic complementarities and interactions among different inputs and factors, and some studies have quantified them.[3] Yet, we still do not fully understand the mechanisms through which the various dimensions of human capital develop and how inputs interact in a dynamic fashion over time to shape the overall development of a child.

In this article, we study the dynamic process of human capital accumulation from birth to age 12, using a unique high quality longitudinal data set from India. We focus on cognition and health because they are likely to be key determinants of future productivity and of the ability to acquire skills through more advanced education. Our model allows for the dynamic interactions among these dimensions of human capital and accounts for the influence of parental investment amongst other factors.

We estimate our model of human capital with an econometric method we develop and allowing for the endogeneity of investments. This builds on the nonlinear latent factor approach of Cunha *et al.* (2010) and uses the additional identification results from Agostinelli and Wiswall (2016b) but is simpler and faster.

Our results yield a set of important findings that are key to understanding the deficits in child development in poor contexts. First, we find that health affects cognitive development, particularly at younger ages. The well-documented morbidity amongst poor populations, reflected in stunting, feeds into cognitive development generating permanent deficits in both health and cognition. These results imply that early health interventions are likely to be an important component in any policy that aims to improve human capital.[4]

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

Third, we find that investments by parents are effective in developing cognition at all ages we consider, but much more so up to age 8. Investments also affect health but only in the first stage of childhood that we consider (up to age 5). Health outcomes, which are measured here mainly by height for age and weight for age, become highly persistent by age 8 and also difficult to shift

2. Almond *et al.* (2009), Chay and Greenstone (2003), and Currie *et al.* (2009) 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 *et al.* (2013) and Behrman (1996) demonstrate vulnerability to nutritional resources and micronutrient deficiencies.

3. See Del Boca *et al.* (2014), Currie and Almond (2011), Cunha *et al.* (2010), Cunha and Heckman (2007), and Heckman (2007).

4. Attanasio *et al.* (2018) illustrate that a cognition and nutritional intervention taking place soon after birth and up to about age 2 did successfully increase height and cognitive development. Further references on health interventions and their impact on child development, including cognition, and consistent with the implications of our production function estimates include Glewwe and Miguel (2007), Hoddinott *et al.* (2008) (the Guatemala intervention); Bharadwaj *et al.* (2013), Miguel and Kremer (2004), Grantham-McGregor *et al.* (1991), Lucas *et al.* (1998), Sazawal *et al.* (1996), Heckman *et al.* (2010), and Campbell *et al.* (2014).

5. See the longer term followups of child stimulation interventions in Walker *et al.* (2005) and Andrew *et al.* (2018).

thereafter. The complementarity we identify between prior outcomes and investments imply that both early and later interventions are important for the final determination of human capital.

Finally, key determinants of parental investments in children are household resources, prices of key goods as well as the number of children, which reflects the extent to which resources need to be shared. The effect of resources goes some way in explaining the differences in investments and hence the wealth gaps in child development that we document. Our results also highlight the empirical importance of accounting for the endogeneity of investments, which seem to respond positively to adverse shocks to child development. Ignoring this feedback underestimates the impact of investments and provides a distorted picture implying a much lower influence of parental actions and indirectly of resources available to them.

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

This study was made possible by the unique data collected by the Young Lives Project, starting in 2002. We use data collected on the same children from age 1 to age 12. The data focus on child development, and provide numerous measures of child health, nutritional status, and cognitive ability.[6] In addition, it has a rich set of household characteristics, including measures of material investments in children, household resources, and household structure. The availability of numerous high quality measures at multiple stages of childhood for cognition, health and investment expenditures in children as well as measures relating to the parents provides the ideal setting for implementation of the nonlinear factor model.

Our article is related to a number of earlier studies that estimate production technologies for child development in the United States using NLSY data, such as Cunha *et al.* (2010), Heckman *et al.* (2010), Cunha and Heckman (2007, 2008), Bernal (2008), and Todd and Wolpin (2007). More recently Agostinelli and Wiswall (2016a) discuss a number of identification and estimation issues relating to the latent factor approach, which are relevant to this context. We build on these contributions and introduce some methodolical innovations, which we discuss below, in the estimation of these models.

Two papers are closest to ours: first, Cunha *et al.* (2010) develop the dynamic latent factor approach we follow in this article.[7] They use this approach to estimate the process of cognitive and non-cognitive skill accumulation over two stages of childhood for children in the U.S. aged 0–14, using NLSY data. We do not model non-cognitive skills (which we do not observe) as they do, but emphasize the interaction between health and cognition and allow investments to react to time varying unobserved shocks.

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

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

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

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

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

2. DATA AND DESCRIPTIVE RESULTS

We use data from the younger of two cohorts of the Young Lives Survey, which started in 2002. Our sample includes 2,011 children and their families surveyed at ages 1, 5, 8, and 12. Children were selected from the Hyderabad district and a "poor" and "nonpoor" district in each of the three major regions in Andhra Pradesh: Coastal Andhra, Rayalaseema, and Telangana, for a total of seven districts, comprising 98 separate communities. We use information from the household, child, and community questionnaires. Restricting our sample to children observed in all rounds, leaves us with 1,910 children. Total attrition from round 1 to round 4, including an overall mortality rate of 2.2%, was only 4.8%.[8]

In Table 1, we present baseline descriptive statistics, and in Table 2, we describe some variables that change across rounds. The sample is very poor with 40–60% below \$2 per day.[9] A significant fraction of the children suffer from stunting, wasting and being underweight, indicating significant morbidity, with no improvement even for wasting and being underweight, despite the decline in poverty as the cohort ages.

In addition to income, the survey contains a number of indicators that Young Lives uses to compute a wealth index, which is an average of measures of housing quality, consumer durables, and access to services.[10] While the units are not easy to interpret, the standardized version indicates that within our sample there is a considerable degree of heterogeneity in socio-economic background.

In Table 2, we also report expenditures on books for children over time, which contribute to our measure of parental investments together with books and stationery, clothing, shoes, and uniforms.[11] These constitute on average of 4% to 5.5% of the household budget across ages, which as a percentage sounds substantial. However, many of these households are extremely poor and the investments are quite low in absolute value.

Parents have very high aspirations for their children: among the 5 year olds, 55% of parents would like to see their children become doctors, engineers, and teachers (the remaining 45% report a variety of careers, most of which are similarly ambitious). Among the 12 year olds, 99% of parents hope their children complete more than 10 years of schooling. Children spend minimal time working at family businesses and doing chores at home. By age 12, children spend

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

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

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

11. We do not include food expenditures (which is not measured separately for children) and public goods like housing.

TABLE 1
Descriptive statistics: baseline

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

Notes: Standard deviations in italics.

TABLE 2
Descriptive statistics: across rounds

	Age 1	Age 5	Age 8	Age 12
Child characteristics				
Fraction stunted	0.31	0.36	0.30	0.29
Fraction underweight	0.32	0.45	0.46	
Fraction wasted		0.19	0.28	0.33
Height for age Z-score	−1.30	−1.66	−1.45	−1.45
	1.48	*0.99*	*1.04*	*1.03*
Standardized PPVT test		0.01	0.74	1.75
		1.00	*0.88*	*1.01*
Amount spent on books		3.48	8.98	13.00
		5.40	*13.02*	*16.97*
Household economic wellbeing				
Annual income		873.57	1,407.98	1,749.95
		1,219.24	*2,033.67*	*1,841.78*
Wealth index	0.40	0.46	0.51	0.59
	0.20	*0.20*	*0.18*	*0.17*
Percent below $2/day		0.63	0.45	0.27
Child work				
Daily hours chores		0.06	0.34	0.82
Daily hours family business		0.00	0.01	0.12
Daily hours paid work			0.01	0.05

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

approximately an hour a day helping out at home, on the farm, or at the family business. Almost no children do paid work.

Child outcomes vary substantially with wealth: in Figure 1, we plot average z-scores for height per age, and PPVT scores standardized (over all periods) against age for three groups of children:

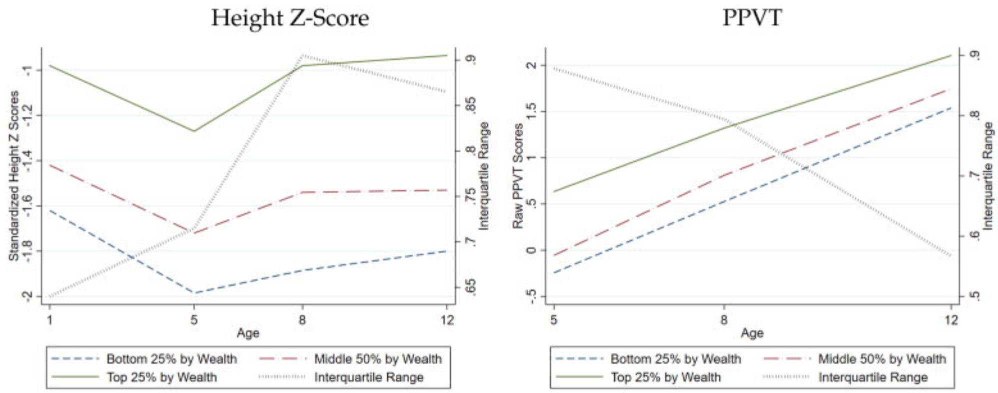

FIGURE 1

Wealth gradient in height and in the peabody picture vocabulary test (PPVT)

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

those living in families in the bottom quartile of the wealth index, those in the middle 50%, and those in the top quartile of the wealth index. We also plot the difference between the top and the bottom 25% of wealth (measured on the right axis). The differences in height per age between the bottom and the top 25% of the wealth distribution is about 0.65 of a standard deviation of the z-score at age 1 and the gap grows to 0.85 of a standard score. The middle 50% are closer to those of the lower wealth quartile than the top one. These measurements thus show an increasing wealth gap in this long-term health measure.

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

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

3. HUMAN CAPITAL ACCUMULATION AND PARENTAL INVESTMENT

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

We start by assuming that human capital at the start of adult life (H_a) has two relevant dimensions, which in our context are cognition (θ_a^c) and health (θ_a^h):

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

Our empirical analysis emphasizes health because it is a major concern: children in developing countries begin life with lower levels of health and throughout childhood they are more frequently exposed to unhealthy environments and diseases such as diarrhoea and malaria. In turn such morbidity, documented in our sample of children in the preceding section, may affect adult human capital and productivity through two channels: by directly shaping adult health and also by impacting cognitive development during childhood. In order to understand how adult human capital is formed we must understand how its constituents are determined throughout childhood. We follow Cunha *et al.* (2010) and express the evolution of cognition and health by a series of dynamic production functions over stages (t) of childhood.

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

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

where θ^I_t is a composite investment good that parents can buy in the market.[12]

The vector X_t includes parental background and temporal shocks, which we leave implicit for the moment. The sequence of investments (θ^I_t) is chosen by the parents and depends on its marginal product at different childhood stages (as perceived by parents), the available resources, and the prices of investment goods. If parents are liquidity constrained, then the timing of income will also affect child development (Carneiro *et al.*, 2015).

The main goal of this article is the study of the production functions, the role played by investment, and how health and cognition interact. We do not estimate a structural economic model of parental investment decisions (as done in Del Boca *et al.*, 2014), although we outline one to set ideas in Supplementary Appendix A.1. As a result, while we cannot explicitly simulate the impact of potential interventions, our estimates do not depend on assumptions about parental beliefs relating to the effectiveness of investments, their knowledge of the production functions, and the extent to which parents face constraints.

3.1. *The production functions*

The production functions for cognition and health at the various childhood stages define how initial conditions and investments get embodied in child human capital and how these relationships evolve over time. Given the available data we model the production of human capital in three stages: ages 1–5, 5–8, and 8–12. We denote child's age by t. Similarly to the model for cognitive and non-cognitive skills in Cunha *et al.* (2010), we assume a CES production function. Child's cognitive skills and health stock $\{\theta_{ct+1}, \theta_{ht+1}\}$ at any period $t+1$ are a CES function of the previous period stock of health and cognitive skills $\{\theta_{ct}, \theta_{ht}\}$, the amount parents choose to invest in their child θ_{It}, the parental stocks of health θ_{hp} and cognitive skills θ_{cp}[13] and TFP terms $\{A_{ct}, A_{ht}\}$, that depend on random shocks $\{u_{ct}, u_{ht}\}$ and on a vector of household characteristics X_t including family composition, birth order, gender, mother's age, ethnicity, and caste. Given the much lower age at marriage in India relative to more developed countries, mother's age may be an important determinant of child human capital development. Regarding caste and ethnicity, there is substantial evidence that these characteristics play important roles in child development

12. In a richer model, one would allow for both material and time investments as in Del Boca *et al.* (2014). However, we do not consider time here because we do not observe time inputs in our data.

13. 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.

in India (*e.g.* see Jayachandran and Kuziemko, 2011). Finally, allowing for family composition is meant to capture the effects of interactions between children. We assume that parental health and cognitive skills are fixed at their initial levels.[14] Thus we have that

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

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

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

$$\begin{aligned} A_{ct} &= exp(d_{0t} + d_{Xt}X_t + u_{ct}) \\ A_{ht} &= exp(a_{0t} + a_{Xt}X_t + u_{ht}). \end{aligned} \tag{6}$$

The parameters of the production function all vary with age t. The parameters ρ_t and ζ_t determine the elasticity of substitution between the various inputs in the cognition and health production function, respectively. If they are equal to one, the production functions are linear and the inputs are perfectly substitutable. For values less than 1 the inputs are complementary, with zero leading to a unitary elasticity of substitution (Cobb–Douglas). Hence, these parameters capture the extent to which the productivity of child investments vary with the child's background, with parental characteristics, and with age.

3.2. *Investment*

Investments depend on parental preferences for child quality, the budget constraint they face (including whether they can borrow) and their beliefs about the effectiveness of these investments. Without separate information on such beliefs, estimating a structural model would require assuming that parents know the true production functions, which goes against existing evidence for the poor in both developed and developing countries (see Cunha *et al.*, 2013; Attanasio *et al.*, 2015; Boneva and Rauh, 2015). Thus, we estimate a reduced form investment equation that depends on parental background, the current state of cognition and health of the child, and household characteristics. We assume that investment also depends on prices and parental resources.

Since there is no obvious price index for child investments and we cannot construct one because we do not observe the shares going to children out of total expenditure, we include a vector of prices for relevant goods (food, medications, educational goods, and clothing) in an unrestricted fashion.[15] The prices capture the effect of both current prices and household expectations of future prices. Finally, we also include current resources.

The empirical specification for investment θ_{It} is

$$\begin{aligned} ln\theta_{It} = \quad & \gamma_0 + \gamma_{ct} ln\theta_{ct} + \gamma_{ht} ln\theta_{ht} + \gamma_{cpt} ln\theta_{cp} \\ & + \gamma_{hpt} ln\theta_{hp} + \gamma^{'}_{Xt} X_t + \gamma^{'}_{pt} lnp_{It} + \gamma_Y ln\theta_{Yt} + v_t, \end{aligned} \tag{7}$$

14. As a referee suggested, young parents may be accumulating skills and health status may change. In our data, we find that parental human capital is not changing (at least not in the measures we observe). We also control for mother's age, which may capture unobservable maternal human capital accumulation.

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

where v_t reflects random shocks, θ_{Yt} represents parental resources, and lnp_{It} represents log prices for child investment goods. All other variables are as defined in the production functions.[16]

3.3. *Controlling for the endogeneity of investments*

If parents choose investments taking into account the evolution of human capital, then their choice will depend on developmental shocks to the production function. In our framework, this implies that the shocks v_t in the investment function (7) may be correlated with those of the production functions, u_{ct} and u_{ht}, making investments endogenous. To allow for this potential endogeneity and thus obtain consistent estimates of the parameters of the production function, we use a control function approach. Specifically, we assume that

$$\begin{aligned} E(u_{ct}|Q_t,Z_t) &= \kappa_c v_t \\ E(u_{ht}|Q_t,Z_t) &= \kappa_h v_t, \end{aligned} \tag{8}$$

where Q_t is the set of variables in the production functions (including investment) and Z_t are the instruments, which are included in the investment equation and excluded from the production function. To allow for endogeneity, we thus include the estimated residual from the investment equation, $\hat{v}_t$, as a regressor in each of the TFP equations (6).[17] Assuming that investments are exogenous amounts to imposing $\kappa_c=0$ and $\kappa_h=0$, which are testable hypotheses; our results indicate that investments are endogenous.

As instruments we include prices as well as household resources, both of which reflect the budget constraint (see model in Supplementary Appendix A.1). The prices are measured at a local level and their validity as instruments rests on the assumption that their variability is due to supply side changes and does not relate to the shocks or unobserved inputs in the human capital production functions. The validity of household resources as an instrument relies on the assumption that conditional on the child initial conditions and parental health and cognition, they are not correlated with omitted inputs or shocks to human capital. We explore the robustness of this assumption by estimating a model that relies only on prices as excluded instruments: as we show below, our estimates are completely unaffected whether we use income as an excluded instrument or not, but using it does improve precision and importantly leads to a reduced from investment equation that is more interesting from an economic point of view. Including it also helps explain the wealth gaps in child development.

3.4. *The measurement system*

We have rich data with multiple measurements for the variables that enter the production functions. This leads to two related challenges. First, how should we efficiently use all of the available data? Second, measurements, such as math, height, or book expenditures are just imperfect proxies for the latent inputs cognition, health, and investments, respectively. Using any one of these proxies without addressing measurement error would lead to biases. And since the production functions are nonlinear, we cannot even sign the bias (Griliches and Ringstad, 1970). We address both these challenges by implementing the factor analytic approach, which was extended to nonlinear models in Cunha *et al.* (2010).[18] This combines the wealth of information included in

16. Excluding other prices is effectively a restriction on preferences. Since we are not estimating a structural model the key assumption is that any omitted prices are not correlated with omitted inputs from the production functions.

17. The residual v_t is a control function as in Gronau (1974) and Heckman (1979). For control functions in a non-parametric context, see Newey *et al.* (1999) and Florens *et al.* (2008).

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

the numerous measurements to identify the underlying joint distribution of the latent factors and thence obtain consistent estimates of the production functions. In our model, the latent factors include child cognition, child health, parental resources, and investments at each age as well as parental cognition and health, which are assumed constant. All other variables are assumed error free.

Let m_{jkt} denote the jth available measurement relating to kth latent factor θ_{kt} in time t. Taking all factors as being strictly positive, we assume a semi-log relationship

$$m_{jkt} = a_{jkt} + \lambda_{jkt} ln(\theta_{kt}) + \epsilon_{jkt}, \tag{9}$$

where λ_{jkt} is the factor loading and ϵ_{jkt} are measurement errors. The assumptions required for the non-parametric identification of the joint distribution of latent factors and also of the distribution of the measurement errors are derived in Cunha *et al.* (2010). They also discuss the more general case of identification when the mapping from the latent factors to the measures is unknown and non-separable in the measurement error. However, we employ a simpler framework that is separable (as above) with normally distributed errors (ϵ_{jkt}) that are independent of the latent factors θ_{kt} and of each other. In general, identification will require at least three measures per factor; however, by exploiting restrictions over time in the way the factors are scaled (ensuring comparability in the units of measurement), we require less measurements, although the use of more, when available, can improve precision.[19]

The location and scale of the latent factors needs to be set based on normalization restrictions. For factors that are constant over time (such as parental cognition and health) or that are not explicitly linked through dynamic relationships, a natural and innocuous normalization is to set the mean of the log to zero. However, factors such as child cognition and health naturally evolve over time as part of the developmental process: cognition grows with age and health can vary relative to an international benchmark, as defined by the WHO.[20] For these it is important to normalize the location *only* at the initial age we observe the child. The mean of the factor in subsequent periods can then be identified relative to this initial point by assuming that the growth in the measurement is due only to the growth of the associated latent factor. Constraining the mean by not allowing for growth in the latent factor can lead to bias in the parameters of the production function (Agostinelli and Wiswall, 2016b) and misses part of the story for the overall developmental outcomes. We treat investments in the same way, allowing them to grow over time relative to the initial point.

The scale of the latent factor can be set to equal the units of one of the measurements, which is equivalent to setting the associated factor loading to 1. As also pointed out by Agostinelli and Wiswall (2016b), valid comparisons over time require that the scaling of the latent factors is the same across periods. One way to meet this condition is to normalize each factor on the same measure every period, assuming that the mapping from measure to factor is invariant with respect to the age of the subject.[21] Fortunately, our data are sufficiently rich that we are able to do this for our model. For child cognitive skills, we always normalize the loading on PPVT to one. Similarly, child health is always normalized on height z scores, investments are normalized on amount spent on books, parental health is normalized on mother's weight, parental cognitive skills is normalized on mother's years of schooling, and resources are normalized on income.

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

20. World Health Organization.

21. Although the variance of the measurement error is allowed to change with age.

4. ESTIMATION

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

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

Formally, let θ represent variables observed with measurement error. Let F_θ denote the joint distribution of all log latent factors in our model across all periods t.[22] Then:

$$F_\theta = \tau \Phi(\mu_A, \Omega_A) + (1-\tau)\Phi(\mu_B, \Omega_B), \tag{10}$$

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

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

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

where $\mathbf{A}$ is a vector of constant terms and Λ is the matrix of factor loadings in the measurement equations. These matrices incorporate the normalization and the zero restrictions (*i.e.* the restrictions that define the scale and metric of each factor, as well as what factors relate to what measures);[23] Σ is the diagonal matrix of standard deviations for the measurement errors and ε is a vector of mutually independent standard normal errors.

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

$$F_M = \tau \Phi(\Pi_A, \Psi_A) + (1-\tau)\Phi(\Pi_B, \Psi_B), \tag{11}$$

22. Demographic variables that can be 0 enter in levels as opposed to logs.

23. For example, with 2 factors, cognition and health, with 3 and 4 measures, respectively,

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

where

$$\Psi_A = \Lambda^T \Omega_A \Lambda + \Sigma; \quad \Psi_B = \Lambda^T \Omega_B \Lambda + \Sigma \tag{12}$$
$$\Pi_A = \mathbf{A} + \Lambda \mu_A; \quad \Pi_B = \mathbf{A} + \Lambda \mu_B$$

and where we impose the mean zero restriction in the first period[24]

$$\tau \mu_{A,t=0} + (1-\tau)\mu_{B,t=0} = 0. \tag{13}$$

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

1. Use MLE to estimate τ, Π_A, Π_B, Ψ_A, and Ψ_B from the data.
2. Use minimum distance to impose the restrictions in equations (12) and (13) as well as the age-invariant assumptions, initial period normalizations, and zero restrictions in Λ to recover Λ, $\mathbf{A}$, Σ, μ_A, μ_B, Ω_A, Ω_B from Π_A, Π_B, Ψ_A, and Ψ_B.
3. Draw a synthetic data set from this joint distribution to estimate the model using regression methods. The joint distribution includes the full amount of information in the data relevant to the model. The larger the data we draw the lower the simulation error.

Regarding the first step we use the expectation–maximization (EM) algorithm of Dempster *et al.* (1977) and further developed in Arcidiacono and Jones (2003). To summarize the procedure, we begin by guessing starting parameters for vectors of means, covariance matrices, and mixture weights.[25] In the E step, we estimate the probability that a given observation is drawn from each of the two possible normal distributions, conditional on the observables. In the M step, we maximize the conditional likelihood function and update the parameter estimates for each of the two normal distributions. In the case of a mixture of normals, the M step has analytical solutions, which helps with computational speed. We then iterate until convergence is reached.

Beyond the latent factors in our model, we use additional variables as controls in the production function (such as number of children and gender) and instruments for investment (such as prices). Hence the joint distribution we estimate has to include them, so as to reflect all the relevant dependencies in the data. We treat the additional variables as error free measures, and we expand the distribution of latent factors to include them. Thus, in step 1 we expand the measurement system to include the control variables and the instruments with no measurement error; *i.e.*, we set the corresponding standard deviation in Σ to zero and the corresponding factor loading to one. In this way, we model the complete structure of dependence between all factors, including the controls and the instruments, with a joint mixture of normals.[26] This augmented distribution is

$$F_{\theta,X} = \tau \Phi\left(\mu_A^{\theta,X}, \Omega_A^{\theta,X}\right) + (1-\tau)\Phi\left(\mu_B^{\theta,X}, \Omega_B^{\theta,X}\right), \tag{14}$$

24. This normalization identifies the constant terms in the measurement equations in the first period. For those measurements, the expected value of the measure is simply equal to the constant. The age-invariant assumption on the constant can then be used to identify μ_A and μ_B in subsequent periods, since for the measurements which are age-invariant, $\Lambda = 1$ and we have identified $\mathbf{A}$ from the first period. The remaining constant terms from the measurement equations can be identified once μ_A and μ_B are known.

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

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

TABLE 3
Monte Carlo simulations when $\log(A_1)=log(A_2)=1$

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

Notes: Monte Carlo simulations with 500 replications. Each sample used is 2,000 individual observations.

where X represents the instruments and the demographic controls we use. The superscripts (θ, X) emphasize that the parameters of the augmented distribution include both the latent factors and these other variables. Equation 14 can be easily extended to allow for a larger number of mixtures approximating more closely the actual distribution of latent factors.

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

4.1. *Monte Carlo simulation*

To demonstrate that our approach is able to recover the values of a CES production function without substantial bias for our sample size, we report results from 200 Monte Carlo Simulations, for two periods of childhood, with a data generating process designed to mimic our actual data. Specifically, first we generate two baseline inputs (θ_1, X) from a mixture of two normals with parameter values based on our results in this paper and given in the first panel of Supplementary Appendix Table 9. Next, we generate the output for the first and second periods using CES production functions specified in equations 15. We simulate with different values of the elasticity of substitution and we allow for growth in the latent factor, as is the case for cognition.

$$ln\theta_2 = \log(A_1) + \frac{1}{\rho_1} ln\left(\delta_1 \theta_1^{\rho_1} + (1-\delta_1) X^{\rho_1}\right) + u_1 \tag{15}$$

$$ln\theta_3 = \log(A_2) + \frac{1}{\rho_2} ln\left(\delta_2 \theta_2^{\rho_2} + (1-\delta_2) X^{\rho_2}\right) + u_2 \tag{16}$$

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

$$m_j^{\Theta} = \lambda_j ln(\Theta) + \epsilon_j, \tag{17}$$

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

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

5. RESULTS

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

5.1. *The information content of measures*

As part of the specification of the empirical model, we assign measurements (proxies) to factors. We use a dedicated measurement system, so that each measure is assumed to depend only on one factor. Table 4 shows the assignment of measures to latent factors. It also reports the signal to noise ratio, which captures the information content of each measure given the specification of the measurement system. The expression for the signal to noise ratio is:

$$s_j^{\ln\theta_{kt}} = \frac{(\lambda_{jkt})^2 \ \mathrm{Var}(\ln\theta_{kt})}{(\lambda_{jkt})^2 \ \mathrm{Var}(\ln\theta_{kt}) + \mathrm{Var}(\epsilon_{jkt})}. \tag{18}$$

We use a variety of tests related to child cognition, which change from age to age. However, we observe the Peabody Picture Vocabulary Test (PPVT) at every age, so we use this as the normalizing measure. This makes the comparisons over time across ages consistent, as discussed in Agostinelli and Wiswall (2016b). The signal to noise ratios are all above 26%, which shows that most cognitive measures include a substantial amount of information. At the same time, they also demonstrate the importance of allowing for measurement error. All these proxies are highly imperfect and could introduce serious bias of unknown sign if any measure were used on its own.

For health, we use the z-score for height per age and weight per age, computed according to WHO algorithms.[27] Height for age may capture longer term health and nutrition issues while weight for age likely reflects shorter term health status. Effectively, we are assuming that the position in the percentile distribution of height at each age is an indicator of health. The justification for this assumption is that disease and malnutrition are reflected in child growth deficits. This measure can change on average to the extent that the health of our specific subpopulation improves or worsens relative to the WHO standard, which is used as the basis of our measurement. The reason we use height for age (rather than just height) is because there is no sense by which an older child who is taller than a younger one is also healthier. The health measure relates to position in the distribution for that age. We also use the parental rating of health status when available, although at age 8 we use the child's rating of health status. We use the height Z-score to scale the health measure.

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

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

TABLE 4
Signal to noise ratios

	Age 1	Age 5	Age 8	Age 12
Child cognition				
PPVT		74%	26%	35%
Math			35%	60%
English				70%
Language				39%
EGRA (rasch)			53%	
CDA (rasch)		43%		
Child health				
Height Z-Score	57%	77%	68%	77%
Weight Z-Score	78%	70%	73%	
Weight in kg				66%
Health status	7%	1%	5%	
Investments				
Books		36%	26%	34%
Clothing		51%	35%	44%
Shoes		58%	42%	37%
Uniform		20%	15%	22%
Meals/day		4%	8%	2%
Food groups/day		21%	10%	0%
Resources				
Income		30%	18%	20%
Wealth		63%	52%	49%
Parental cognition (fixed over age)				
Mother's education		79%		
Father's education		52%		
Literacy		45%		
Parental health (fixed over age)				
Mother's weight		62%		
Mother's height		13%		

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

We take parental cognition to be constant over time and use mother's and father's education along with caregiver literacy as proxies. We find no evidence of systematic changes in the measures: of the small fraction who report differences in parental cognition measures over time, an equal number report increases and decreases which suggests measurement error. Moreover, we do not observe measures for parental cognition in the third round. For parental health we use mother's weight and height. Parental health is normalized on mother's weight and parental cognitive skills is normalized on mother's years of schooling. To measure resources, we use both wealth and income. In doing this, we obtain a less noisy measure of household spending power. Resources are always normalized on income. Additional summary statistics on all of the measurements are reported in Supplementary Appendix Table 10.

Given the specification of the measurement system and the normalizations we employ, log cognition is measured in units of the PPVT test score which is a measure that is standardized across rounds by Young Lives in a way that also captures mean growth. Although we can take this measure as cardinal, it would be better to be able to express child cognition in terms of earnings or years of schooling: *i.e.*, how does an extra PPVT score translate into earnings? This is the issue of anchoring discussed in detail by Cunha *et al.* (2010).[28] In practice, one can anchor cognition and health to wages once the children have reached adulthood. However, we only observe the children in our sample up to age 12 and thus no such conversion is possible. We are thus constrained to

28. See also Bond and Lang (2013), Currie (2009), Nielsen (2015a), and Nielsen (2015b).

using PPVT units to measure cognition (a test that is widely used internationally and across ages) and the height Z-score for health, both of which we take to be cardinal. Finally, our investment measure is measured in monetary units, reflecting cost. The units we use for skills does not prevent us from estimating the importance of child investments and how cognition and health interact. However, the complementarity structure that we identify is conditional on the specific scale on which these constructs are measured. Using different scales via a general anchoring function, which may capture an underlying nonlinear monotonic transformation, could change the estimates of complementarity between inputs. Without extra assumptions this is unavoidable.

The distribution of the measures. The mixing parameter τ is estimated to be 0.56 (90% confidence interval [0.54,0.58]). This, together with the differences in the means and covariances across the mixtures, points to a potentially substantial departure from the normal distribution overall. The extent to which the overall distribution actually departs from normality depends on the extent to which the means and variances of the corresponding normal distributions being "mixed" are different.[29]

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

In Figure 2, we plot the mean of the health and cognitive factors against age for various wealth percentiles; we also plot the difference in cognition between the top and bottom quartile of wealth, which we show on the right axis. This is a counterpart to the descriptive exercise in Figure 1, except that now we combine the various measures and strip out the measurement error component. As a result, it provides a more accurate picture and reveals growing gaps in the developmental measures across the wealth distribution. This evidence provides a much clearer picture, revealing substantial differences in child development across the wealth distribution, and substantial growth in cognition over time. The striking result here is that the largest differences seem to be between those in the top quartile of the distribution and those below the median. The health gap increases substantially with age, and seems to worsen vis a vis the international standard, catching up again fully only for the top quartile. The gap in cognition increases slowly at the start and then grows to a very large gap between ages 8 and 12. There is also significantly more overall growth in cognition between ages 8 and 12.

5.3. *The determinants of parental investments in children*

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

In Table 5, we report the coefficient estimates for the investment equation (see equation 7) and the 90% bootstrap confidence intervals for the three age groups. In the investment equation for five year olds we do not include lagged cognition at age 1 because no measures are available. All variables except the 0/1 dummies are in logs so the coefficients are elasticities.

29. The estimates of the mean of the two mixtures are presented in Supplementary Appendix Table 12. The variance–covariance matrices for the two mixtures are available upon request and will be published with the data replication files.

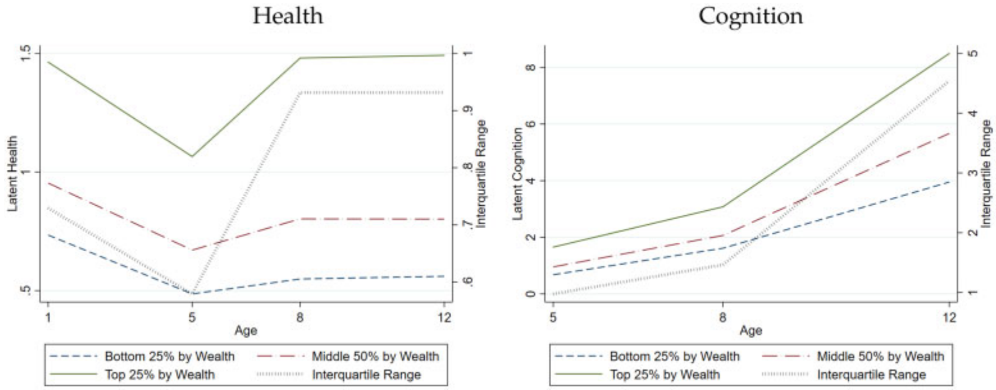

FIGURE 2

Wealth gradient in latent health and cognition

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

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

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

Turning now to resources, we find a large and significantly positive effect at all ages with an elasticity between 0.16 and 0.80.[30] At age 8, for example, a 10% increase in resources leads to a 6.3% increase in child investments. To the extent that investments translate to better child outcomes (as we confirm below), these results point to one of the potentially important roots of inequality and are consistent with the wealth gaps in both cognition and health that we documented earlier. However, it is interesting to note that investments have an elasticity below one, making them a necessity. It is also important to see that the resource effect is *conditional* on parental health and cognition. The fact that parental background does not matter directly suggests that it works through available resources, which do matter and are correlated with parental human capital.

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

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

TABLE 5
The coefficients of the investment equations

	Age 5	Age 8	Age 12
		Child human capital	
Cognition		0.029	0.436
		[−0.01, 0.05]	[0.22,0.55]
Health	0.033	-0.001	0.042
	[0.02,0.04]	[−0.03,0.03]	[−0.02, 0.13]
Gender	-0.005	-0.022	0.029
	[−0.03, 0.02]	[−0.1, 0.03]	[−0.09, 0.16]
		Parental human capital	
Parental cognition	0	0.01	-0.146
	[−0.02, 0.03]	[−0.02, 0.09]	[−0.2, −0.03]
Parental health	−0.014	−0.021	−0.073
	[−0.04, 0.01]	[−0.06, 0.04]	[−0.23, −0.01]
		Prices	
Price clothes	−0.022	0.051	0.189
	[−0.05, 0.01]	[−0.08, 0.12]	[0.02, 0.38]
Price notebook	−0.11	−0.175	−0.414
	[−0.16, −0.07]	[−0.32, −0.05]	[−0.56, −0.26]
Price mebendazol	0.015	-0.117	0.032
	[0, 0.03]	[−0.2, −0.08]	[−0.06, 0.09]
Price food	−0.035	−0.287	−0.416
	[−0.11, 0.04]	[−0.59, 0.03]	[−0.65, −0.17]
		Household characteristics	
Resources	0.163	0.628	0.797
	[0.1, 0.2]	[0.43, 0.69]	[0.58, 0.97]
Older siblings	0.013	0.052	−0.026
	[−0.01, 0.03]	[−0.01, 0.1]	[−0.11, 0.07]
Number of children	−0.03	−0.044	−0.073
	[−0.05, −0.01]	[−0.09, 0]	[−0.16, 0]
Urban	0.119	0.088	0.117
	[0.08, 0.19]	[0, 0.23]	[−0.06, 0.34]
Hindu	−0.001	−0.013	0.001
	[−0.01, 0]	[−0.02, 0]	[−0.01, 0.02]
Muslim	−0.029	−0.224	−0.009
	[−0.1, 0.03]	[−0.35, −0.04]	[−0.31, 0.23]
Mother’s age	−0.001	−0.096	−0.039
	[−0.05, 0.04]	[−0.21, 0.08]	[−0.23, 0.19]
Scheduled caste	−0.023	−0.028	−0.375
	[−0.06, 0.02]	[−0.16, 0.12]	[−0.6, −0.13]
Scheduled tribe	0.035	−0.002	−0.313
	[−0.02, 0.07]	[−0.12, 0.1]	[−0.52, −0.07]
BC caste	−0.008	0.093	−0.205
	[−0.05, 0.03]	[0, 0.21]	[−0.4, −0.03]
Prices and income (p-values)	0	0	0
Prices (p-values)	0	0.017	0

Notes: 90% confidence intervals based on 100 replications in square brackets. The F-statistics corresponding to the p-values for “Prices and income” for each column from left to right are 13.34, 14.29 and 11.08. For Prices these are respectively 6.38, 2.98 and 6.10.

We estimate price effects by exploiting the spatial variation in prices at the community level. In most cases, the effect of prices is indeed negative, and in a number of cases quite strong. Generally, like for resources, the elasticities are larger for older children. The food elasticity is small at age 5, but becomes much larger for ages 8 and 12, always below one though. The price of the deworming drug Mebendazol has a significant negative elasticity at age 8. Finally, the price of a notebook, relevant for schooling, has a strong negative impact at every age. Thus, overall prices matter, as we would expect. Indeed their joint significance is shown for each age at the bottom of the table: the p-values are zero at ages 5 and 12 and 1.7% at age 8. This is of substantive economic importance and also supports the value of our instruments to account for the endogeneity of investments.

The excluded instruments for estimating the effect of investment in the production function are the prices and resources and they are highly significant. The key justification for using resources as an excluded instrument lies in the fact that the production function includes sufficient background variables (parental and child cognition and health, and family composition), which control for the household characteristics that determine permanent wealth, allowing us to view resources as representing a random liquidity shock. Thus the identifying assumption is that these prices we include are not correlated with omitted inputs in the production function. Below we provide evidence that the exclusion restriction is acceptable and the results robust.

5.4. *Production function estimates*

We now turn to the estimation of the production functions (see equations 4 and 5), which define the way that health and cognition evolve over time. Our estimates characterize the process of child development and how it varies during childhood. They also allow for complementarities of different inputs and take into account explicitly the endogeneity of investment. Results obtained considering investments as exogenous for the production functions are given in Supplementary Appendix Table 13.

Cognition. The estimated production function is close to being Cobb–Douglas. Indeed the substitution elasticity is very close to and not significantly different from one at all ages. This implies complementarity of the inputs, whose implications we will discuss below. It also implies that the coefficients of the inputs (parental cognition and health, investment, earlier child cognition, and child health) can be interpreted as elasticities.[31]

As we would expect cognition is self-producing, which was also found by Cunha *et al.* (2010) in the U.S. context. The effect becomes much larger with age, implying a partial fade out of early experiences but eventually an increasing persistence of past human capital accumulation. This lower level of persistence may well underlie the partial fade out of early interventions.[32]

One of the most important results, which in large part motivates this article, is the impact of health on cognition. Children in poor environments often suffer from various diseases, such as diarrhoea or infection by worms, both of which undermine nutrition. In addition, pre-birth maternal nutrition is also often deficient and gets reflected in our measures. All these factors can feed into cognitive development, particularly as they accumulate with age. Indeed our results show exactly this: health has an increasing and strong effect on cognitive development. By age 12 this no longer matters, but of course the earlier impacts have become embedded and persistent through the self-productivity of cognition. Thus the high levels of morbidity among the poor in developing countries, which is documented in the first section, leads to developmental deficits in children with long-term consequences. Designing interventions that prevent ill health from an early stage is likely to be important for the accumulation of human capital.

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

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

32. See Walker *et al.* (2005) and Andrew *et al.* (2018) as examples.

TABLE 6
Production of cognitive skills and health with endogenous investments

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

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

cognition may enter strongly at age 5 because it is also capturing genetic endowment, earlier child skills, and earlier investments, all of which are unobserved. Controlling for child skills at later stages mitigates the influence of parental background, but it is still there: an interpretation is that parental cognition improves the productivity of investments.

The next crucial parameter is that of investment itself. We find that investments have a very large influence, which declines substantially for age 12 children. At a young age the elasticity of cognition with respect to investments is 0.53, rises to 0.66 but at age 12 it is down to 0.19. This is consistent with the sensitivity of child development to investments at early ages as demonstrated by work on interventions and understood to be the case in the literature (Engle *et al.*, 2007).[33] This result is of critical importance because it demonstrates that interventions increasing parental investments can alter the path of child development in very poor contexts. It also shows the importance of parental resources: we already showed that these exercise a major influence on the amount of investment; the picture is completed by now showing that lack of investment seriously inhibits child development.

In the last line of the table, we show the coefficient on the investment residual. This is negative and significant. An interpretation of the negative coefficient is that parents increase investments to compensate for negative shocks to development. Ignoring this leads to an underestimate of the impact of investment on child development, as shown in the OLS results reported in Supplementary Appendix Table 13, where the coefficient on investment is much lower, particularly for ages 8 and 12.

Of the characteristics that affect TFP, the most notable are the positive effect for mother's age and a large and positive effect of belonging to a scheduled tribe for a young child. Being a boy has a positive impact on cognitive development (ages 5 and 8) but a negative one later on (age 12).

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

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

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

In interpreting these results, it is useful to remember that health is a combination of weight and height z-scores. These measures capture both longer term malnutrition as well as the cumulative effects of morbidity that prevents child growth. In many ways, this is a useful health measure because it focuses on longer term status that may be most pertinent for adult human capital; indeed we have shown that health is an important input in cognitive development. On the other hand, as implied by the results, the long-term health measure is highly persistent and hard to change past early childhood. Given this, and given the importance of health for cognitive development as we document here, health deficits need to be addressed as early as possible. With deprived populations this is a challenge, given poor living conditions and the frequent lack of sanitation.

5.5. *Robustness to the use of resources as an instrument*

Our model includes resources in the investment equation, but not in the production function. This has various advantages: it allows us to estimate the sensitivity of investments to wealth, which explains in part the source of wealth disparities, and statistically it offers a strong instrument. However, if our resource measure is correlated with omitted variables affecting child development,

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

TABLE 7
Robustness to using resources as an excluded instrument

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

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

this exclusion restriction may not be valid. The risk is small because we include parental background and various demographic characteristics that should capture the role of long-term factors affecting child human capital. Nevertheless, we can evaluate whether using resources as an instrument distorts the results in any substantive way, as the remaining price instruments are strong enough to identify the model (see Table 5).

We first try a version of the model where we include resources in both the investment equation and the production functions. Estimates of this version of the production functions are presented in the Supplementary Appendix Table 14. In Table 7, we compare the investment coefficients of our preferred specification and the one we obtain relaxing the exclusion restriction. The differences are very small, certainly not of any economic significance and in most cases statistically insignificant. Moreover, excluding income from the production function of cognition is only rejected at age 8 for cognition and marginally so for health. Importantly, whether income is included as an instrument or not leaves the results unaffected.[34]

In Supplementary Appendix Table 15, we also present estimates of a version of the model that excludes resources from all equations. Again this does not change the coefficients on investment substantively. The only difference of note is that the investment coefficient for cognition at age 12 becomes small and insignificant but the difference from the results where we include resources as an instrument is not significant. We conclude that using our resource measure as an instrument is acceptable and provides a better and more precise picture of the determinants of investment.

6. USING THE MODEL

6.1. *Implications for human capital accumulation in India*

Using the estimated production function, we show how changes in period t level of cognition and health affect next period's $(t+1)$ levels, allowing for the response of investment.[35] The top panel of Figure 3 shows that persistence of cognition is lower at younger ages and decreases with current cognition (x-axis), implying that external factors (positive or negative) are more at play early on and more influential for children with higher levels of initial cognition.[36] The bottom left graph shows that health at younger ages affects the development of cognition; the impact is

34. All these tests are carried out using the bootstrap.

35. For example, the marginal product of past cognition on current cognition is $\frac{d\theta_{ct+1}}{d\theta_{ct}} = \frac{\partial\theta_{ct+1}}{\partial\theta_{ct}}|_{\theta_{It}} + \frac{\partial\theta_{ct+1}}{\partial\theta_{It}}\frac{\partial\theta_{It}}{\partial\theta_{ct}}$. Similarly for other marginal products.

36. Remember we do not observe cognition at age 1 so it is not possible to consider all ages. We do not report the effect of a change in cognition on health at any age as these effects are not significantly different from zero.

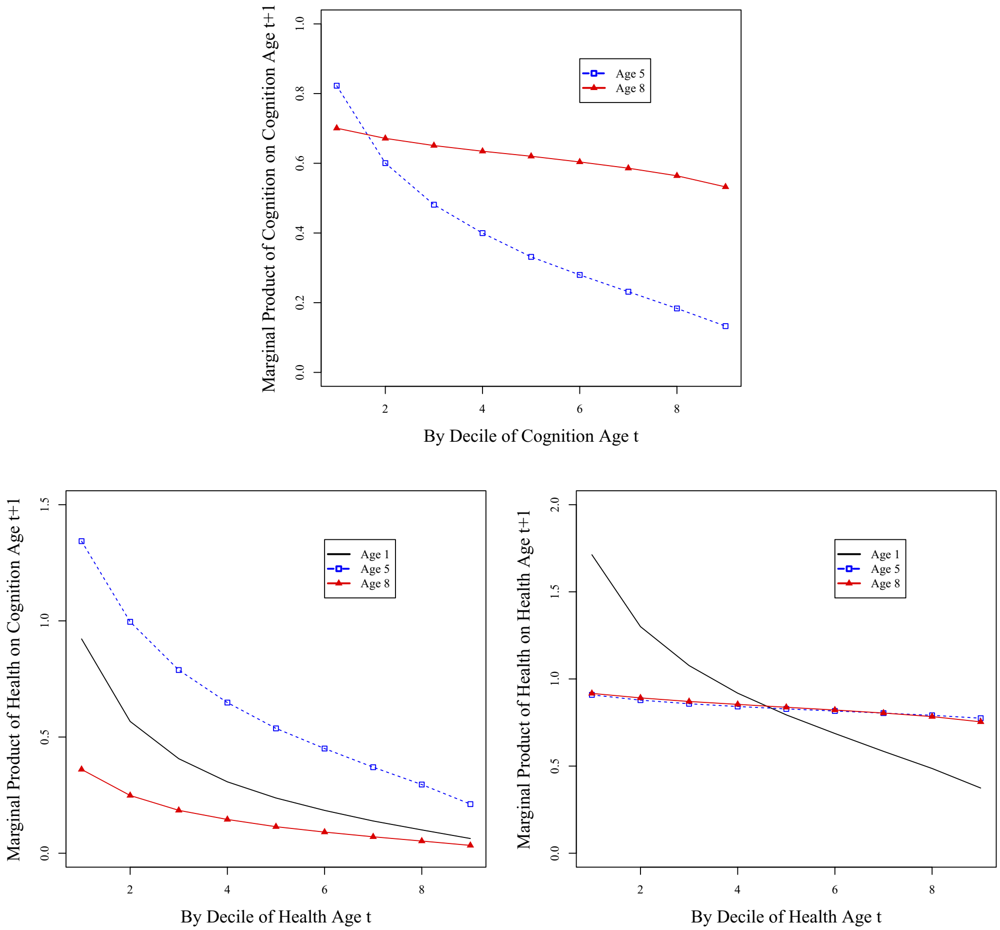

FIGURE 3

Marginal product of health and cognition

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

largest for the most unhealthy children. This result demonstrates the role that endemic diseases (such as diarrhoea, malaria, parasitic worms, and others), which lead to low nutritional status, can have in inhibiting children from reaching their full potential. From the bottom right graph, it is also evident that health is highly persistent, and slightly more so for lower health children. Thus, ensuring good health early on is crucial for future outcomes.

In Figure 4, we show the marginal product of investments for cognition and health for each period of childhood ($\frac{\partial\theta_{kt+1}}{\partial\theta_{It}}$, for $k=c,h$). When considering the production of cognitive skills (left-hand graph) the productivity of investments is much higher at younger ages: investments are more able to affect cognition earlier on. The increasing slope of the marginal productivity graph is a reflection of complementarity between investments and the current level of cognition.[37]

The effect of investments on health is important both early on and at age 12; the complementarity with initial health as with initial cognition is evident, which raises the question of

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

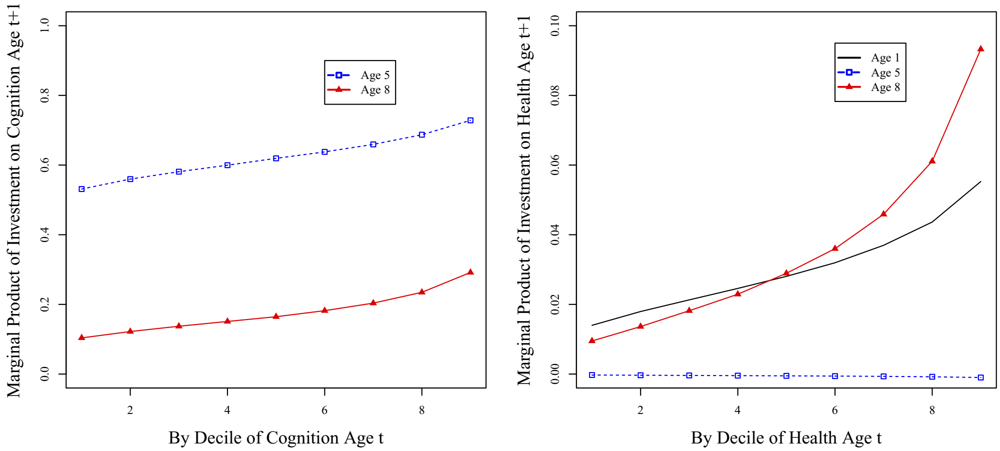

FIGURE 4

Marginal product of investment

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

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

6.2. *Dynamic impact of two possible interventions on skills and inequality*

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

Income transfer. First, we analyse the impact of a one time transfer of income equal to 25% of the mean income in the entire sample. We report the results separately for the bottom 25%, the middle 50%, and the top 25% of households. The first row of figures depicts the impact of such a transfer at age 5, and the second row at age 8. Figure 5 depicts the resulting change in standard deviation units of cognition (left) and health (right) at each age relative to the baseline.

For this exercise, assume that the income is spent entirely in the age at which it is given (and is not saved). The impact of income on investments is determined by the investment equations we estimated. As we would expect, cognition and health increase as a result of this intervention. In terms of timing, the largest impact is obtained if the transfer takes place when the children are between 5 and 8 for cognition, but before 5 for health. The result is driven by the combination of the coefficient on investment and the values of other inputs at each of the ages because of the complementarities we document.

Health improvement. One central question in the literature, and in this article specifically, is the extent to which ill-health and long-term malnutrition, which are reflected in our health measures, can affect cognitive development. Our estimates imply that they can. To consider

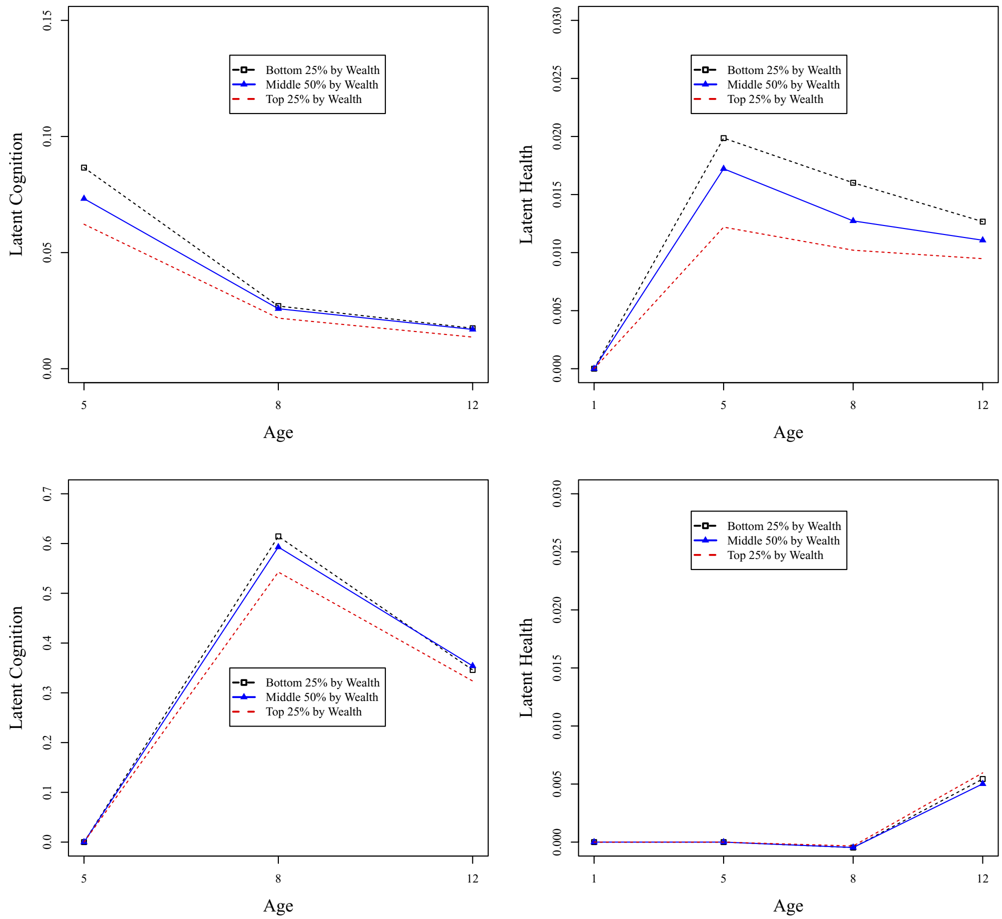

FIGURE 5

Dynamic impact of income transfer

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

the extent to which this might be important for child development we implement an artificial intervention where we increase the health of children by 1 standard deviation of health in the population. We again analyse the effect separately for the poorest 25%, the middle 50%, and the richest 25%. We consider such an intervention at ages 1, 5, and 8 and show the resulting impacts in Figure 6.[38]

The effects on health itself are persistent as we could already predict based on the production function coefficients. The most interesting result here is the impact on cognition. In this setting, it is clear that improving health has a strong impact on cognitive development. And because health is so persistent, early interventions do have long run persistent effects. The results show that if health increases at an early age this feeds into cognition, and the effect does not fade out. For example, a one standard deviation improvement in initial health leads to between 10% and 20% of a standard deviation improvement in cognition by age 12. However, interventions

38. In Supplementary Appendix Figure 7, we show how this counterfactual simulation would have turned out if we did not account for measurement error, while, of course, keeping the scaling the same.

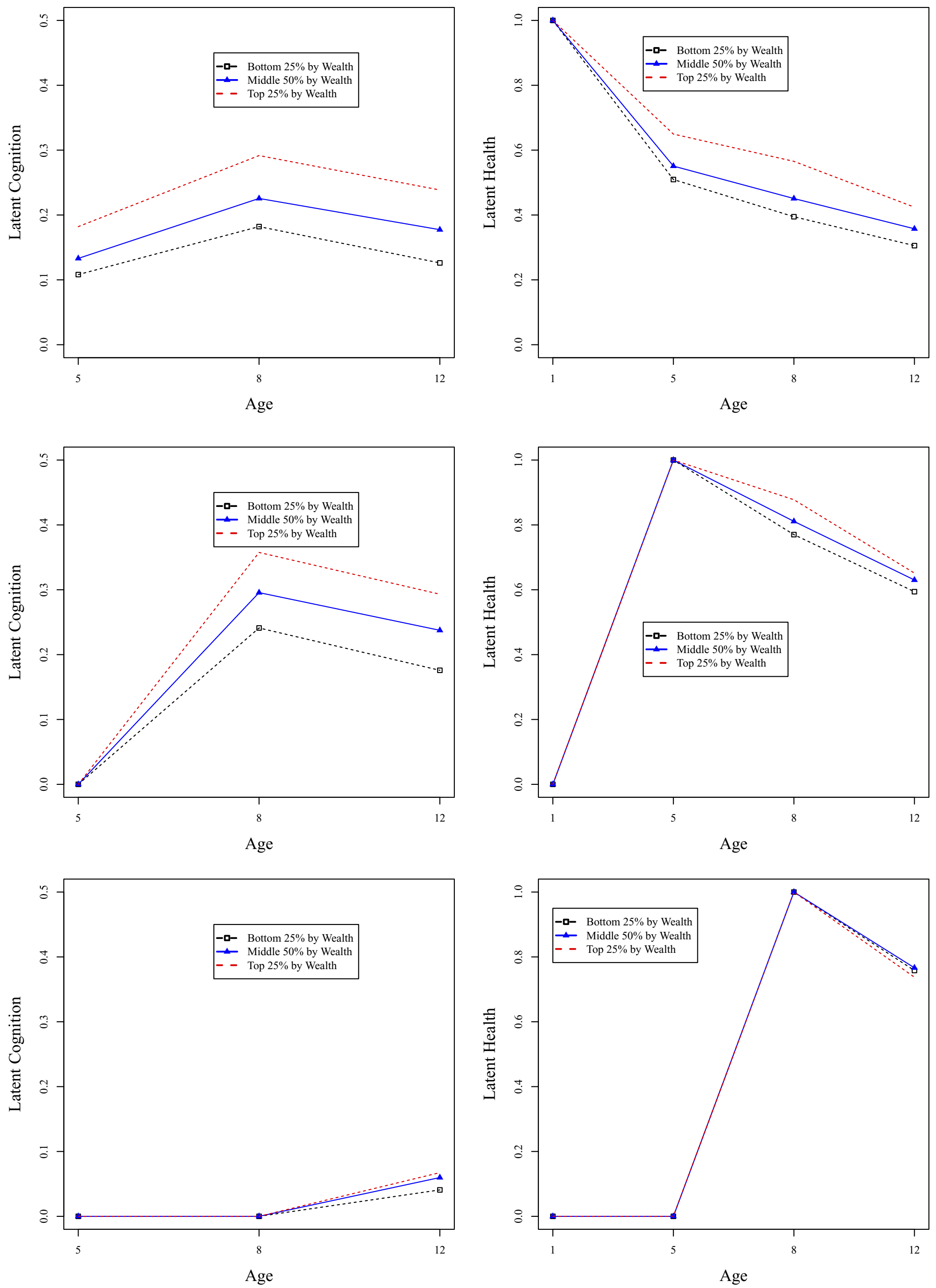

FIGURE 6

Dynamic impact of health intervention

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

TABLE 8
The optimal path of investment

Share of cognition in human capital (α)	Age		
	5	8	12
0.25	0.405	0.281	0.314
0.50	0.265	0.452	0.283
0.75	0.175	0.563	0.262
1.00	0.112	0.640	0.248

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

improving health and nutritional status are hard to design and are likely to be much more effective early on and can have important impacts on cognition. Starting during pregnancy may be the key to achieving the best results: the most effective design of health interventions is an important research question.

6.3. *When is it best to invest*

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

$$H_a = A(\theta_a^c)^{\alpha}(\theta_a^h)^{1-\alpha}. \tag{19}$$

Since the parameter α in equation (19) is not known, we find the optimal investment paths for different assumptions about its value, starting with 0.25. One of course could take the view that ultimately only cognition matters and that health (at least the way it is measured here) is important to the extent that it matters for cognitive development. In addition, we should take these results with some caution, as we have nothing to say about the role of non-cognitive skills that are not measured in our data. The appropriate definition of adult human capital is an empirical question to which we do not know the answer, so we have opted for presenting the results under various alternatives.

The results are presented in Table 8. If cognition is assigned a low weight (0.25) and thus health a large one, investments shift to a younger age because that is when they are most productive for health, which also is highly persistent from very early on. However, when cognition is given an increased weight more of the investment share is shifted to between ages 5 and 8 mainly because cognitive development becomes more persistent at that stage and investments are still very productive.

The early childhood literature has placed a lot of weight on the importance of investments at a very young age. These results are not inconsistent with that: much of the early stimulation activities that have been emphasized in the literature are not high cost in a financial sense.[39] The interventions focus on changing parenting behaviour towards stimulating play activities, language development through interaction and play materials with greater educational content, such as picture books or simple stacking toys; these do not imply high levels of expenditure. Indeed most of the successful interventions are parenting ones, involving low costs in materials, including in developing countries.[40]

39. See for example Attanasio *et al.* (2014).

40. See above reference and Walker *et al.* (2005) as examples.

Compared to the optimal allocations based on the production function, parents in our data allocate 15.8%, 25.2%, and 59% to each age group, respectively given total resources spent on children. These allocations may reflect distorted beliefs about child development as documented by Attanasio *et al.* (2015) and Cunha *et al.* (2013). But they may in addition reflect liquidity constraints: as we show in Table 2 there is substantial parental income growth as the cohort ages, and the growth in child investments may just be tracking income if households cannot reallocate resources over the lifecycle.[41]

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

7. CONCLUSION

We examine the human capital development of children from age 1 to 12 focussing on the role of parental investments and the interaction of health and cognition, using the younger cohort of the Young Lives Survey for India. Based on the nonlinear latent factor model developed by Cunha *et al.* (2010), we estimate a model of parental investment in children jointly with the production functions for cognition and health. Investments are taken as endogenous and can respond to unobserved shocks affecting child human capital.

We obtain a number of important results. First, ill health at a young age causes permanent cognitive deficits. This result is crucial for understanding the developmental deficits of children growing up in poor environments characterized by high levels of morbidity, such as diarrhoea, which are a cause of nutritional deficits. The key implication is that we need interventions that address health and malnutrition among the poor from a very early age and quite possibly during pregnancy (although our results do not speak directly to the latter). Second, investments in children are central in producing improved cognitive and health outcomes. They are important at all ages for cognition (albeit with a diminished impact by age 12) and up to age 5 for health. In interpreting this, it is important to remember that our health measure relates to longer-term malnutrition reflected in height for age and weight for age. Finally, we find that there are complementarities in the production function, such that the marginal product of investments increases with cognition and health. This fact accentuates lifetime inequalities and calls for special focus on interventions for children with lower initial conditions, all the while recognizing that such interventions are likely to be harder.

Understanding the development of human capital and how various determinants interact is central to addressing poverty and its intergenerational transmission. Our paper, together with others referred to here, demonstrate the complexity of the problem and point to the need for sustained intervention. The answer is unlikely to be a simple early versus late investment trade-off, but rather designing interventions over the entire span of childhood and addressing key issues at each stage. As we show, early health interventions can provide crucial boosts in cognition. However, interventions and investments throughout childhood can improve cognition as well. Creative field experiments addressing these issues combined with cohort studies such as this one are likely to be an important tool for better understanding human capital development from an early age.

41. See Carneiro *et al.* (2015) on this issue in a wealthier context.

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Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

REFERENCES

AGOSTINELLI, F. and WISWALL, M. (2016a), "Estimating the Technology of Children's Skill Formation", (NBER Working Paper 22442).

AGOSTINELLI, F. and WISWALL, M. (2016b), "Identification of Dynamic Latent Factor Models: The Implications of Re-normalization in a Model of Child Development", (NBER Working Paper 22441).

ALMOND, D. (2006), "Is the 1918 Influenza Pandemic Over? Long-term Effects of In Utero Influenza Exposure in the Post-1940 US Population", *Journal of Political Economy*, **114**, 672–712.

ALMOND, D., EDLUND, L. and PALME, M. (2009), "Chernobyl's Subclinical Legacy: Prenatal Exposure to Radioactive Fallout and School Outcomes in Sweden", *The Quarterly Journal of Economics*, **124**, 1729–1772.

ANDREW, A., ATTANASIO, O., FITZSIMONS, E., *et al.* (2018), "Impacts 2 Years after a Scalable Early Childhood Development Intervention to Increase Psychosocial Stimulation in the Home: A Follow-up of a Cluster Randomised Controlled Trial in Colombia", *PLoS Med*, **15**, e1002556.

ARCIDIACONO, P. and JONES, J. B. (2003), "Finite Mixture Distributions, Sequential Likelihood and the EM Algorithm", *Econometrica*, **71**, 933–946.

ATTANASIO, O., BAKER-HENNINGHAM, H., BERNAL, R., (2018), "Early Stimulation and Nutrition: The Impacts of a Scalable Intervention", (NBER WP 25059).

ATTANASIO, O., CUNHA, F. and JERVIS, P. (2015), "Parental Beliefs and Investments in Human Capital", (Mimeo UCL).

ATTANASIO, O., FERNÁNDEZ, C., FITZSIMONS, E. O. *et al*. (2014), "Using the Infrastructure of a Conditional Cash Transfer Program to Deliver a Scalable Integrated Early Child Development Program in Colombia: Cluster Randomized Controlled Trial", *BMJ*, **349**, g5785.

BANERJEE, A. V., COLE, S., DUFLO, E. *et al.* (2007), "Remedying Education: Evidence from Two Randomized Experiments in India", *The Quarterly Journal of Economics*, **122**, 1235–1264.

BARCELLOS, S. H., CARVALHO, L. S., and LLERAS-MUNEY, A. (2014), "Child Gender and Parental Investments in India: Are Boys and Girls Treated Differently?", *American Economic Journal: Applied Economics*, **6**, 157–189.

BEHRMAN, J. R. (1996), "The Impact of Health and Nutrition on Education", *The World Bank Research Observer*, **11**, 23–37.

BERNAL, R. (2008). "The Effect of Maternal Employment and Child Care on Children's Cognitive Development", *International Economic Review*, **49**, 1173–1209.

BHARADWAJ, P., LØKEN, K. V., and NEILSON, C. (2013), "Early Life Health Interventions and Academic Achievement", *The American Economic Review*, **103**, 1862–1891.

BLEAKLEY, H. (2007), "Disease and Development: Evidence from Hookworm Eradication in the American South." *The Quarterly Journal of Economics*, **122**, 73–117.

BOND, T. N. and LANG, K. (2013), "The Evolution of the Black-White Test Score Gap in Grades K–3: The Fragility of Results", *Review of Economics and Statistics*, **95**, 1468–1479.

BONEVA, T. and RAUH, C. (2015), "Parental Beliefs about Returns to Educational Investments: The Later the Better?", (Technical Report, Human Capital and Economic Opportunity Global Working Group).

CAMPBELL, F., CONTI, G., HECKMAN, J. J., *et al.* (2014), "Early Childhood Investments Substantially Boost Adult Health", *Science*, **343**, 1478–1485.

CARNEIRO, P., GARCIA, I. L., SALVANES, K. G. *et al.* (2015), "Intergenerational Mobility and the Timing of Parental Income", (Mimeo, University College London).

CARNEIRO, P., LOPEZ-GARCIA, I., SALVANES, K. *et al*. (2015), "Intergenerational Mobility and the Timing of Parental Income", (Mimeo UCL).

CASE, A., LUBOTSKY, D. and PAXSON, C. (2002), "Economic Status and Health in Childhood: The Origins of the Gradient", *American Economic Review*, **92**, 1308–1334.

CHAY, K. Y. and GREENSTONE, M. (2003), "Air Quality, Infant Mortality, and the Clean Air Act of 1970", (NBER Working Paper 10053).

CUNHA, F., ELO, I. and CULHANE, J. (2013), "Eliciting Maternal Expectations about the Technology of Cognitive Skill Formation", (NBER Working Paper 19144).

CUNHA, F. and HECKMAN, J. (2007), "The Technology of Skill Formation", *American Economic Review*, **97**, 31–47.

CUNHA, F. and HECKMAN, J. J. (2008), "Formulating, Identifying and Estimating the Technology of Cognitive and Noncognitive Skill Formation", *Journal of Human Resources*, **43**, 738–782.
CUNHA, F., HECKMAN, J. J., and SCHENNACH, S. M. (2010), "Estimating the Technology of Cognitive and Noncognitive Skill Formation", *Econometrica*, **78**, 883–931.
CURRIE, J. (2009), "Healthy, Wealthy, and Wise: Socioeconomic status, Poor Health in Childhood, and Human Capital Development", *Journal of Economic Literature*, **47**, 87–122.
CURRIE, J. (2011), "Inequality at Birth: Some Causes and Consequences." (NBER Working Paper 16798).
CURRIE, J. and ALMOND, D. (2011), "Human Capital Development before Age Five", *Handbook of Labor Economics*, **4**, 1315–1486.
CURRIE, J. and HYSON, R. (1999), "Is the Impact of Health Shocks Cushioned by Socioeconomic Status? The Case of Low Birthweight", *American Economic Review*, **89**, 245–250.
CURRIE, J., NEIDELL, M., and SCHMIEDER, J. F. (2009), "Air Pollution and Infant Health: Lessons from New Jersey." *Journal of Health Economics*, **28**, 688–703.
CURRIE, J. and STABILE, M. (2003), "Socioeconomic Status and Child Health: Why Is the Relationship Stronger for Older Children?", *American Economic Review*, **93**, 1813–1823.
DEL BOCA, D., FLINN, C. and WISWALL, M. (2014), "Household Choices and Child Development", *The Review of Economic Studies*, **81**, 137–185.
DEMPSTER, A. P., LAIRD, N. M. and RUBIN, D. B. (1977), "Maximum Likelihood from Incomplete Data via the EM Algorithm", *Journal of the Royal Statistical Society. Series B (Methodological)*, 1–38.
ENGLE, P. L., BLACK, M. M., BEHRMAN, J. R., *et al.* (2007), "Strategies to Avoid the Loss of Developmental Potential in More Than 200 Million Children in the Developing World", *The Lancet*, **369**, 229–242.
FERNALD, L. C., WEBER, A., GALASSO, E. *et al.* (2011), "Socioeconomic Gradients and Child Development in a Very Low Income Population: Evidence from Madagascar", *Developmental Science*, **14**, 832–847.
FLORENS, J. P., HECKMAN, J. J., MEGHIR, C., *et al.* (2008), "Identification of Treatment Effects Using Control Functions in Models with Continuous, Endogenous Treatment and Heterogeneous Effects", *Econometrica*, **76**, 1191–1206.
GALAB, S., KUMAR, S. V., REDDY, P. P., *et al.* (2011), *The Impact of Growth on Childhood Poverty in Andhra Pradesh: Initial Findings from India: Round 3 Survey Report*, (Oxford, UK: Young Lives, Department of International Development, University of Oxford).
GERTLER, P., HECKMAN, J., PINTO, R., *et al.* (2013), "Labor Market Returns to Early Childhood Stimulation: A 20-Year Followup to an Experimental Intervention in Jamaica", (NBER Working Paper 19185).
GLEWWE, P. and MIGUEL, E. A. (2007), "The Impact of Child Health and Nutrition on Education in Less Developed Countries", *Handbook of Development Economics*, **4**, 3561–3606.
GRANTHAM-MCGREGOR, S., CHEUNG, Y. B., CUETO, S., *et al.* (2007), "Developmental Potential in the First 5 Years for Children in Developing Countries", *The Lancet*, **369**, 60–70.
GRANTHAM-MCGREGOR, S. M., POWELL, C. A., WALKER, S. P., *et al.* (1991), "Nutritional Supplementation, Psychosocial Stimulation, and Mental Development of Stunted Children: The Jamaican Study", *The Lancet*, **338**, 1–5.
GRILICHES, Z. and RINGSTAD, V. (1970), "Error-in-the-Variables Bias in Nonlinear Contexts", *Econometrica: Journal of the Econometric Society*, 368–370.
GRONAU, R. (1974), "Wage Comparisons—A Selectivity Bias", *Journal of Political Economy*, **82**, 1119–1143.
HAMADANI, J. D., TOFAIL, F., HUDA, S. N., *et al.* (2014), "Cognitive Deficit and Poverty in the First 5 Years of Childhood in Bangladesh", *Pediatrics*, **134**, e1001–e1008.
HECKMAN, J. J. (1979), "Sample Selection Bias as Specification Error", *Econometrica*, **47**, 153–161.
HECKMAN, J. J. (2007), "The Economics, Technology, and Neuroscience of Human Capability Formation", *Proceedings of the National Academy of Sciences*, **104**, 13250–13255.
HECKMAN, J. J., MOON, S. H., PINTO, R. *et al.* (2010), "The Rate of Return to the HighScope Perry Preschool Program", *Journal of Public Economics*, **94**, 114–128.
HECKMAN, J. J., SCHENNACH, S., and WILLIAMS, B. (2010), "Matching with Error-laden Covariates", (Unpublished Manuscript, Department of Economics, University of Chicago).
HODDINOTT, J., MALUCCIO, J., BEHRMAN, J., *et al.* (2008), "Effect of a Nutrition Intervention during Early Childhood on Economic Productivity in Guatemalan adults", *Lancet*, **371**, (9610).
HU, Y. and SCHENNACH, S. M. (2008), "Instrumental Variable Treatment of Nonclassical Measurement Error Models", *Econometrica*, **76**, 195–216.
JAYACHANDRAN, S. and KUZIEMKO, I. (2011), "Why Do Mothers Breastfeed Girls Less Than Boys: Evidence and Implications for Child Health in India", *Quarterly Journal of Economics*, **126**, 1485–1538.
KUMRA, N. (2008), "An Assessment of the Young Lives Sampling Approach in Andhra Pradesh, India", (Oxford, UK: Young Lives).
LU, C., BLACK, M. M. and RICHTER, L. M. (2016), "Risk of Poor Development in Young Children in Low-Income and Middle-Income Countries: An Estimation and Analysis at the Global, Regional, and Country Level", *The Lancet Global Health*, **4**, e916–e922.
LUCAS, A., MORLEY, R. and COLE, T. J. (1998), "Randomised Trial of Early Diet in Preterm Babies and Later Intelligence Quotient", *BMJ*, **317**, 1481–1487.
MIGUEL, E. and KREMER, M. (2004), "Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities", *Econometrica*, **72**, 159–217.

NEWEY, W. K., POWELL, J. L. and VELLA, F. (1999), "Nonparametric Estimation of Triangular Simultaneous Equations Models", *Econometrica*, **76**, 565–603.

NIELSEN, E. R. (2015a), "Achievement Gap Estimates and Deviations from Cardinal Comparability" (FEDS Working Paper No. FEDGFE2015-40).

NIELSEN, E. R. (2015b), "The Income-Achievement Gap and Adult Outcome Inequality" (FEDS Working Paper).

RUBIO-CODINA, M., ATTANASIO, O., MEGHIR, C. et al. (2015), "The Socioeconomic Gradient of Child Development: Cross-sectional Evidence from Children 6–42 months in Bogota." *Journal of Human Resources*, **50**, 464–483.

SAZAWAL, S., BENTLEY, M., BLACK, R. E., *et al*. (1996), "Effect of Zinc Supplementation on Observed Activity in Low Socioeconomic Indian Preschool Children", *Pediatrics*, **98**, 1132–1137.

SCHENNACH, S. M. (2004), "Estimation of Nonlinear Models with Measurement Error", *Econometrica*, **72**, 33–75.

TODD, P. E. and WOLPIN, K. I. (2007), "The Production of Cognitive Achievement in Children: Home, School, and Racial Test Score Gaps", *Journal of Human Capital*, **1**, 91–136.

WALKER, S. P., CHANG, S. M., POWELL, C. A., *et al.* (2005), "Effects of Early Childhood Psychosocial Stimulation and Nutritional Supplementation on Cognition and Education in Growth-Stunted Jamaican Children: Prospective Cohort Study", *The Lancet*, **366**, 1804–1807.