An Age Profile Perspective on Two Puzzles in Global Child Health: the Indian Enigma & Economic Growth*

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Abstract

We provide an empirical perspective and two classes of regression models that make progress on differentiating between two types of determinants of child health: *health endowment* effects provided to the child at birth; and *health investment* effects determined by the post-birth stream of health inputs provided to the child and the productivity of those investments. We apply the framework to two existing puzzles in the child health demography literature: the apparent lack of strong correlation between economic growth and child height-for-age z-score (HAZ); and the Indian Enigma, where Indian children are on average less tall than similarly economically situated African children. In the context of the Indian Enigma, we find that the Indian-African child HAZ gap (between 0.4sd and 0.5sd) is present immediately after birth and maintains a similar magnitude across the first three years of life. We interpret this as evidence that causes affecting health endowments likely explain the greater part of the Indian Enigma. We also estimate a robust association between a 10% increase in (log) GDP per capita and a 0.04sd increase in child height by age 2. However, this correlation is not present at birth and is instead driven by differences in child growth rates. We interpret these results as indicating that differences in the post-birth health input stream, and/or the biological productivity of those inputs, likely explain the greater part of the economic growth association.

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1 Introduction

We revisit two puzzling empirical findings in the global child health literature. We first examine the Indian Enigma, the fact that children in India are shorter than children in less economically prosperous African countries (Jayachandran and Pande, 2017) . We then turn our attention towards an analysis of the association between economic growth and child height more broadly, where recent research using similar data has argued that the correlation between changes in (ln) GDP per capita (GDPpc) and child height-for-age Z-score (HAZ) is weak to non-existent (Vollmer et al., 2014). In contrast to previous studies, which analyzed mean child height-for-age Z-score (HAZ) or stunting rates[1], our perspective is based on an analysis of changes in the level and shape of the entire HAZ-age profile. The resulting dynamics of the age-specific estimates allow us to rule-out large sets of potential causal mechanisms and to provide insight for policy makers and researchers on where to target their efforts. Our findings indicate that the Indian Enigma is broadly explainable by differences in the average child health endowment as measured by implied HAZ at birth. The gap is present at birth and maintains a similar magnitude over the first several years of life. We also find that the reportedly weak association between changes in GDPpc and changes in HAZ conceals a moderate and robust association that grows over the first two years of life from close to 0 to around 0.04sd. We interpret this as evidence that the GDPpc association is likely explained in large part by differentials in the (effectiveness of the) post-birth health input stream.

Our age-profile perspective applies two families of regression models to each of the two puzzles. These models allow us to distinguish between associations generated by mechanisms related to *health endowments* available at birth and those related to the level and productivity of post-birth *health investments*. The first is a family of individual-level age-profile fixed-effects models that generate age-specific estimates of the association of interest, allowing

[1]Stunting is defined as a child being more than 2 standard deviations below the median reference child using the 2004 WHO child growth standards as a reference.

researchers to visualize how a covariate of interest correlates with the shape of the entire HAZ-age profile. The models require a re-conceptualization of the role of space and time fixed effects, and we provide intuition linking our "country-specific age profile" and "child lifespan" fixed-effects to "within" and "between" variation interpretations of standard panel fixed-effects models. The second is a family of ecological models that separately estimate the association between the covariate of interest and two parameters of the HAZ-age profile: HAZ at birth and the rate of change of HAZ over the first years of life. The models employ a two-step procedure that first estimates space and time specific parameters of a stylized child growth model, and then estimates the determinants of those parameters using a standard panel fixed-effect model. Both sets of models are designed to be useful on data from DHS and similar large scale demographic surveillance surveys of the type commonly employed in global health research.

We first apply our models to the so-called Indian Enigma in child growth patterns. The fact that Indian children are generally shorter than children from sub-Saharan Africa, despite Indian children generally enjoying better economic conditions throughout their lives, has received considerable attention from economists in the past several years (Jayachandran and Pande, 2017; Bergstrom and Dodds, 2016; Spears, 2018; Spears et al., 2019). While there is general agreement on the existence and size of the height gap, there is significant disagreement and uncertainty over the root causes of the difference, with explanations ranging from preferential investment in first sons, to differential fertility patterns, to disease environment. Our estimates suggest that the difference between mean Indian and African HAZ, about 0.3sd-0.5sd depending on birth order, is present at birth and persists at an approximately equal magnitude (in units of standard deviations of the reference population) throughout the first three years of life. We interpret this as an association that operates primarily through the child's health endowment. Researchers investigating mechanisms and policy makers looking for solutions ought to focus on determinants of the health endowment: fertility timing and birth parity, maternal physiology and pre-pregnancy health history, and

in-utero consumption patterns.

We then turn our attention to the broader association between economic growth and HAZ. Recent research using a large, geographically diverse, individual-level dataset of child height observations from developing countries has estimated a surprisingly weak to non-existent correlation between medium-term economic growth and child physical growth (Vollmer et al., 2014). Our results indicate that the age-aggregated estimates in Vollmer et al. (2014) obscure a relatively stable and modestly large correlation. However, this relationship is not present at birth and instead accumulates over the first two years of life, peaking around age 3, when a 10% change in GDPpc associated with a 0.04-0.05sd increase in child HAZ. We interpret this as evidence that various types of improvements to the post-birth health input stream likely drive the correlation. This interpretation points to mechanisms that operate through improvements in (effective) child health investment and/or increases in private and public goods consumption.

1.1 Graphical Representation: the HAZ-Age Profile

We provide Figure 1 as an intuitive graphical representation of our findings. Both figures graph mean-HAZ across child age using Demographic and Health Survey (DHS) data on over 1,000,000 children from 44 countries. The top figure compares Indian children and African children, while the bottom figure compares children from above and below median GDPpc (based on sample median). All four age profiles exhibit the characteristic shape of the HAZ-age profile in developing countries (Victora et al., 2010; Rieger and Trommlerová, 2016). The y-intercept, the implied HAZ at birth among children in our sample is well below 0, the median birth HAZ of children in the healthy and well-nourished reference population. Children also exhibit the characteristic loss of HAZ over the first two years of life that is endemic among children in the developing world.

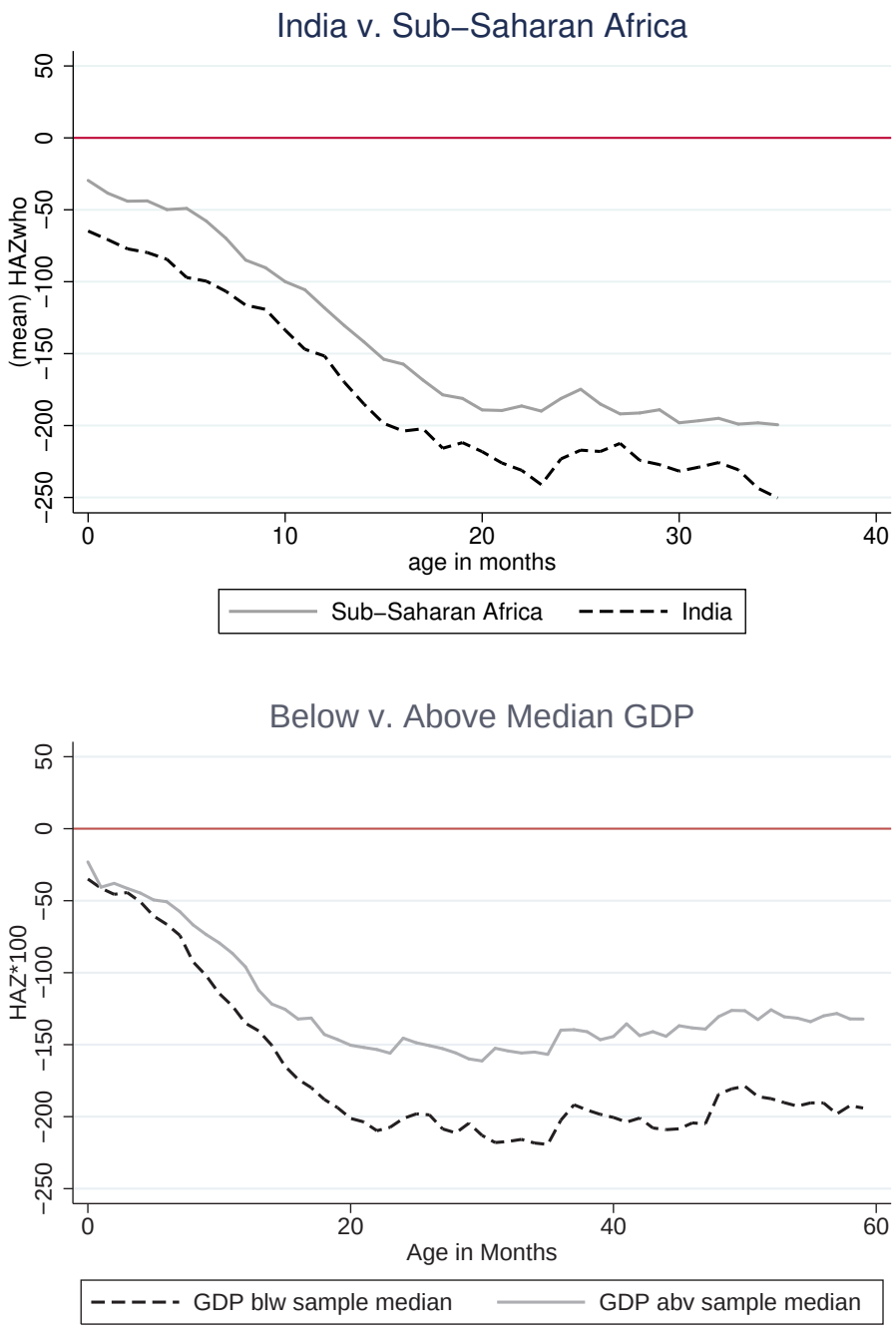

Figure 1: HAZ-Age Profiles: Indian Enigma and GDP per capita

Top panel presents the (weighted) mean HAZ age-profiles for children under the ages of three, graphed separately for Sub-Saharan Africa (gray) and India (black). Bottom panel presents the (weighted) mean HAZ age-profiles for children under the age of five aggregated by above (gray) or below (black) sample median PPP-adjusted GDP per capita.

The top panel of Figure 1 traces out aggregate HAZ-age profiles comparing children from India (dashed black) with children from Sub-Saharan Africa (solid gray). The two age-profiles start at different levels but then remain roughly parallel throughout the first 3 years of life. We argue that this initial level difference is the result of an *endowment effect*, passed on to children from their parents at birth. If we assume that a stable HAZ deficit is evidence of similarity in investments independent of this initial health endowment, then the inter-generational effect could explain the entire difference between the two growth trajectories. But even without that strong assumption, it would be nearly impossible to explain the dynamics of the India-Africa height gap as purely the result of differentials in the post-birth stream of inputs, e.g. from differential feeding patterns for eldest sons. Post-birth inputs cannot affect birth length.

In the bottom panel, we aggregate countries based on being above or below median GDPpc for countries in our sample. Unlike in the case of the India-Africa height gap, children in both groups of countries start at similar HAZ at birth (just below the reference group median of 0). While the groups start at similar levels, the rate of loss of HAZ is much faster for children in poorer countries (dashed black) compared to richer countries (solid gray) over the first 24 months of life. Assuming that beginning at a similar level of HAZ implies that children receiving similar streams of inputs would produce similar changes in HAZ, then this differential *growth rate* can be interpreted as evidence that a *health investment* effect is likely to explain a large share of the association between GDPpc growth and child physical growth. Again, such an explanation requires non-credible assumptions regarding the unobserved components of the health endowment, the health production function, and the measurement units of HAZ. But again without those assumptions, the *prima facie* evidence of a differential that is not present at birth, grows as children age and is correlated with a process associated with improvements in household consumption. This points to evidence in the changes from the post-birth investment stream.

To quantify the patterns above, and to determine their robustness to statistical adjustments

for observable factors, we apply the two regression models described above to the two empirical puzzles at hand. The remainder of this work is dedicated to conceptualizing and formalizing our age-profile empirical framework, demonstrating its application and highlighting how such a framework can provide insights that cannot be gleaned from methods focused on mean HAZ or stunting rates.

2 Background

Before describing our econometric models and providing our estimates, we provide background on the two demographic puzzles and the empirical perspective we adopt for our analysis. We then provide background on the process of growth faltering, which motivates our overall age-profile empirical perspective. In turn, we use this empirical motivation to frame the growth faltering process in terms of health capital theory, allowing for interpretations of our results that are economically meaningful and policy relevant. Finally, we describe the structure of DHS data, which determines the types of identifying variation available.

2.1 Two Empirical Puzzles

Economic growth is valuable insofar as it improves human wellbeing, and long-term economic development has clearly generated benefits for millions of people. Yet even with steady growth in the global economy over the last several decades, child physical growth faltering induced by chronic under-nutrition and heavy disease burden still affects around 150 million children worldwide[2]. Despite the major differences in stunting rates and mean HAZ between children in developed and developing countries, two recent and inter-related empirical puzzles have led researchers to reconsider the welfare benefits of economic growth for the broad population of children in poor countries. Both of these findings are puzzling to economists

[2]Date Accessed 02/25/2020 - https://data.unicef.org/topic/nutrition/malnutrition/

because they seem to defy a clear economic rule: households in richer countries should be able to provide higher quality health inputs to their children (in terms of both private and public goods) relative to those in poorer countries, and thus their children should exhibit better health outcomes.

Mean child HAZ in India is well below mean child HAZ in sub-Saharan Africa (between 0.2 and 0.5sd depending on birth order), despite generally higher household purchasing power in India. The term "Asian Enigma" appears first in Adamson (1996) and Ramalingaswami et al. (1997), which document a child *weight* gap between India and sub-Saharan Africa and investigate. The authors consider, and then subsequently disregard, a number of potential explanations including poverty levels, agricultural productivity, diet, and even the growth standards themselves. As summarized in (Underwood, 2002), "Nonetheless, Dr. Ramalingaswami and colleagues conclude that the discrepancy in South Asia must mean that mothers and children in South Asia are not as well fed, not as well protected from disease, not as well cared for, or all of the above." In a similar multi-causal investigation, Headey et al. (2015) points out that Bangladesh has not followed the same pattern, and thus the Asian Enigma is largely an Indian Enigma. The causal mechanisms they credit for this process of nutritional improvement range from economic growth, to antenatal care, to demographic factors, to NGO engagement, ultimately endorsing sanitation and wealth mis-measurement as potentially important mechanisms to investigate.

Most of these initial hypotheses focused on causes related to differential post-birth inputs to children in India compared to Africa, and the subsequent economics literature has largely focused on such explanations as well. Both Jayachandran and Pande (2017) and Bergstrom and Dodds (2016) argue that son preference leads to differential investment in children who are or are not first born males. Differences in sanitation and disease environment have also been proposed as mechanisms (Spears, 2018), presumably operating through post-birth exposure to pathogens.

Several papers, though, argue for mechanisms that operate on mothers and households prior to a child's birth, that is, mechanisms that will ultimately affect the health endowment provided their children. Spears et al. (2019) argues that birth order and fertility differences can explain much of the gap without reference to son preference, adding to a long literature on the effects of birth order, birth spacing and overall fertility on child health trajectories. Coffey (2015) documents that women of child-bearing age in India are more likely than their counterparts in sub-Saharan Africa to be underweight.

The second puzzle stems from more general findings in two recent papers, Subramanyam et al. (2011) and Vollmer et al. (2014), which argue that there is a surprisingly weak correlation between medium-term economic growth and nutritional status broadly across less-developed countries. These papers stand in contrast to previous work that estimated relatively robust effects of macroeconomic conditions on child anthropometric outcomes (Smith and Haddad, 2002; Haddad et al., 2003; Klasen, 2008; Harttgen et al., 2013).[3] Using a larger dataset covering more children and individual level observations not analyzed in previous studies, Vollmer et al. (2014) find no statistically meaningful relationship between medium-term economic growth and child height across the developing world. This work followed a similar analysis done within India using regional variation in economic productivity that also failed to find a meaningful correlation between aggregate output measures and child growth (Subramanyam et al., 2011). Beyond their use of individual-level data and their broader coverage of countries and time periods, the estimates from these two papers were the first to address a known weakness in previous empirical studies regarding controls for secular time trends. By applying both spatial and temporal fixed-effect models, the authors could identify the effect of within-country changes in GDPpc while still controlling non-parametrically for secular time trends. However, as we show below, their specification of country and year fixed-effects ignores the reality that space and time effects can only be time-invariant when

[3]Appendix Table A1 lists previous papers estimating the association between economic growth and various measures of child nutritional status

holding age fixed. More importantly, by estimating a single correlation across child age, the Vollmer et al. (2014) estimates average out the correlation among older children with the non-existent correlation among the youngest children, generating a small, positive and statistically insignificant estimate that obscured a robust association among older children.

2.2 Growth Faltering

HAZ is an age- and gender-normalized measure of child height relative to the median height of a population of well-nourished and healthy children. The reference population growth curves reflect globally comparable normal early childhood growth under relatively good household and community conditions. They are estimated from a sample of children between the ages of 0 to 5 years olds born to healthy mothers and in healthy environments across six countries - the United States, Oman, Norway, Brazil, Ghana and India. The median and standard deviation from these growth curves are used as the standards against which HAZ is calculated. An HAZ of 0 implies that a population of children are growing in conditions that are gauged to be nutritionally sufficient with adequate health protections. An HAZ of -2, indicating a child is two standard deviations below the age- and gender-specific WHO standards, defines the threshold for stunted growth. In the World Health Organization (1995) report, an expert committee on child health showed that HAZ calculated using the above mentioned growth curves did well to reflect the interaction between social determinants of health and the physical development of children.

The process of growth faltering is represented in the HAZ-age profiles in Figure 1. This process has two characteristics that appear in poor populations around the world (Victora et al., 2010). First, children in poor households are born smaller than children in rich households. This is represented by the intercept of the HAZ-age profile, the implied HAZ at birth, which is well below zero for almost all of the countries in our sample. Second, children in developing countries also grow less quickly than children in richer countries. The steep

decrease of mean HAZ from birth to around age 2 is indicative of an insufficient stream of nutritional and health inputs provided to the child. As children grow into adulthood, the lasting effects of early life growth faltering include increased morbidity and mortality, loss of lifetime growth potential, lowered cognition, elevated risk of chronic disease and lower socio-economic attainment into adulthood (World Health Organization, 1995; Glewwe and Miguel, 2007; Hoddinott et al., 2008; Almond and Currie, 2011; Prendergast and Humphrey, 2014; De Onis and Branca, 2016).

Our age-profile perspective is most similar to the one adopted in Rieger and Trommlerová (2016) to examine how categorical variables correlate with HAZ as children age, and demonstrating the stability of the underlying HAZ-age profile across sub-groups. In both cases the aim is to develop models capable of quantifying the differences between groups in the growth faltering process. The key differences between our empirical approaches stem from the differences in the underlying data structure. Our methods extend the domain of non-parametric analysis of HAZ-age profiles to situations where the variable of interest varies not only by characteristics measured at survey time (e.g. the India-Africa height gap) but also to situations where it varies by cohort (e.g. the economic growth regressions).[4]

Beyond these econometric modeling advances, our theoretical framework makes progress linking metaphysical health economic concepts to empirical analogs in the world. Adding a small amount of theoretical structure, as we do in the next section, allows us to discuss when these differences can and cannot be ascribed to endowment effects or to post-birth investment effects.

[4]This is a non-trivial extension, as it expands the domain of potential research applications to include the analysis past events or policies that may have affected children in different locations at different points in time and at different ages. The models presented here focus on estimating determinants that are fixed by location and/or birth year. But they easily accommodate the inclusion of cohort-varying exposures experienced at other ages simultaneously. We hope these models help move the technical frontier towards the ability to estimate the impact of events occurring at ages A-1, A-2, ... A-N on a child's outcomes at ages A+1, A+2, ... A+T. This line of inquiry is explored more deeply in Cummins and Aiyar (2018)

2.3 Health Capital Accumulation

Health capital theory conceives the biological process of human growth as the output of a health capital production function that takes as a starting point a child's health endowment H_o. This health capital endowment should not be confused with genetic inheritance, which may be an underlying determinant of the health endowment but is not by any means the exclusive determinant, and any genetic role in determining the health endowment is fundamentally inseparable from the epigenetic environmental conditions within which the genes operate. The concept of health endowment is instead a metaphysical economic concept related to the overall robustness of an individual's health at the beginning of their lives. It is an initial stock of health capital, an initial amount of life potential with which we are born[5].

In this framing, the endowment itself is endogenous to parental health and consumption patterns prior to a child's birth, and even to longer-term inter-generational transmissions caused by environmental or nutritional insults to parents or grandparents decades in the past. While conceding that any choice of a point in human development where an endowment is officially bequeathed is necessarily arbitrary to some degree, we believe it is reasonable to define health endowments as coming into being at birth. We thus refer to differences in factors affecting HAZ at birth as *endowment effects* on HAZ, since they relate exclusively to the (observable portion of the) stock of health capital with which a child is born.

Child growth is then modeled as an iterative process that begins with H_o and is updated each period based on the stream of optimally chosen health inputs I_a^* provided to the child after birth and translated biologically into height through a human capital production function $H_a = f(H_0, I_a^*)$. The effect of this stream of inputs on attained height is what we call an *investment effect* in the child, whether that effect is driven by changes in the levels of I_a^* or differences in the productivity of inputs at generating human capital, or both.

[5]The main channels through which health capital operates in Grossman (1972) are not through marginal productivity or intellectual potential, but through the budget constraint for time and the length of your life.

2.3.1 Empirical Implications of the Health Capital Framework

Empirical Proposition 1: *Differences in birth length across populations reflect differences in the health endowment.*

If two populations differ in mean birth length, then our health capital framework defines these as differences in the health endowment. The post-birth stream of inputs cannot impact HAZ at birth. However, while the claim is almost tautologically true, it also obscures an important assumption. The measure of H_0 would have to be a fully sufficient statistic for the biologically multi-dimensional heath endowment itself for equivalent HAZ at birth to be interpreted as equivalent health endowments. This assumption would be violated if, for instance, some populations of children have high endowments (in terms of future potential) that are not physically realized until later in life. Certainly, HAZ is not such a sufficient statistic, and the comparisons we make are only as good as the measure we use. We want to acknowledge that HAZ at birth (or at any point in a child's development) is not the only relevant measure of the underlying health endowment and that it is not known precisely what aspects of the health endowment are and are not revealed in birth HAZ. We do, however, believe birth HAZ to be an informative measure that, at a population level, captures at least some important aspects of the (average) child health endowment.

Empirical Proposition 2: *Differences in the slope of the HAZ-age profile across populations represent differences in the interaction between the initial health endowment and the post-birth stream of inputs provided to children.*

The model makes the intuition clear: length at age A, defined by the health capital model as $f(H_0, I_a^*)$, is determined by the initial health endowment and the stream of health inputs provided to the child after birth. If two populations diverge in their age-profiles after beginning with a common H_0, this can only be the result of differentials in the stream of post-birth inputs and/or differentials in the efficiency of inputs at producing health capital (or at least its observable component in HAZ). We refer to both of these mechanisms,

changes in input levels and differences in input productivity, as investment effects, since they involve the interaction between the initial health endowment and the subsequently realized stream of health inputs and insults experienced by the child.

The interpretation of this proposition requires care. First, any claims about similarities in slope of the HAZ-age profile as reflective of differential investment levels requires assumptions over the productivity of the health capital production function in relation to H_0. If lower health endowment (smaller) children also grow less quickly (in units of HAZ) given the same nutritional and health inputs, then divergences between two HAZ-age profiles that start in different places would not be interpretable as differences in investment levels, but would be due to different productivity of investment. Alternatively, even when birth HAZ is the same across two populations, the multi-dimensionality of the underlying biological health endowment may be such that multiple types of health endowments produce the same birth HAZ but interact differently with the same subsequent stream of health inputs.

In general, it is not possible, by simply comparing outcome dynamics, to determine whether subsequent growth differentials are attributable to differences in input levels (I_a^*) or differences in the productivity of those inputs (e.g. through interactions with the unobserved component of the health endowment in the health capital production function). In this work we thus refer to both of these as *investment effects*.

2.4 Data

Our individual level observations of child health outcomes and household covariates come from the Demographic and Health Surveys (DHS). We supplement this data with economic data from the World Bank.

2.4.1 The Demographic and Health Surveys (DHS)

Our child-level dataset of outcomes and covariates was generated by appending data from 160 DHS from 44 countries surveyed between the years 1986 and 2016 (I C F, 2011). Since the DHS collects information from children who are at most 5 years old, the sample includes cohorts of children born between 1982 and 2016.

DHS surveys are generally conducted every few years in a given country. Each individual DHS round is a large-scale, multi-stage cluster sample survey used to gather health, demographic and socioeconomic information on women (aged 15-49 years), children (aged 0-5 years) and their households. Our main sample consists of all of the DHS surveys meeting our basic requirement that a country had at least 2 rounds with HAZ data on children from ages 0-3 years old. The final dataset consists of more than 1 million children below the ages of 5.

We provide sample summary statistics in the Appendix in Table B1. Mean HAZ across regions varies from a high of -1.3 in Asia to a low of -1.7 in India, with African children in between. Birth orders are similar across most of the world but are skewed towards higher birth orders in India in large part due to differences in sampling design[6]. We also present an overview of the regional and temporal variation available in the DHS data collection rounds in Table B2. Three-fourths of the surveys come from Africa, accounting for slightly more than 50 percent of the individual observations in the data. Data from Asia account for close to 45 percent of the observations, with India providing most of these.

[6]The two most recent rounds of the Indian DHS only collect data on children born within the five years preceding the survey, but the preceding two rounds collected information only children up to the age three.

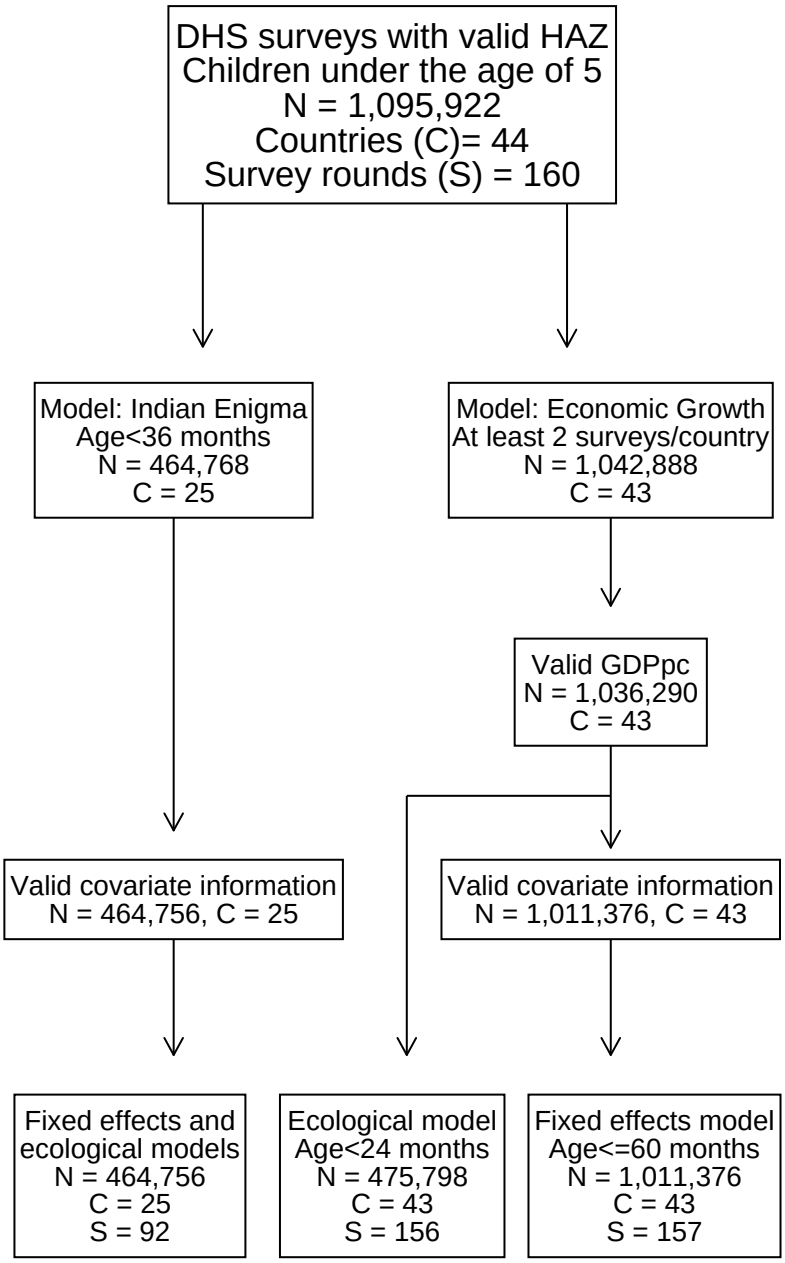

Figure 2: Sample Construction

The estimation samples for the two sets of empirical analyses are slightly different. In comparing India and Africa, we include only children under age 3, as several rounds of the Indian DHS do not include data on 3 and 4 year olds. In estimating the association between economic growth and HAZ, we include all surveys with children up to age 5. Figure 2 shows the sample selection criteria and loss of sample size for each model. We discuss particulars of each estimation sample in the corresponding empirical sections below.

2.4.2 GDP data

GDP per capita time-series data for individual countries is available in the World Development Indicators Series of the World Bank[7]. We use the natural log of GDP per capita in purchasing power parity (PPP) terms comparable to 2011 U.S dollars for the analysis. We use World Bank data instead of the Penn World Tables data favored by Vollmer et al. (2014) for reasons explicated in O'Connell and Smith (2016) to do with comparability within countries over time.

In the next section, we lay out the general problem of applying an age-profile perspective to this data structure and discuss the context-specific implementation of these models in the associated sections that follow.

3 Individual-Level Age-Profile Regression Models

Most demographic level analyses of the determinants of child growth focus on estimating effects on stunting rates (usually for children under-5) or mean HAZ, using either individual-level data or aggregated ecological level observations. In the case of individual-level data analysis, it is common to apply "spatio-temporal" fixed effects of various types. Often this means including region and year or region-x-year fixed-effects, where region is defined as some

[7] accessed from http://databank.worldbank.org/; May 2019

geographic unit and year is defined either by survey year or cohort year. Such is the case with the two most influential recent papers related to the empirical contexts we investigate here. Jayachandran and Pande (2017) use location fixed effects, defined by primary sampling unit (PSU), to make comparisons of children across birth orders. Vollmer et al. (2014) use country and survey-year fixed effects on aggregated and individual-level data to estimate the association between economic growth and child stunting rates. Subramanyam et al. (2011) use a similar setup for their within-India estimates of the effects of regional GDPpc growth in India, shifting the fixed effects from the country level to the state level[8].

Consider an individual-level fixed-effects model for repeated cross-sectional data, with variable of interest D that varies by region and survey year:

$$HAZ_{irt} = X'_{irt}\beta + \delta * D_{rt} + \mu_r + \lambda_t + u_{irt} \tag{1}$$

A standard interpretation is that estimating this equation provides a "difference in difference" estimate of δ. The temporal fixed-effects control for time (t) trends and force comparisons across regions (r). The regional fixed effects control for place-based factors and force comparisons within a particular region (over time).

We argue that these models lack empirical or theoretical grounding when they are applied to harness the types of spatio-temporal variation used in our applications. As we show in Figure 1, HAZ is not a stable outcome across age. The design of the DHS survey, which samples children ages 0-5 in a given country every few years, ensures that birth cohort and age-at-measure are mechanically co-determined within any given survey. Thus, not only in HAZ not stable across age, it is also cyclical across cohort.

This artifact of survey design, discussed at length in Cummins (2013), in conjunction with the nature of annual cohort variation in GDP, make violations of the assumptions undergirding the use of such fixed-effects likely. First, any effect of growing up in, say, South Africa

[8]Subramanyam et al. (2011) also include random effects at the maternal and PSU level.

relative to Ethiopia is unlikely to be a level difference that is common to children of all age. Instead, it is likely to vary with age, increasing or decreasing over the first few years of life. Second, secular time trends may be common across regions but will not be common across ages. The effect of living through 1999 will be different for a one year old compared to a 4 year old.

The main concern with estimating an equation such as Equation 1 is not simply that it is misspecified. The problem is that it is misspecified in ways that are likely to generate strong biases in the estimates of δ. First, the estimates will average over the true correlations that, in the world, vary by child age (e.g. in Vollmer et al. (2014)). But even more importantly, such estimates often latch on to age-profile variation that is spuriously correlated with cohort variation as described in Cummins (2013). This bias arises because the sampling methods of the DHS induce a correlation between a child's age at measure and their cohort, allowing the misspecification of the HAZ-age profile in the models to translate into bias in the estimate of δ. This is not a concern when comparing time-invariant characteristics like country of birth. However, Cummins (2013) shows that applying such models to estimating serially-correlated variables of interest like GDPpc can lead to significant bias and poor inference properties. By properly modeling the time and space fixed-effects to force comparisons between children of the same age, our models are not susceptible to the bias.

3.0.1 Estimating Equations for Individual-Level Age-Profile Models

One way to avoid both the interpretation and bias concerns over aggregating results across ages is to simply estimate the model on each age group separately. The following equation represents the regression analogue of that thought-experiment, containing observations for only children aged A born into cohort year c in country r.

$$HAZ^A_{irc} = X'_{irc}\beta^A + \delta^A * D_{rc} + \mu^A_r + \lambda^A_c + \epsilon^A_{irc} \tag{2}$$

In the case of estimating the India-Africa height gap, D varies only at the country (r) level. We thus can identify the effect only from spatial variation - the exercise by nature involves comparing children born in different places. However, the repeated cross-sectional nature of the dataset allows us to still control non-parametrically for age-specific cohort trends in the outcome variable that are common across units (λ_c^A). These cohort-period-age fixed-effects generate "between" variation in our models, identifying coefficients from differences across children who were born in the same year and measured in the same year, but who lived in different parts of the world.

In the case of our GDPpc estimates, we have a continuous variable of interest that varies across both space and cohort[9]. The key difference from the India-Africa regression lies in the presence of cohort variation in addition to spatial variation, allowing us to compare children born in the same country under different GDPpc levels. Standard country-level fixed effects would de-mean each observation using the average of all children in a single country, exploiting variation "within" a country. Our concept of "within" variation instead involves comparing children who grew up to the same age in the same country.

We next model the above thought experiment in a multi-age framework where we can estimate the entire vector of δ^A simultaneously for children of all ages. We alter the preceding equation by allowing μ_r^A and λ_c^A, representations of the country and cohort fixed-effects in the age-aggregated regression described above, to become μ_{ra} and λ_{ca}. We interpret these fixed-effects as controlling for *country-specific HAZ-age profiles* (μ_{ra}) and for a child's *lifespan*, their growing up from birth to age A over the years C to $C + A$ (λ_{ca}).

$$HAZ_{irca} = X'_{irca}\beta + \sum_a \delta^a * D_{rc} + \mu_{ra} + \lambda_{ca} + \epsilon_{irca} \tag{3}$$

Estimates of the vector δ^a from Equation 3 provide the age-profile difference-in-difference estimates of the association between HAZ and D. Compared to traditional difference-in-

[9]We assign children the GDPpc measure for their country in their year of birth.

difference estimates, instead of differencing out the effects of region and year, we difference out the effect of growing up to age A in some particular place, and the effect of growing up to age A over the same calendar years.

Figure 3 provides a graphical representation of the variation that identifies Equation 2. The three time-series plot HAZ and GDPpc against cohort and represent data from three geographically and socioeconomically diverse countries: Bangladesh, Colombia and Uganda, from top to bottom. The gray dashed line represents the GDPpc trend. Each vertical red line represents a DHS survey year for that country, and the black lines represent the HAZ age profiles of that country generated from that survey year and averaged by age and cohort. The within country variation we exploit is represented in the top panel by the gray circles, which are 2 year olds, growing up in Bangladesh at different points in time. This is the comparison forced by the country-specific age-profile controls μ_{ra}, which replace the standard year fixed-effects and de-means the data within each country-age group. The square gray markers represent one set of the cross-country comparisons induced by λ_{ca}, our replacement for country fixed-effects. This holds constant the effect of growing up to age 2 over the same calendar years (in this case children born in 1998 and measured in 2000). The black diamond represents the group of 2-year olds in Bangladesh that also grew up between the years of 1998 and 2000, and thus represents the country-lifespan cell that is affected by both fixed-effects.

3.1 Survey-Level Aggregate Model: Age-Profile Intercept and Slope

A common alternative strategy to estimating associations between calendar-time exposures and child health outcomes is to aggregate a survey (or part of a survey) into a single observation. This "ecological" method reduces the complexity of the data environment, can aid in interpretation, solves problems with constructing appropriate and comparable survey weights, and is computationally less demanding. The common form these approaches take

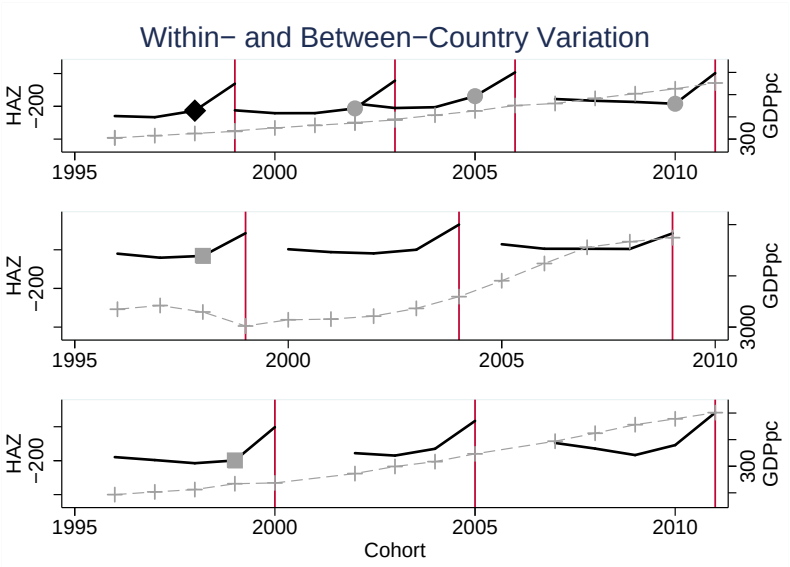

Figure 3: Visualizing Age-Profile Variation

Graphical representation of the identifying variation for Equation 8 comes from three countries representing different HAZ-age dynamics and different levels of GDPpc: Bangladesh, Colombia and Uganda, from top to bottom. The graphs plot mean HAZ and GDPpc across cohorts. Each vertical line represents a DHS survey year for that country, and the black lines represent the HAZ age profiles of that country generated from that survey year and averaged by cohort. The observations with the circular gray markers are observations share a common country and age (country-specific age-profile fixed-effects); the observations with square gray markers share a common cohort and age (lifespan fixed-effect); and the black diamond observation marks the group subject to both fixed-effects.

is to replace the individual-level observations from one survey with mean HAZ or stunting rates.

However, the defining feature of the HAZ-age profiles presented in Figure 1 is the rapid and relatively linear decrease of HAZ over the first two years of life. The age profile then becomes essentially flat (or slightly positively inclined) from ages 2 through 5. We define two parameters to characterize this empirical regularity: a) we define α as the *intercept of the HAZ-age profile on the Y-axis*, that is, the implied HAZ at birth; and b) we define β as the *rate of loss of HAZ from birth to age 2*, that is, how much more slowly children are growing relative to the WHO reference median child (in units of a monthly rate of loss of standard deviations relative to the reference population). As simple as they are, these

summary measures provide a reasonably complete characterization of the HAZ-age profile over the first two years of life.

It is important to note that we are estimating the parameters of an empirical HAZ-age profile constructed from a cross-section of children. An approach with more fidelity to the underlying thought experiment would require panel data following children from birth to age 5. This would eliminate sampling variation across ages and ensure that all the children experienced the same cohort effects. In the absence of such data, we use estimates of the empirical HAZ-age profile generated from our sample, which forces us to model a cross-section of children born across cohorts as representing the growth trajectory of a single cohort.

3.1.1 First-Stage: Estimating the Intercept and Slope Parameters

We estimate α & β separately for each fixed aggregation-group G, defined here as a particular survey round in a particular region, using an OLS regression of HAZ on child age and an intercept[10].

$$HAZ_{ia}^{G} = \alpha^{G} + \beta_{age}^{G} * Age_{ia}^{G} + u_{ia}^{G} \tag{4}$$

Equation 4 allows us to estimate α^G, a group-specific measure of the HAZ at birth and β^G, a measure of the rate of loss from that initial birth HAZ over the first two years of life, each region 'r' and survey year 'y'. We then take the estimates of α^G and β^G and merge these data with a cohort-time panel of treatment variables, generating an unbalanced panel of observations at the country-year level. The parameter estimates from the first stage then become the dependent variables in the second stage regression on the determinants of the

[10]In practice, a key choice in implementation involves defining an "observation", a unit at which to estimate $\hat{\alpha}^G$ & $\hat{\beta}^G$ and for which they are relevant measures of group-level child health. This involves a trade-off: smaller levels of aggregation provide more observations for the second stage regression, but each observation is estimated with increasing error. On the other hand, choosing a higher level of aggregation can lead to too few observations for the second-stage regression.

shape of the HAZ-age profile over the first two years of life (α_{ry} and β_{ry}).

3.1.2 Second-Stage: Estimating the Determinants of the Parameters

The second stage regression takes a form involving some or all of the elements of the fully saturated regression model below, for region r in survey year y, where P_{ry} represents either α_{ry} and β_{ry}. While each parameter in the first stage regression is estimated from a regression weighted by the probability weights provided by the DHS, the second stage regressions of the parameters on GDPpc are not weighted, and each aggregation group is thus given an implicit total weight of 1.

$$P_{ry} = \delta * D_{ry} + \mu_r + \lambda_y + \eta_{ry} \tag{5}$$

Again the choice of fixed-effects depends on the comparison of interest and the variation in D across space and time. In the case of estimating the India-Africa height gap, we focus on models using only survey-round fixed effects to net out common time trends in the parameters of the HAZ-age profile. In the case of the GDPpc analysis, we use classic panel fixed effects models with survey-time and group-level fixed-effect specifications.

3.1.3 Inference for α/β Regressions

We employ two strategies for estimation of standard errors for $\hat{\delta}$ in Equation 5. First, we provide analytic standard errors clustered by country, following standard practice for spatio-temporal fixed-effects models. These standard errors are likely to be too small relative to the true sampling distribution of $\hat{\delta}$, since they do not account for the uncertainty in the left-hand side variables which are themselves just estimates (Elbers et al., 2005). To account for this, we provide a second set of standard errors estimated from a 2-stage bootstrap procedure. In that procedure, we first choose (with replacement) an equal number of groups G to the

original regression, and give each observation a new ID number. We then bootstrap sample, within each ID number, by the primary sampling unit (PSU) and estimate $\hat{\alpha}$ and $\hat{\beta}$ for each group. We then re-estimate the coefficient on the variable of interest, replacing country based fixed effects with ID based fixed effects. We repeat the double bootstrap sampling 500 times and report the standard deviation of the estimates as the bootstrap standard error estimate of $\hat{\delta}$. Empirically, the large sample sizes from each survey seem to make this secondary source of variation rather small, and the two standard error estimates are similar.

4 Indian Enigma

Our analysis suggests that much of the India/Africa height gap can be explained as an effect of an intergenerational health endowment gap. The gap is increasing by birth order, but in all cases it is present at birth and HAZ differentials remain consistent in size through the first three years of life. We first describe our estimation sample in the next sub-section. We then provide regression specifications and discuss the results in the remaining sub-sections.

4.1 Sample for Indian Enigma

Our sample for comparing children from India and Africa includes all children between the ages of 0 to 36 months for the fixed-effects regressions, and 0 to 24 months for the ecological regressions. We include all children with valid HAZ measures and relevant covariates from countries in the sample used in Jayachandran and Pande (2017) that also had at least two DHS survey rounds. Aside from 4 DHS surveys in India, this includes 88 surveys from 24 African countries. More details can be found in Figure 2, and in Table B1 and Table B2. Our estimation sample ultimately includes 464,756 children, with about 1/3 of those observations being dropped due to age restrictions.

4.2 Estimating Equations: India/Africa Height Gap

We observe HAZ^B_{irca}, the HAZ score for child i in region r and born in cohort year c and age a, given a fixed birth order B. We then specify the regression model:

$$HAZ^B_{irca} = X'^B_{irca}\beta + \sum_A \delta^B_a * India_{ira} + \lambda^B_{ca} + \epsilon^B_{irca} \tag{6}$$

The birth order indicator limits the sample to children of birth order B, defined as first, second and higher born. The variable $India$, takes a value 1 if the child was born in India and 0 if they were born in Africa. We include a vector of explanatory variables X'_{irca} that includes mother's age at the child's birth and her education level, the birth interval in months (except for first borns), and the gender of the child. The regressions are weighted so as to maintain within-survey national representativeness, but so that each survey round's weights sum up to one. This is accomplished by dividing each individual's given sampling weight by the sum of the sampling weights for that survey round.

Identifying variation comes from comparing Indian children with the African counterparts of the same age and born in the same cohort (those who lived the same temporal lifespan). The vector of coefficients $\hat{\delta}$ is interpreted as providing estimates of the age-specific differences in mean HAZ between children born in India and those born in Africa. Graphing these coefficients allows us to visualize the age-dynamics of the India-Africa height gap.

We also apply our ecological model to quantifying the height gap. We first run the regressions described in Equation 4 to obtain estimates of the intercept and slope of HAZ age profiles ($\hat{\alpha}^G$ & $\hat{\beta}^G$) for each birth order in each Indian region (province) or African country for each survey round. This level of aggregation leaves us 110 observations at the region (r) and year (y) level.

In the second stage we regress the above values P_{ry} in region r in survey year y on an indicator variable for India, a vector of survey-time fixed effects, and a constant as represented in

Equation 7.

$$P_{ry} = \delta * India_{ry} + \lambda_y + \eta_{ry} \tag{7}$$

Similar to the between country variation that identifies the coefficients in Equation 6, the model compares each survey round by region in India with survey rounds of African countries measured around the same time. The estimate of the treatment effect is interpreted as a weighted average of these across-space/within-time differences. Our specification for λ_y includes fixed-effects for three year bins, so that each Indian survey is compared with African surveys taken at approximately the same time. This guarantees that the estimate of $\hat{\delta}$ is not dependent on comparisons with only a few African countries that were surveyed in the exact same year.

4.3 Results: India-Africa

In the left panel of Figure 4, we present the aggregate HAZ age-profiles for children under the ages of three, graphed separately for Africa (solid gray) and India (dashed black) and by birth order (increasing down rows). At each birth order, Indian children are born shorter than African children. This birth HAZ difference increases across birth order, from about 0.3sd for first born children to about 0.5sd for birth orders 3 and above. The gap remains consistent in size between the ages of zero to three within each birth order, as Indian children continue to lose HAZ at about the same rate as their African counterparts.

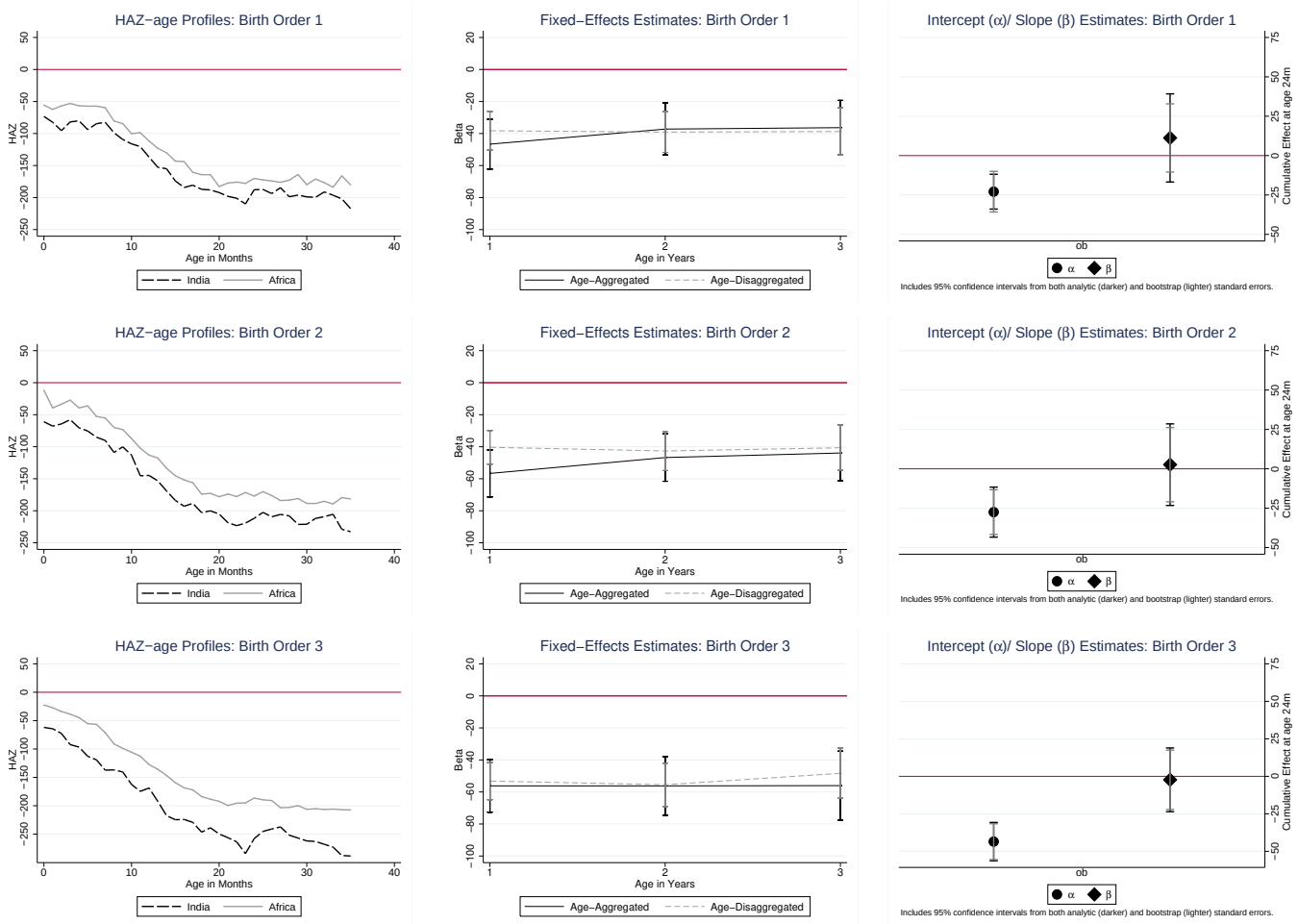

Figure 4: Results: India-Africa HAZ Gap

The left panel presents aggregate HAZ age-profiles for children under the ages of three, graphed separately for Africa (solid gray) and India (dashed black) and by birth order (increasing down rows). Each of the points are weighted by survey weights provided by the DHS. The middle column graphs out estimates and 95% confidence intervals from the individual-level age profile models estimated both independently (disaggregated) and simultaneously (aggregated). Disaggregated (gray) estimates include cohort fixed effects and aggregated estimates (black) include lifespan (cohort-age) fixed effects. The right column presents point estimates and 95% confidence intervals from analytic and bootstrap standard errors for the difference in HAZ-age profile intercept (α) and slope (β), re-scaled to 24 months of age estimated with survey year fixed-effects in the second stage.

The middle column of Figure 4 graphs out results from the age-disaggregated model described in Equation 2 and the simultaneously estimated age-profile models described in Equation 6. The x-axis represents a child's age group, binned by age in completed years, the y-axis represents the adjusted mean difference between Indian and African children, and we graph the estimates and 95% confidence intervals. For each birth order, the height gap is present at birth and our confidence intervals remain far from zero. The magnitudes reflect approximately those of the raw age profiles in the left column, with an estimated differential ranging from about 0.4 to 0.5sd. The difference is again relatively stable within-birth order as children age. In general, the point estimates get somewhat closer to 0 by age three, though our confidence intervals still remain far from zero and we cannot reject that all age correlations are the same. Precise point estimates are available in Table C1, Table C2 and Table C3.

The right column presents results from our ecological regressions. Here we graph our point estimates for the India-Africa differential on the estimated intercept (α) and slope (β) of aggregated HAZ-age profiles. We re-scale our estimate of β, multiplying by 24 months, so as to show the cumulative difference over two years since β is estimated as a monthly rate, and we inflate the confidence interval in the same manner. This allows comparability of the magnitudes between the associations with the slope and the intercept. Precise point estimates can be found in Table C4.

Our ecological estimates reveal similar patterns as those in the first two columns. The association is large very early in life (α is negative) and maintains a constant size as children age (β is very close to zero). The estimated association is somewhat smaller than the individual-level estimates, but of a similar magnitude. Our estimates of the India-Africa difference on α ranges from about 0.2sd for first-born children to 0.4sd for those of birth orders 3 and above. In all cases we estimate a very small and statistically insignificant difference in the rate of loss of HAZ (β) between Indian and African children.

4.4 Discussion of Indian Enigma Results

Like Jayachandran and Pande (2017) we find that later-born children in India have a significant height disadvantage of around 0.4sd compared to their African counterparts. However, we also find that first-borns in India exhibit a height disadvantage at birth of a similar or only slightly smaller magnitude. More importantly, our results indicate that the HAZ difference between Indian and African children is present at birth and maintains a relatively constant magnitude over the first few years of life, regardless of the child's birth order. This leads to our argument that health endowment effects are central to understanding the Indian Enigma, in contrast to the focus on health inputs to children in Jayachandran and Pande (2017) and Bergstrom and Dodds (2016).

While our analysis does not pinpoint particular mechanisms, we argue that children in India are shorter than their African counterparts because their parents and their households were different (physiologically, demographically, environmentally, etc.) before the children were born, but not necessarily after. A health differential present at birth is unlikely to be the result of differentials in health investments that arise when parents prefer some children (boys for example) over others (e.g. in Jayachandran and Pande 2017). It is also unlikely that child vaccination rates, generally available post-birth, explain the consistent differences in HAZ as children age (Bergstrom and Dodds, 2016). Our results also appear inconsistent with post-birth exposure to a poor sanitation environment explaining the child height differential (e.g. in Spears (2018)).

Alternatively, explanations linking the Indian Enigma to fertility decisions, such as those in Coffey (2015) and the medical literature on birth spacing (Varela-Silva et al., 2009), are fully consistent with our results. So are a number of other well-understood determinants of birth length. Short maternal stature, common in India, can reduce uterus space leading to low birth length and birthweight (Victora et al., 2008; Gluckman and Hanson, 2004). Under-nutrition during pregnancy itself, including micronutrient deficiency and in-utero en-

vironmental conditions, can also predict short stature in children (Almond and Currie, 2011; Godfrey et al., 2010; De Onis and Branca, 2016; Bhutta et al., 2008). And while post-birth exposure to open defecation does not seem able to explain the gap at birth, in-utero exposure to a poor health and sanitation environment can affect the health endowment (Spears, 2018).

5 GDP per capita and HAZ

Both of our econometric models provide evidence of a modest and robust association between relative changes (ln) GDPpc in a child's birth year and relative changes in their subsequent HAZ as they grow. Using our ecological level α/β regression model, we estimate that exposure to a 10% increase in GDPpc during early childhood is associated with a decrease in the rate of loss of HAZ relative to the World Health Organization (WHO) reference median of 0.002 sd/month. This adds up to an effect of around 0.04 - 0.05sd by the child's third birthday. Similarly, our age-profile fixed-effect model estimates a statistically insignificant association of about 0.01sd before a child's first birthday, but that by a child's third birthday a 10% increase in GDPpc is associated with a cumulative effect of 0.03-0.04sd, which then largely persists through age 5. We interpret this as evidence that medium-term changes in the macroeconomic environment likely correlate with child HAZ through mechanisms related to the post-birth investment stream, as opposed to operating through health endowment channels.

5.1 Sample for GDPpc Regressions

The sample for the individual level fixed effect analysis includes children between the ages of 0 to 60 months with valid HAZ scores, a measure of GDPpc, and all included covariates from countries with at least two rounds of DHS data. After following the inclusion criteria,

our estimation sample consists of a total of 1,011,376 children in 43 countries across 157 surveys. For the ecological models, we restrict the analysis to children between the ages of 0 to 24 months, reducing the sample to 475,798 children in 43 countries and 156 surveys.

5.2 Estimating Equations: GDP per capita

Our individual level age profile fixed effects model is specified as:

$$HAZ_{irca} = X'_{irca}\beta + \sum_{a} \delta_a * GDP_{rc} + \mu_{ra} + \lambda_{ca} + \epsilon_{irca} \tag{8}$$

HAZ_{ijca} is the HAZ score of child i in country r born in cohort c and measured at age a. μ_{ra} and λ_{ca} are the country-specific age profiles and lifespan fixed-effects, respectively. (X'_{irca}) includes maternal age and education level, and child sex and an indicator variable for urban areas. The variable GDP_{rc} is defined as the natural log of GDPpc in the birth year of a child in cohort c born in country r.

We also apply our ecological-level models to estimate the correlation between birth year GDPpc and HAZ. We estimate $\hat{\alpha}$ & $\hat{\beta}$, separately for each survey round y for each country as an OLS regression of HAZ on age as described in Equation 4. We then merge these parameter estimates with a panel of (ln) GDPpc measures, generating an unbalanced panel of observations at the country-year level.

The second stage regression takes a form involving some or all of the fixed-effects in the fully saturated regression model from Equation 9, for country R in survey year Y.

$$P_{ry} = \delta.GDP_{ry} + \gamma_r + \lambda_y + \eta_{ry} \tag{9}$$

In Equation 9, $\hat{\delta}$ is the estimate of the association of (ln) GDPpc on the outcome P, either α or β. We interpret $\hat{\delta}$, divided by 1,000 as the association between a 10% change in GDPpc

and change in HAZ (in units of standard deviations).[11] With the inclusion of both λ_y and γ_r, the model now implicitly compares changes in the HAZ-age profile in a country with low growth to changes in the profile in a country with high growth. We also provide estimates, in the appendix, which exclude one or both of the fixed-effects to show the pure OLS, within, and between estimates separately.

5.3 Results: GDP per capita

Figure 5 presents the country-specific HAZ age profiles (top), the individual-level age-profile fixed-effects estimates (middle) and the the ecological estimates on α and β (bottom). All show the same pattern, with the association between GDPpc and HAZ being small to non-existent at birth and growing in magnitude over the first two years of life.

is a disaggregated version of Figure 1, and

The top panel of Figure 5 graphs country-specific HAZ age profiles, shaded by GDPpc level, with lighter shades indicating higher GDP. This provides us a country-level disaggregated version of the bottom panel in Figure 1 and allows for visualization of cross-country variation in HAZ. The shading scheme provides a visual gradient, with countries binned into 10 GDPpc deciles with bins shading down from black to light gray as GDPpc increases, and also serves to demonstrate the consistency and robustness of the correlation represented in Figure 1. On the left hand side, the shades are jumbled together, covering a relatively small fraction of the Y-axis, indicating little association between GDPpc and birth HAZ. However, as we move across child age, the age-profiles sort themselves, and by age 5 there is a clear ordering of the HAZ-age profiles with the highest GDPpc countries in gray at the top shading down to the lowest GDPpc countries in black at the bottom.

The middle panel of Figure 5 graphs, across child age, the coefficients and confidence intervals

[11] The calculation above is based on a change of 0.1 in the log of GDPpc, given that our measure of HAZ is the WHO measure multiplied by 100.

from both the simultaneous fixed-effects regressions outlined in Equation 8 and a version of the age-specific regressions described in Equation 2. The estimates from age-disaggregated regressions on children at each age in years are graphed in black, the estimates from simultaneous estimation are graphed in gray, and both estimates are of similar magnitude and precision. The coefficient estimates on children under age 1 are small and statistically indistinguishable from zero. However, as the child reaches their third birthday, the magnitude of the correlation grows and the confidence intervals remain of similar magnitude. By age 3, a 10% increase in birth year GDPpc is associated with a 0.04sd increase in HAZ. The point estimate for children age 4 (48 to 60 months of age) is somewhat smaller, returning to level around a 0.02sd, as the poorest countries in the sample see mean HAZ increases around age 4 that are smaller or non-existent in the middle-income countries.

We provide the corresponding point estimates for the age-disaggregated models in Table D1 and from the simultaneously estimated models in Table D2. Table D2 also provides several alternative fixed-effects estimates for comparison. The specification in column 1 includes only country and survey fixed effects, adjusting for child age with a series of indicator variables for age in months. Column 2 includes country-specific age indicators, along with survey fixed effects, and column 3 includes country fixed effects with lifespan (cohort-by-survey) fixed effects. The specification in column 4 includes both the country-age and lifespan fixed effects and is our preferred, saturated model. After controlling non-parametrically for child age using age-in-months indicator variables, all of the point estimates are similar, and standard errors for all models are of similar size.

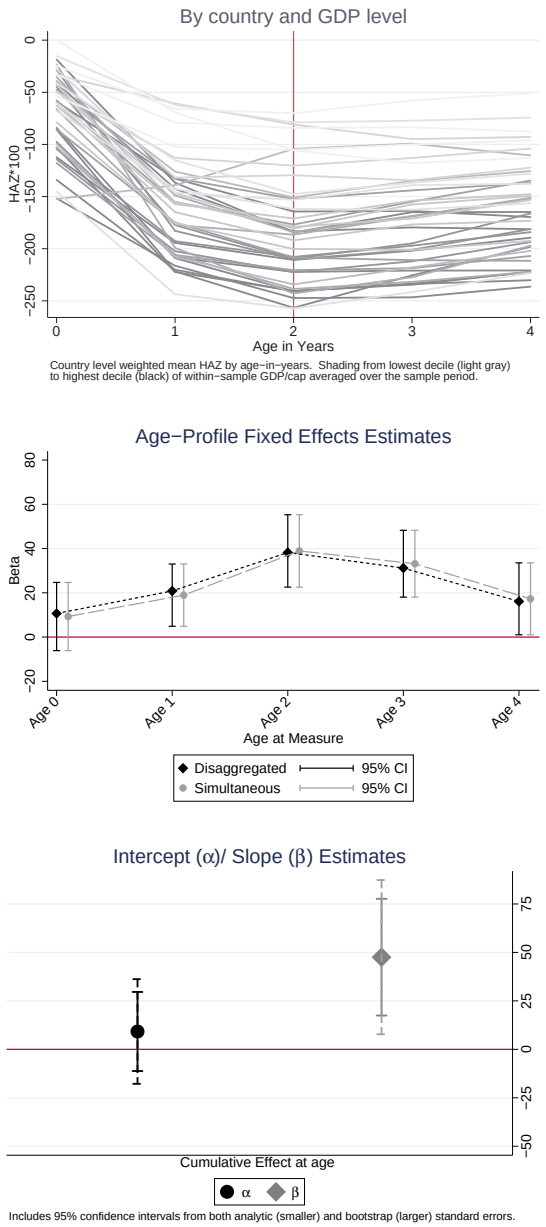

Figure 5: Results: ln(GDP per capita) and HAZ

The top panel presents HAZ age-profiles for children under the ages of 5 aggregated by country and shaded by mean birth year GDPpc among observations from that country. Countries move from higher to lower GDPpc as the shade moves from gray to black. The middle panel graphs estimates and 95% confidence intervals from the individual-level age profile models estimated both independently (disaggregated) and simultaneously (aggregated). Disaggregated estimates (black) include country and cohort fixed effects and aggregated estimates (gray) include country-age and lifespan (cohort-age) fixed effects. The bottom panel presents point estimates and 95% confidence intervals from analytic and bootstrap standard errors for the intercept (α) and slope (β) of the HAZ-age profile, re-scaled to effect at 24 months of age and estimated with survey year and country fixed-effects in the second stage.

The ecological estimates displayed in the bottom panel provide additional evidence of a changing association over the first two years of life. Our estimates for the association between GDPpc and HAZ at birth (α) are centered on 0. However, our estimates for the association with growth rate (β) are large and statistically significant, implying an association between a 10% increase in GDPpc and cumulative increase of 0.045 standard deviations of HAZ over the first two years of life.

We provide estimates from alternative specifications in Table D3. The first column provides the OLS estimate with no fixed effects included, while the "within" specification (columns 3 & 4), includes γ_r, the "between" specification ((columns 5 & 6) includes λ_y, and the "DnD" specification (columns 7 & 8) present estimates when both are included. Across specifications, the coefficient estimates on α are generally small, highly variable across specifications and imprecisely estimated. The coefficient estimates on β, on the other hand, are robust across specifications and fairly precise. A 10% increase in GDPpc is associated with around a 0.002 sd decrease in the rate of loss of HAZ. In a country whose median child becomes exactly stunted on their second birthday after being born 0.25sd below the reference children (reasonable given Figure 1), the child's overall average rate of loss of HAZ would be around 0.07 sd/month, meaning a 10% change in GDPpc is associated with approximately a 3% change in the base rate of loss.

5.4 Discussion: GDP per capita

Prior studies that have estimated the relationship between economic growth and child health have often assumed away the actual process of child development and growth faltering, preferring instead static measures of population average health. Our re-analysis of the question, focused on the age-profile itself, pushes our understanding of the issue in two major ways.

First, our work goes a long way to reconciling the old cross-country literature on economic growth and child health, which found large effects, with an emerging literature finding small

or no effects. The association is larger and more robust than suggested in Vollmer et al. (2014), but still of modest size.

But beyond reconciling the empirical literature, the small and statistically non-significant estimates on HAZ at birth can be considered to be representative of a similar average health endowment and height potential at birth across high and low economic growth countries. The biologically, economically and statistically large correlation between GDPpc and the slope of the HAZ age-profile post birth likely captures differential investment effects post-birth.

This is perhaps unsurprising, or at least easily explainable ex-post. During periods of economic growth, households are more likely to find employment, and conditional on finding employment, likely to receive more income (Topel, 1999). Increases in GDPpc are also likely to increase the provision of public goods, broadly construed, which enter the health production function as post-birth investments. While these effects could, in theory, come from either increases in input levels or input productivity, an income effect channel, affecting input levels is a likely mechanism.

Whether the investment effect is driven more or less by levels or productivity of inputs, these results do appear to lend weight towards a focus on economic explanations (income, consumption, household wealth and distribution of resources). They also provide very little evidence to suggest that other demographic changes affecting birth outcomes are driving the association. Economic growth is strongly correlated with demographic change in a mutually reinforcing causal loop. Increases in economic growth can affect not only the number of children in the household (and thus resource availability post-birth), but also birth spacing and thus the availability of maternal energy during pregnancy and lactation that can be transferred to the fetus or breast-feeding child (Walker et al., 2008; Kramer et al., 2016). That would generate a causal pathway from economic growth to the health endowment, but we do not observe such an association in the data, and our estimates are relatively precise, indicating if such an association exists it is likely to be small.

6 Conclusion

The health capital production function is what distinguishes models of human development from other microeconomic choice models. Without an ability to map our understanding of the health capital production function onto biologically meaningful measures in the world, global health economists risk misinterpreting analyses and misguiding policymakers regarding both problems and solutions. The two families of regression models we present here are an attempt at improving the coherence between health capital accumulation theory and biological process of child growth faltering. The empirical puzzles we analyze demonstrate that our framework can provide new insights that previous methods could not.

Our analysis indicates that the Indian Enigma is largely the result of inter-generational transmissions affecting Indian children's health endowment. While we cannot rule out post-birth investments as potential partial explanations, it is clear that they cannot explain the entire India-Africa height deficit. On the other hand, our analysis also provides evidence that increases in GDPpc tend to improve child HAZ in a cumulative fashion post-birth, a result obscured in previous work that averaged effects across age. Within country relative changes in GDPpc do not alter birth HAZ in the medium term, and yet children born in relatively higher GDPpc times grow more quickly than their counterparts in lower GDPpc times, generating an increasingly large association over the first two years of life.

We hope the framework we develop and apply in this work will prove useful to practitioners interested in estimating the determinants of child growth in a wide variety of contexts. Beyond the potential academic research gains, we hope policy makers will benefit from the resulting research through improved targeting potential. This is particularly important in policy contexts like combatting global child growth faltering, where heterogeneity in program effectiveness across populations has proven difficult to explain. Policymakers would surely benefit from knowing whether the root causes of the particular growth faltering situation they face are likely to stem from inter-generational biological causes or changes to the post-

birth stream of inputs and exposures. Programs targeted at young children are unlikely to be successful if the underlying problem is present at birth; and programs aimed at young women and pregnant mothers are unlikely to be effective if the underlying causes relate to the post-birth stream of inputs.

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A Literature Review

Table A1: Cross Country Studies

Cross Country	**(No.)**	**Yrs Spanned***	**Data**	**Agg****	**N**	**Outcomes**	**Child Age*****	**VoI**	**Timing[E]**	**Method**	**Effect Size[R]**
Smith and Haddad (2002)	63	1970-1996	DHS	Country / Survey Year	179	WAZ	0to5	GDPpc-WDI	survey year	CountryFE	6.3% reduction in undernutrition
Haddad et al. (2003)	61	1970-1995	WHO	Country / Survey Year	175	WAZ	0to5	GDPpc - WB	survey year	Country FE, Decade FE	32pp increase in WAZ
Headey (2013)	89	1977-2007	DHS	Country / Survey Year	160	Stunting	0to5	GDPpc-WDI	survey year	Country FE	1.8pp decrease in stunting
Harttgen et al. (2013)	28	1991-2009	DHS	Child / Survey Year	380,000	Wasting , Stunting, Underweight	0to5	GDPpc - PWT	survey year	Country FE, Survey Year FE, Linear Age	1.5-1.7 LOR reduction in stunting
Vollmer et al. (2014)	36 (127 surveys)	1990-2011	DHS	Child/ Survey Year	460,000	Wasting , Stunting, Underweight	0to3	GDPpc - PWT	survey year	Country FE, Survey Year FE, Linear Age	No / weak association
Subramanyam et al. (2011) on India	India	1992, 1998, 2004	DHS	Child/ Survey Year	77,000	Stunting	0to3	GDPpc (state), linear age,	survey year	State and survey year FE	No Association

No. - Number of countries, *Years Spanned, not necessarily included. **Agg - Level of Aggregation, ***Age in years (Unless specified),
VoI - Variable of Interest, [E] - Timing of exposure, [R] - Effect Size in relation to a 10% increase in GDP, DHS - Demographic Health Surveys,
WHO - World Health Organization, WDI - World Development Indicators, GDPpc - GDP per capita, FE - Fixed Effects, LOR - log odds ratio

B Sample Construction and Variable Description

B.1 Summary Statistics

Table B1: Summary Statistics

	(1) Africa mean/sd	(2) India mean/sd	(3) Asia mean/sd	(4) Latin America mean/sd
HAZ (x 100)	-153.79	-164.07	-132.53	-114.51
	(176.17)	(170.79)	(158.48)	(144.53)
GDP in birth Year(Log)	6.19	6.92	6.87	7.61
	(0.71)	(0.46)	(0.99)	(0.61)
Preceeding Birth Interval	30.81	24.13	29.69	31.04
	(24.83)	(25.08)	(28.55)	(33.36)
Age in months	27.23	28.45	29.50	28.66
	(17.03)	(16.76)	(17.21)	(17.01)
Percent 0-24 months	0.47	0.44	0.42	0.44
	(0.50)	(0.50)	(0.49)	(0.50)
Percent 0-36 months	0.67	0.65	0.62	0.65
	(0.47)	(0.48)	(0.49)	(0.48)
Female Child = 1	0.50	0.48	0.49	0.49
	(0.50)	(0.50)	(0.50)	(0.50)
Birth Order (BO)	3.74	2.38	3.17	3.05
	(2.49)	(1.60)	(2.31)	(2.29)
Percent BO = 1	0.21	0.35	0.27	0.29
	(0.40)	(0.48)	(0.44)	(0.46)
Percent BO = 2	0.19	0.30	0.23	0.24
	(0.39)	(0.46)	(0.42)	(0.43)
Percent BO >2	0.61	0.34	0.50	0.47
	(0.49)	(0.47)	(0.50)	(0.50)
Any Older Brother	0.64	0.41	0.55	0.53
	(0.48)	(0.49)	(0.50)	(0.50)
Illiterate mother	0.47	0.37	0.25	0.12
	(0.50)	(0.48)	(0.44)	(0.33)
Percent Primary Educ (mother)	0.33	0.14	0.28	0.43
	(0.47)	(0.35)	(0.45)	(0.50)
Percent Secondary Educ (mother)	0.18	0.40	0.36	0.34
	(0.38)	(0.49)	(0.48)	(0.47)
Percent Higher Educ (mother)	0.02	0.09	0.11	0.11
	(0.15)	(0.28)	(0.31)	(0.31)
Mother's Age (Yrs)	28.88	26.53	28.18	28.46
	(6.87)	(5.11)	(6.50)	(6.80)
Urban = 1	0.26	0.27	0.44	0.57
	(0.44)	(0.44)	(0.50)	(0.49)
N	522968	317888	88673	166385

All DHS surveys are included here

In the analysis of the Indian Enigma, we use data from the following countries: India, Cameroon, Chad, Congo, Dominican Republic, Ethiopia, Ghana, Guinea, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Namibia, Niger, Nigeria, Rwanda, Sao Tome, Senegal, SierraLeone, Tanzania, Uganda, Zambia, Zimbabwe. For the economic growth analysis, we use data from all the countries listed above and include Armenia, Bangladesh, Benin, Bolivia, Brazil, Burkina Faso, Burundi, Cambodia, Colombia, Egypt, Guatemala, Haiti, Jordan, Kenya, Morocco, Mozambique, Pakistan, Peru and Turkey. Only Sao Tome is not included in this part of the analysis.

Table B2: DHS Sample Information

	(1) Africa	(2) India	(3) Asia	(4) Latin America
Number of countries	30	1	6	7
Number of surveys	107	4	21	28
DHS Interview Year (range)	1986-2014	1992-2016	1990-2013	1986-2013
Birth Years(range)	1982-2013	1989-2015	1986-2012	1982-2013
N	522968	317888	88681	166385

All DHS surveys are included here, Asia excludes India

B.2 Variable Definitions

Children's height and age are converted to HAZ using the 2005 WHO standards. As per the WHO recommendations, anthropometry scores between -6 and 6 are considered valid and only children with valid scores have been included in the analysis

Age: The DHS collates age in months as the difference between the interview year and month and the child's birth year and month. We use this information to identify the child's age in months. Any value greater than 59 is considered as missing in our analysis.

Cohort (age): Children who are between 0 to 12 months in age, are considered as belonging to the cohort of age 0. Children who are between 12 to 24 months, belong to the cohort of age 1. Children who are between 24 to 36 months, belong to the cohort of age 2. Children who are between 36 to 48 months, belong to the cohort of age 4. Children who are between 48 to 60 months, belong to the cohort of age 5

Rate of loss of HAZ: Refers to how much more slowly a child is growing relative to the WHO reference median child. It measures the monthly rate of loss of standard deviations relative to the reference population of children (x100)

Modal Birth Year: This is the modal value of birth year of the child in a particular age cohort an particular survey during the DHS interview. It is calculated as the difference between the DHS interview year and the cohort age of the child (in years)

GDPpc in birth Year(natural log): This value contains the modal value of the (log) GDP values during the birth year of the child in a particular cohort. The value is assigned by the country and the birth year of the child.

Urban: The defacto residence of the person when they are interviewed. It is defined based on whether the cluster within which the individual was sampled was classified as urban or rural.

Female: This captures whether or not the child is a girl. This information collated from mother's birth history in the DHS surveys. Birth order: It is the order in which the child is born. An older child is assigned a lower number and a younger child has a higher birth order.

Mother education: This is a categorical variable that classifies women as being illiterate, having primary education (1-5 years), having some secondary education(6-10 years) or higher education(>10 years). Using this, we create dummy variables for each category.

Mother's Age (Yrs): This is the number of years of age a respondent has completed. It is self-reported when respondents don't recall birth dates. If respondents report an age less than their completed age, the numbers are rounded up to maintain consistency with age calculations using date of birth.

C Additional Results: Indian Enigma

Table C1: India v. Africa (FE): Birth Order 1

	(1) Age 0 b/se	(2) Age 1 b/se	(3) Age 2 b/se	(4) All Ages b/se
India1	-38.28***			-46.64***
	(6.15)			(7.95)
India2		-39.10***		-37.23***
		(6.47)		(8.29)
India3			-38.73***	-36.34***
			(7.51)	(8.68)
N	41078.00	41696.00	38937.00	125517.00
r2	0.04	0.09	0.10	0.15

Regressions weighted by transformed sample weights such that surveys have equal weight. Controls include lifespan fixed-effects, maternal age and education, child's gender and child's age in months (linear within age in years).

Table C2: India v. Africa (FE): Birth Order 2

	(1) Age 0 b/se	(2) Age 1 b/se	(3) Age 2 b/se	(4) All Ages b/se
India1	-40.37***			-56.68***
	(5.37)			(7.49)
India2		-42.64***		-46.75***
		(6.27)		(7.56)
India3			-40.66***	-43.92***
			(7.22)	(8.92)
N	35827.00	36638.00	34519.00	110042.00
r2	0.05	0.07	0.09	0.17

Regressions weighted by transformed sample weights such that surveys have equal weight. Controls include lifespan fixed-effects, maternal age and education, child's gender and child's age in months (linear within age in years).

Table C3: India v. Africa (FE): Birth Order 3

	(1) Age 0 b/se	(2) Age 1 b/se	(3) Age 2 b/se	(4) All Ages b/se
India1	-53.20***			-56.20***
	(5.93)			(8.37)
India2		-55.50***		-56.21***
		(6.89)		(9.35)
India3			-48.34***	-56.04***
			(7.98)	(10.95)
N	76451.00	74667.00	71000.00	229197.00
r2	0.05	0.06	0.04	0.15

Regressions weighted by transformed sample weights such that surveys have equal weight. Controls include lifespan fixed-effects, maternal age and education, child's gender and child's age in months (linear within age in years).

Table C4: Intercept and Slope Regressions by Birth Order

	BO1		BO2		BO3	
	alpha b/se/bse	beta b/se/bse	alpha b/se/bse	beta b/se/bse	alpha b/se/bse	beta b/se/bse
India	-22.9***	0.47	-27.5**	0.11	-43.5***	-0.097
	(5.64)	(0.59)	(8.10)	(0.55)	(6.52)	(0.45)
	[6.94]	[0.42]	[7.05]	[0.43]	[6.60]	[0.43]
Mean	-26.8	-7.1	-9.2	-8.2	-10.3	-8.7
r2	0.11	0.04	0.12	0.02	0.18	0.04
N	760	760	708	708	860	860

Robust standard errors clustered at the country level for 41 countries
Analytic cluster standard errors in ( ), 2-stage Bootstrap SE in [ ]

D Additional Results: GDP per capita

Table D1: GDP in Year of Birth (Disaggregated)

	(1) HAZ b/se	(2) HAZ b/se	(3) HAZ b/se	(4) HAZ b/se	(5) HAZ b/se	(6) HAZ b/se
age0GDP	10.5					9.1
	(7.7)					(7.9)
age1GDP		20.9***				19.0**
		(6.9)				(7.2)
age2GDP			38.2***			38.9***
			(8.4)			(8.3)
age3GDP				31.2***		33.1***
				(7.9)		(7.7)
age4GDP					16.1*	17.3**
					(8.3)	(8.3)
Country	X	X	X	X	X	
Lifespan	X	X	X	X	X	X
Controls	X	X	X	X	X	
Country-Age						X
r2	0.023	0.050	0.064	0.067	0.070	0.048
Obs	234883	211875	201634	194322	168662	1011376

Ordinary Least Squares, * 0.10 ** 0.05 *** .01

All Controls Included

Standard errors clustered at the country level

Table D2: GDP in Year of Birth (Simultaneous)

	(1) HAZ b/se	(2) HAZ b/se	(3) HAZ b/se	(4) HAZ b/se
Age 0	-0.5	0.5	4.1	9.1
	(5.7)	(6.3)	(6.4)	(7.9)
Age 1	18.2**	22.1***	23.1***	19.0**
	(7.0)	(5.9)	(6.8)	(7.2)
Age 2	27.8***	41.1***	31.0***	38.9***
	(7.0)	(7.9)	(6.9)	(8.3)
Age 3	24.1***	35.3***	27.9***	33.1***
	(7.3)	(7.3)	(7.0)	(7.7)
Age 4	20.8***	20.3***	25.1***	17.3**
	(7.5)	(7.1)	(6.8)	(8.3)
Urban	27.9***	28.0***	28.0***	28.0***
	(3.2)	(3.2)	(3.2)	(3.2)
Mat. Age	0.9***	0.9***	0.9***	0.9***
	(0.10)	(0.09)	(0.10)	(0.09)
Female	13.0***	13.0***	13.0***	13.0***
	(1.5)	(1.5)	(1.5)	(1.5)
Sample Mean	-144.93	-144.93	-144.93	-144.93
FE	X	X		
Country	X		X	
Country-Age		X		X
Lifespan			X	X
r2	0.115	0.048	0.116	0.048
Obs	1011376	1011376	1011376	1011376

Ordinary Least Squares, * 0.10 ** 0.05 *** .01

All Controls Included

Clustered at the country level

Table D3: Rate of HAZ Loss and GDP

	OLS		Between		Within		DnD	
	Alpha b/se/bse	Beta b/se/bse	Alpha b/se/bse	Beta b/se/bse	Alpha b/se/bse	Beta b/se/bse	Alpha b/se/bse	Beta b/se/bse
GDP	10.1^{+}	1.62^{***}	10.1^{+}	1.60^{***}	35.2^{**}	1.79^{*}	9.21	1.98^{**}
	(5.35)	(0.32)	(5.29)	(0.32)	(11.6)	(0.71)	(10.4)	(0.64)
	[5.19]	[0.34]	[5.12]	[0.34]	[13.8]	[0.83]	[13.8]	[0.85]
Mean	-20.6	-7.7						
r2	0.05	0.31	0.11	0.32	0.10	0.07	0.23	0.10
N	156	156	156	156	156	156	156	156

Robust standard errors clustered at the country level for 41 countries

Analytic cluster standard errors in ( ), 2-stage Bootstrap SE in [ ]